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Research Article

Applying Hierarchical Mapping Techniques to the Study of Interpersonal Communication: Descriptive Features of the Social Network

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Abstract: Social networks remain a relatively understudied topic in the field of interpersonal communication. As such, the hierarchical mapping technique (HMT) can help shed light on the levels of closeness that people share with their network members. For interpersonal, organizational, and family communication researchers, this gap is tremendously important, as uncovering trends in relationship closeness is pivotal to understanding the individuals/roles/relationships that bear the most weight in a person's life. The present study utilized HMT to explore which type(s) of relationships people believe are closest to them, as well as which people are mildly close and also rather distant. Results demonstrated that most people consider their parents, siblings, children, best friends, and roommates as first-tier network members. Common second-tier relationships included cousins, aunts/uncles, friends, and non-biological siblings. Common third-tier relationships included patrons, acquaintances, neighbors, and idols. Moreover, there were statistical similarities across a variety of network relationships, indicating that there is substantial variance in the sorts of relationships that people typically consider close, interpersonal, and distant. Results are discussed in terms of both theoretical and methodological significance.

***Keywords*: social networks, relationships, research methods**

1. Introduction

The field of interpersonal communication is saturated with studies, theories, and methodologies related to close relationships (e.g., Afifi & Robinson, 2014; Brisini, 2022; Mason & Carr, 2022). Far less interest has been placed on the social networks (individual and shared) that surround these partnerships. These network members are important to consider because myriad research shows that network members intentionally attempt to alter the trajectory of close interpersonal relationships (Parks & Adelman, 1983; Sprecher, 2011). Moreover, the members of a romantic dyad notice and place substantial weight on the nature of these interruptions (Knobloch & Donovan-Kicken, 2006; Stein et al., 2020).

As communication research begins to uncover the role that social networks (and their members) hold over dyadic partnerships, several important areas of study emerge. Historically, most dyad-network research has assessed the network as a single unit (see Parks et al., 1983; Sprecher & Felmlee, 2000; Stein, 2021). Attempts to quantify a person's

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social network have either focused on the elements that characterize a person's network (Surra, 1988) or explored how a person's full network influences their relationship progression (see Murphy et al., 2020; Stein & Davidson, 2019). Recent efforts in the study of social network interaction usually focus on computer-mediated communication (Sinanan & Gomes, 2020; Sutcliffe et al., 2018), or specific in-groups to explore how culture and identity alter the nature of a social network (González-Rivera et al., 2019; Pan, 2018). Alternatively, the aim of this study is twofold. First, we seek to develop a better understanding of the typical size of a person's network, as well as which relationship types most commonly appear within that network. Second, we wish to uncover which relationship(s) are usually self-reported as the closest.

1.1 *Understanding the social network*

One of the difficulties in defining a social network relates to the variety of relationship types that qualify for membership (e.g., Shinn et al., 1984). This is because the size of a person's network is directly linked to the number and type of relationships in a person's life. Hill and Dunbar (2003) characterized a network member as someone with whom a person has a general affinity and hopes to continually interact. Terms such as *kin* (Parks & Adelman, 1983) have been used to help participants identify network members, whereas other studies have explicitly asked people to identify friends and family (e.g., Felmlee, 2001). By this understanding, there is a finite but voluminous number of relationships that could fall under the category of "social network member."

Another way to conceptualize the social network is by defining its characteristics, rather than locating specific relationship types. Surra (1988) revealed five key elements of a social network: size (total number), density (closeness within), clustering (the number of sub-groups vis-à-vis the total number of members), reachability (the extent to which a member can actually be interacted with), and overlap (the number of shared members within a network). This perspective allows researchers to speculate which relationships are most relevant to a person's social network. For this study, we are most interested in size, density, and clustering. Although reachability and overlap are important elements of the network, the tool implemented in this study is not designed to gauge these two network features.

One issue in measuring the network is evaluating size vis-à-vis clustering and density. For example, Hill and Dunbar (2003) determined that people have an average network of approximately 124 members by tracking to whom people sent holiday cards. However, it is likely that close relationships were present in only a small percentage of those reported relationships. Alternatively, when asked to consider people with whom their participants lived, contacted "with varying degrees of frequency," relied on for advice, and considered biological/extended family, Dunbar and Spoors (1995) found that the average network size was between 11 and 12. Additional research has estimated that the network size is roughly 20 people per individual (see Lev-Ari, 2018; Stiller & Dunbar, 2007). As such, the means through which the "social network" is explicated and operationalized is of the utmost importance if researchers are interested in learning about the average size, density, and clustering of the social network.

As illustrated above, different disciplines and paradigms provide distinct wrinkles in their respective definitions and measures of the social network. In other words, the definition of a network is directly linked to the way(s) in which that network is operationalized. The size, density, and clustering of networks are all elements of their defining features. For interpersonal communication scholars, defining the network is best understood as a series of interdependent and, at times, intertwining interchain sequences (Stein, 2019). Therefore, the first goal of this study is to estimate the average network size and explore which relationship types are most commonly reported when people are asked to identify their "social network members." Two hypotheses (Hs) address these simple, but important queries.

H1: Participants will report an average network size between 11 and 20

H2: Participants will report on friendships, family members, community members, and co-workers when describing their social networks.

1.2 *Hierarchical mapping techniques*

One tool that researchers can use to distinguish the relationships with a social network is called the hierarchical mapping technique (HMT; Antonucci, 1986). This technique asks participants to draw a series of circles, the centermost representing them (i.e., the bullseye), and each surrounding circle representing a different tier of their social network (see Figure 1). Extant work has shown that HMT can help explain the types of attachments that people share with their network members (Rowe & Carnelley, 2005), explore discrepancies between perceived and actual network qualities (McCarty et al., 2007), and help differentiate which network members are trusted with end-of-life interactions (Canaway et al., 2019). Both social and clinical sciences have employed HMT to better understand the nature of human interaction; however, interpersonal communication has yet to adopt HMT as a method for understanding the specific people that comprise a social network. It is necessary to parse the makeup of the social network as a means of learning which extradyadic relationships are most likely to impact relational development.

Thus, the second goal of this study is to employ HMT as a way of better understanding the size, density, and clustering within people's networks (Surra, 1988). In other words, we are interested in uncovering which self-reported network relationships are the closest. Previous literature has documented that network members can indeed hold sway over a couple's relationship (see Knobloch & Donovan-Kicken, 2006; Sprecher, 2011). Using Surra's (1988) conceptualization of the network, it is reasonable to speculate that certain relationships within a social network (i.e., those with high levels of clustering and density) hold more influence than others. Uncovering which relationships within a social network are typically the closest will allow future researchers to compare the influence of varying network tiers. Our research questions (RQs) address this initial area of inquiry.

RQ1a: Which relationship types are typically included in a person's innermost tier?

RQ1b: Which relationship types are typically included in a person's middle tier?

RQ1c: Which relationship types are typically included in a person's outermost tier?

RQ1d: Which relationship types (if any) appear with similar regularity across multiple tiers?

2. Method

2.1 *Participants*

Data were collected from a large, Southwestern university and were comprised of 254 individuals (95 men). Most participants were Caucasian (*n* = 168); however, other ethnicities included Asian (*n* = 27), Latinx (*n* = 23), Mixed race (*n* = 15), African American (*n* = 13), and "other" (*n* = 8). To qualify, participants must have been at least 18 years old (M_{age} = 25.35, *SD* = 8.94) and have been in a committed romantic and/or sexual relationship (M_{length} = 3.81 years, *SD* = 5.99) at the time of data collection. There were various types of relationships reported by participants including seriously dating (*n* = 117), married, engaged, or in a civil union (*n* = 51), friends with benefits (*n* = 47), casually dating (*n* = 35), and "other" (*n* = 4). Moreover, most participants were heterosexual (*n* = 221); however, bisexual (*n* = 16), homosexual (*n* = 9), and "other" (*n* = 8) orientations were also reported.

2.2 *Procedure*

As part of a larger, online, self-report survey on romantic relationships and social networks, participants were asked to view the image displayed in Figure 1. Only data from the HMT analysis were used in this study; however, numerous self-report questions that inquired about participants' romantic relationships were included in this survey. Those data are not used in this report. Upon viewing the image, participants were given the following prompt:

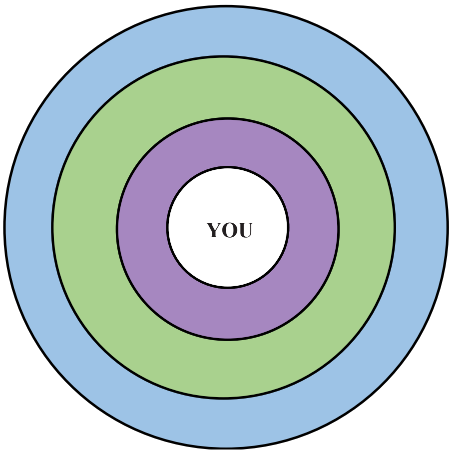
> Throughout the remainder of this survey, we want to ask you about your social network. **NOTE: WE ARE NOT ASKING YOU ABOUT YOUR USE OF SOCIAL MEDIA (e.g., Facebook, Twitter, Instagram, etc.)**. Our social network members are those people with whom we generally enjoy spending time with and expect to see relatively frequently. Please do not include [your partner] in any of these answers. Consider the following picture:
>
> We understand that some of the people in your social network are closer than others. In this first section, we want to find out about the people who are the closest to you, and whom you cannot live without. Please consider the [first] circle as you think of these people.

A series of boxes were displayed below the picture displayed in Figure 1, each with a corresponding relationship type (e.g., parent/caregiver, cousin, best friend, etc., for a full list of choices, see Appendix A). Once a box was selected, participants were instructed to write the initials of the person with whom they held that relationship. Participants were allowed to include as many sets of initials as desired, separated by commas. Moreover, there was no limit to the number of boxes that a person could select. Participants who could not find their desired relationship types were invited to select "other" and write in the relationship type that was missing. Participants were asked to avoid listing their partners because, traditionally, people make categorical and conceptual distinctions between their significant others and their social network members (Murphy et al., 2020; Sprecher, 2011).

Next, participants were shown Figure 1 a second time and given the following prompt:

> Now consider the [second] circle. These are the people that you might not feel as close with but are still important to you. NOTE: We understand that for some people, one roommate (for example) might fall into the [first] circle, and a different roommate might fall into the [second]. This is okay, feel free to select the same relationship categories as you did for the [first] circle, as long as you are talking about a different person for each one.

Finally, participants were asked to complete the same procedure for the outermost circle (see Figure 1). Throughout the remainder of a larger survey, individuals were asked questions about each of the three circles and were presented with prompts displaying the initials of those in question using piped text.



Note: Participants were asked to "refer to the _____ colored circle" when determining which network members populated which tier.

Figure 1. Visual representation of the three circles presented to participants during data collection

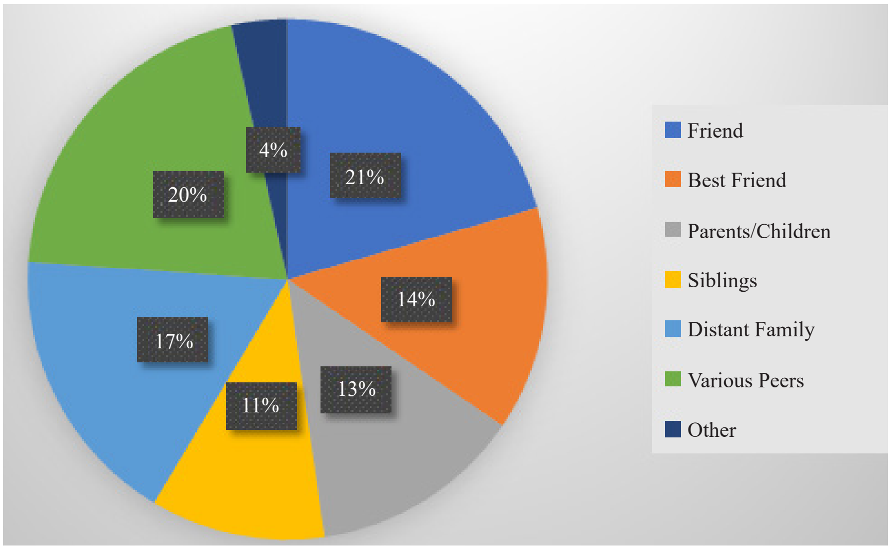
2.3 *Results*

The 254 participants in the study reported on *N* = 3,753 network members, an average of 14.78 (*SD* = 3.17) network members per person, not including romantic partners. This initial report appropriately answers H1. To answer H2, we observed the types of reported network relationships and explored what percentage of the total sample each relationship type represented. A total of 16 relationship types were reported. In descending order, relationships included friends (*n* = 772, 20.57%), best friends (*n* = 523, 13.94%), parents/caregivers (*n* = 447, 11.91%), biological siblings (*n* = 320, 8.53%), aunts/uncles (*n* = 299, 7.97%), cousins (*n* = 286, 7.62%), co-workers (*n* = 284, 7.57%), roommates (*n* = 171, 4.56%), peers (*n* = 155, 4.13%), acquaintances (*n* = 89, 2.37%), non-biological siblings (*n* = 88, 2.34%; see Appendix A for full typology of non-biological siblings), people of reverence (*n* = 86, 2.29%), in-laws (*n* = 71, 1.89%), neighbors (*n* = 68, 1.81%), children (*n* = 49, 1.31%), and patrons (*n* = 45, 1.20%). None of the participants in this study listed an "other" member of their social network. These results provide an adequate answer to H2. Table 1 details the frequencies and percentages of each relationship type vis-à-vis the total sample, and Figure 2 provides a visual representation of these data.

Table 1. Frequency and percentage of each relationship type in descending order

Relationship Type	*n*	% of *N*
Friend	772	20.57%
Best Friend	523	13.94%
Parent/Caregiver	447	11.91%
Bio-sibling	320	8.53%
Aunt/Uncle	299	7.97%
Cousin	286	7.62%
Co-worker	284	7.57%
Roommate	171	4.56%
Peer	155	4.13%
Acquaintance	89	2.37%
Non-bio-sibling	88	2.34%
Person of Reverence	86	2.29%
In-law	71	1.89%
Neighbor	68	1.81%
Child	49	1.31%
Patron	45	1.20%
Total	3,753	100%

Note: Answers reported by 254 participants, for an average network size of 14.78 people per respondent, not including romantic partners. *N* is used to refer to the total number of participants/responses in this study, whereas *n* is used to distinguish sub-groups within that total sample.



Note: Percentages have been rounded and categories have been compressed from 16 to seven. Full results can be viewed in Table 1.

Figure 2. Relationship types identified during analyses

The final research questions explored the different frequencies with which certain relationship types appeared in certain tiers. Said differently, we wanted to explore which relationship types are most likely to be in someone's inner, middle, and outer tiers. To answer this question, the data needed to be unitized, such that each individual response (i.e., each listed set of initials) counted for a tally in the appropriate tier. From there, the data were counted manually to observe the frequency and percentage with which each relationship type appeared within each tier. To determine which relationships were "common" in each tier, we utilized the first-principles approach (see Irwin, 1988; Jonsen, 2022), wherein previous approaches to solutions/categorizations (or in this case, a lack of previous approaches) are foregone in favor of allowing organic trends in the data to emerge. Given that no previous uses of HMT have attempted to categorize the "commonality" with which certain relationship types appear within certain tiers, the first-principles approach was deemed appropriate.

After unitizing the data and exploring the frequencies and percentages in which each relationship appeared within each tier, we decided to use a cutoff of 40%, meaning that if at least 40% of a given relationship type's total *n* appeared in one tier, it was considered common. For example, if "best friend" appeared 42% of the time in tier 1, 45% of the time in tier 2, and 13% of the time in tier 3, it would mean that the "best friend" is common in both tier 1 and tier 2 of participants' networks.

First, RQ1a asked which relationships commonly appear in participants' innermost tier. The most common relationships presented in this tier, in descending order, were parents/caregivers (n = 341, 76.29%), children (n = 36, 73.47%), biological siblings (n = 231, 72.19%), and best friends (n = 372, 71.13%). After a large drop-off, several other relationship types were still considered common, including: non-biological siblings (n = 40, 45.45%), roommates (n = 77, 45.03%), and patrons (n = 19, 42.22%).

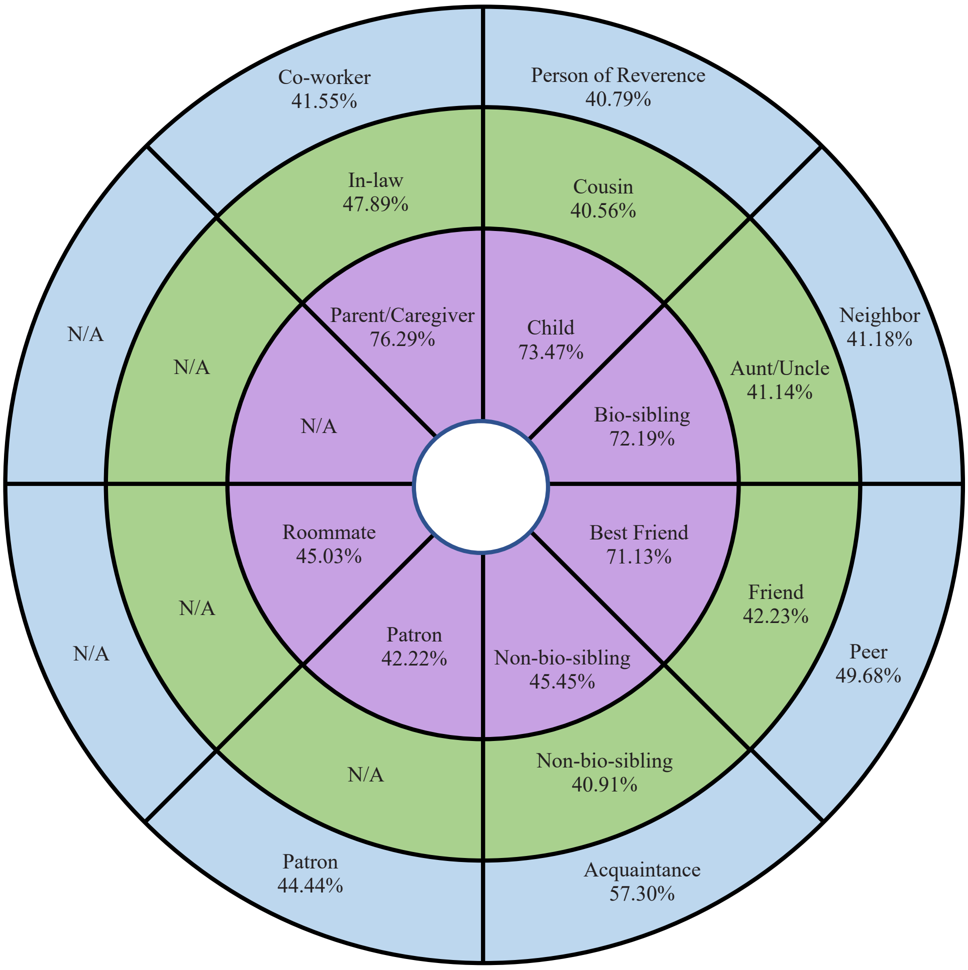
Second, RQ1b asked which relationships are commonly represented in participants' middle tier. Unlike the tier 1, there were no overwhelmingly common answers; however, a number of categories reached the threshold for commonality, including: in-laws (n = 34, 47.89%), friends (n = 326, 42.23%), aunts/uncles (n = 123, 41.14%), non-biological siblings (n = 36, 40.91%), and cousins (n = 116, 40.56%).

Third, RQ1c asked which relationship types commonly fall in participants' outermost tier. Similar to the tier 2, there were no overwhelmingly common responses; however, there were several common categories, including: acquaintances (n = 51, 57.30%), peers (n = 77, 49.68%), patrons (n = 20, 44.44%), co-workers (n = 118, 41.55%), neighbors (n = 28, 41.18%), and people of reverence (n = 35, 40.70%). To sum up, all 16 relationship categories were considered common in at least one of the three tiers. Table 2 displays how each common relationship is represented in each tier and Figure 3 provides a visual representation of these data.

Table 2. Representation of relationship types in each tier of participants' networks

Relationship Type	*n*	% of *N*
	Tier 1	
Parent/Caregiver	341	76.29%
Child	36	73.47%
Bio-sibling	231	72.19%
Best Friend	372	71.13%
Non-bio-sibling*	40	45.45%
Roommate	77	45.03%
Patron*	19	42.22%
	Tier 2	
In-law	34	47.89%
Friend	326	42.23%
Aunt/Uncle	123	41.14%
Non-bio-sibling*	36	40.91%
Cousin	116	40.56%
	Tier 3	
Acquaintance	51	57.30%
Peer	77	49.68%
Patron*	20	44.44%
Co-worker	118	41.55%
Neighbor	28	41.18%
Person of Reverence	35	40.70%

Note: For this table, *n* represents the total % of each relationship category. In order to be considered a common occurrence, at least 40% of all responses need to have fallen in a given tier. As such, it is possible for a relationship to be common in more than one tier simultaneously. Relationships that populate multiple tiers are marked with asterisks. In this table, *N* represents the total number of each relationship type.



Note: Both *patron* and *non-bio-sibling* appear twice in this figure, as each category was represented in multiple tiers with relative similarity.

Figure 3. Visual representation of the relationship types that appeared in each tier of participants' networks

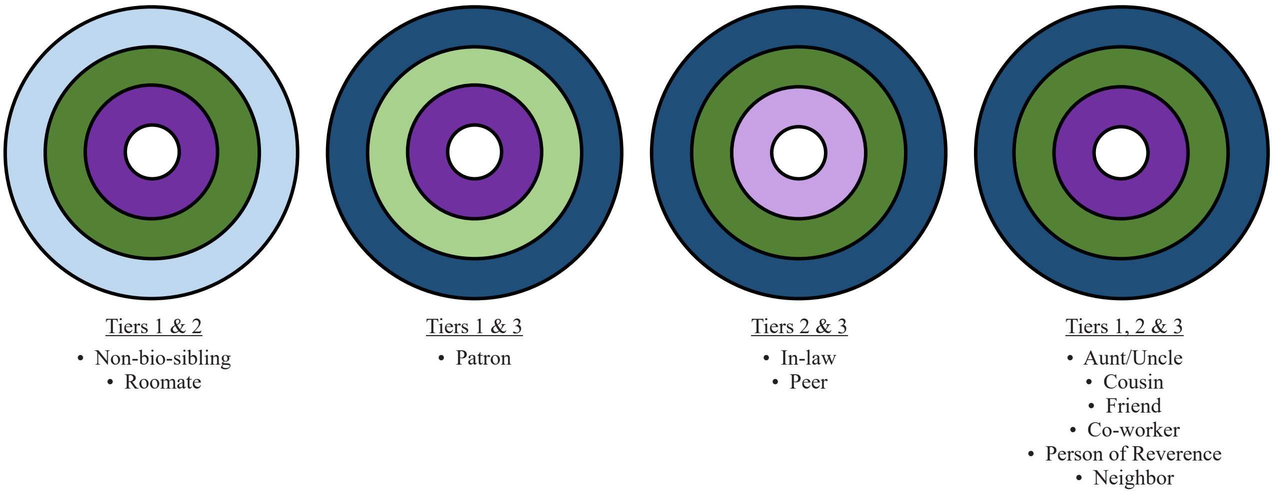
The final question (RQ1d) inquired about which relationship types appeared with similarities across multiple tiers. To answer this, we once again took a first-principles approach. Ultimately, this resulted in a 20% cutoff with a x2 caveat — in that any relationship category that appeared in at least two tiers with 20% would be thought to appear in those two circles with relative similarity, so long as one percentage did not exceed 2x the size of any other. For example, "best friends" appeared in tier 1 with 71.13% of all responses. "Best friends" appeared in tier 2 with 22.34% of all responses; however, because the percentage in tier 1 is more than double the percentage of tier 2, we did not consider "best friends" as appearing in these two tiers at a similar rate.

Relationship types that appeared in both the first and second tier with relative similarity were non-biological siblings (45.45% and 40.91%, respectively) and roommates (45.03% and 32.75%, respectively). Only patrons appeared in both the first and third tiers with relative similarity (42.22% and 44.44%, respectively). Relationship types that appeared in both the second and third tier with relative similarity were in-laws (47.89% and 32.39%, respectively) and peers (27.10% and 49.68%, respectively). Finally, aunts/uncles (34.11%, 41.14% and 24.79%, respectively), cousins (25.66%, 40.56% and 23.78%, respectively), friends (25.13%, 42.23% and 32.64%, respectively), co-workers (26.76%, 31.69% and 41.55%, respectively), people of reverence (31.40%, 27.91% and 40.70%, respectively), and neighbors (29.41%, 29.41% and 41.18%, respectively) appeared across all three tiers with relative similarity. The results of RQ1d are illustrated in Table 3 and Figure 4 provides a visual representation of these data.

Table 3. Relationship types that appear in multiple tiers with relative similarity

Relationship Type	% of responses in first tier	% of responses in second tier	% of responses in third tier
		Tiers 1 and 2	
Non-bio-sibling	45.45%	40.91%	N/A
Roommates	45.03%	32.75%	N/A
		Tiers 1 and 3	
Patron	42.22%	32.39%	N/A
		Tiers 2 and 3	
In-law	47.89%	32.39%	N/A
Peer	27.10%	49.68%	N/A
		Tiers 1, 2 and 3	
Aunt/Uncle	34.11%	41.14%	24.79%
Cousin	25.66%	40.56%	23.78%
Friend	25.13%	42.23%	32.64%
Co-worker	26.76%	31.69%	41.55%
Person of Reverence	31.40%	27.91%	40.70%
Neighbor	29.41%	29.41%	41.18%

Note: In order to be considered a category appearing in more than one group with similarity, a relationship must represent at least 20% of responses in a given tier without any one tier having a percentage equal to or over twice as much as any other percentage.



Note: Darkened colors indicate the tiers being referenced in each visual representation. Percentages are not shown in this figure. Full results and percentages can be viewed in Table 3.

Figure 4. Visual representation of relationship types that appear in multiple tiers with relative similarity

3. Discussion

The goal of this investigation was to use HMT to explore the size, density, and clustering of individuals' social networks (Surra, 1988). The results of our investigation detailed a number of descriptive elements of participants' networks. Below, we offer a methodological discussion of our findings, as well as some potential future directions for HMT research in the study of human communication

3.1 *Defining the network*

First, it is worth noting that the average network size in this investigation was just under 15 people, not including romantic partners (H1). This number is substantially larger than the estimates in some studies (see Dunbar & Spoors, 1995; Hill & Dunbar, 2003), but lower than other studies (see Lev-Ari, 2018; Stiller & Dunbar, 2007). This may be partly because most participants in this study were college-aged. Previous data suggest that network size tends to shrink with age (Röhr et al., 2020). Thus, further use of HMT is needed to explore network size both prior to and after college. Importantly, this result did not include the romantic/sexual partners of participants, of which each respondent had at least one. We were specific not to ask our sample to include their partners in this study, as foundational research has largely deemed a person's partner as both conceptually (Felmlee, 2001; Sprecher, 2011) and empirically (Knobloch & Donovan-Kicken, 2006; Parks et al., 1983) distinct from other network members in terms of their influence on relational cognition.

In addition to size, we also wondered if there are a finite amount of relationship types that appear in people's social networks (H2). Although likely not exhaustive, our results discovered 16 types of relationships, 18 if researchers wish to split the three types of non-biological siblings. Shinn and colleagues (1984) expressed difficulty in properly defining the social network. Other studies have lumped all network members into one large, encompassing group (e.g., Parks & Adelman, 1983; Sprecher & Felmlee, 2000; Stein et al., 2020). Our results illuminate more accurate and specific options for researchers in their defining and categorizing of people's social networks.

3.2 *Assessing network ties*

The second goal of this study was to explore which relationships were most prevalent in people's inner (RQ1a), middle (RQ1b), and outer (RQ1c) network circles. We found this question particularly important due to the recent calls for a better understanding of which types of members are most commonly thought of when people consider their "social networks" (Sprecher, 2011; Stein, 2021), as well as which relationship types are the most impactful on relationship perceptions (Murphy et al., 2020; Stein & Davidson, 2019). Overwhelmingly, immediate biological family members and best friends populated the innermost tier (RQ1a; see Table 1). Non-biological siblings, roommates, and patrons/customers also appeared in this circle, although far less frequently. This trend suggests that a person's innermost network connections are usually relatively similar at the top, but can include a variety of relationships.

In regard to RQ1b, another distinct trend emerged in that secondary biological family and non-best friends were the most commonly represented in the second tier. The data answering RQ1c expressed a third clear pattern in that familiar, but not intimate, associates populated the outer tier. It is worth noting that none of the relationships identified in the second or third circle reached 50%. This implies that, unlike the inner circle, the middle and outer circles are a bit less defined, structured, and consistent. One explanation for these findings is that the dynamism of a person's less intimate network relationships creates a scenario in which certain people are shifting in, out, and between the second and third tiers over time. Hill and Dunbar (2003) speak to this dynamism in their efforts to define the network.

This line of thought is backed by our findings related to RQ1d. Indeed, 11 of the 16 relationship types appeared in multiple network tiers with relative similarity, with seven of them appearing across all three tiers. Notably, parents/caregivers, children, best friends, and biological siblings, which dominated people's innermost tiers, did not appear with regularity in either of the other circles. This clear trend demonstrates that for most people, those highly intimate relationships are static in their place of importance. This is valuable for emerging research on dyad-network interaction (e.g., Murphy et al., 2020; Stein et al., 2020), as it assuages some of the ambiguity surrounding which network members people consider the most influential in their lives and relationships.

Determining which network members tend to be closest (and least close) to people can be estimated using common sense; however, HMT offers participants the opportunity to craft their own networks, and then answer questions specifically about each network circle and the members in it. For example, the survey that these data were gathered from asked participants a series of Likert-style questions regarding the influence they feel their networks have on their romantic/sexual relationships. Using piped text, we specifically asked them to refer to the individuals that they marked as being in their inner tier. This technique allows future researchers to collect data specifically about the network members that are closest to a person, ultimately producing more rich, accurate data.

Whereas classic (e.g., Parks & Adelman, 1983; Sprecher & Felmlee, 2000) and contemporary (Solomon et al., 2016; Stein & Davidson, 2019) research has considered the network as a single entity, scholars using HMT can ask people to answer questions about their inner, middle, and outer network tiers to see how, if at all, network perceptions and influence differ. We strongly encourage these investigations.

3.3 *Measurement suggestions and future research*

The data from this study can inform ongoing and future research in three important ways. First, it is clear that HMT can be used in the study of interpersonal communication to explore existing theories that are linked to a person's (or couple's) social network. For example, Stein (2021) illustrated that network-based measures produce both direct and indirect effects within the tenets of relational turbulence theory (Solomon et al., 2016). Moreover, Stein and Bennett (2021) demonstrated that network-based measures partially mediate the associations outlined by the investment model (Rusbult et al., 2011). As such, it stands to reason that theories such as communication accommodation theory (Giles, 2016), communication privacy management theory (Petronio, 2010), and the theory of motivated information management (Afifi & Robinson, 2014), among others, can benefit from the inclusion of network-based measures and perspectives.

Second, HMT can be useful in uncovering a couple's duocentric (i.e., shared) network (Kennedy et al., 2015). It may be that when analyzed in conjunction with a partner, the parameters of a person's network change. For example, Stein and Bennett (2021) have tested for associations' self-reported measures of network overlap and levels of relationship satisfaction, investment, and commitment. Whereas HMT does not measure network overlap, coupling this tool with existing network overlap measures can paint a more complete picture of a couple's network. Moreover, using HMT with a duocentric perspective (see Kennedy et al., 2015) promotes the collection of dyadic data and allows couples to estimate their reachability, thus complementing the shortcomings of HMT. Both of these strategies are necessary to completely answer questions about how social networks influence the progression of close relationships.

Third, scholars must use HMT to compare how, if at all, people's perceptions of network influence vary based on tiers. We speculate that people will report higher means of network interference and facilitation (Stein & Davidson, 2019) when reporting on their inner tier, compared to their middle or outer tiers. Moreover, developing measures focused on dyad-network communication is predicated on a more complete understanding of which network members are most likely to communicate with a dyad and the members in it.

Our HMT results aid interpersonal communication studies in two ways. Researchers will have a clearer picture of the individuals in a person's network most likely to hold sway over personal decisions, relational cognitions, and everyday interactions. Moreover, future relational scholars will be able to survey and interview participants about specific network members, rather than forcing all potential network members together into a single, amorphous group.

3.4 *Limitations*

Like all methodological inquiries, this study features multiple limitations. The most glaring hurdle we faced in this project was an overly homogeneous sample. Specifically, age, ethnicity, sexuality, and life stage (i.e., college convenience sample) limit the generalizability of our findings. This should be remedied in two ways. First, additional homogeneous HMT studies should occur, exploring how distinct age groups (e.g., senior citizens, working adults, and children) differently (or not-so-differently) construct their networks. Second, a fully heterogeneous study using HMT is necessary. Together, these projects will paint a clearer picture of what the "average" social network looks like, as well as how networks appear in specific co-cultures.

Another important limitation of this study is its descriptive nature. No inferential statistics were run and as a result, we cannot make generalizations about populations. That said, the goal of this manuscript was to introduce and revive HMT as a method for communication research. Moving forward it is important to take this technique and couple it with advanced statistical analyses (e.g., multilevel modeling, advanced regression analyses, and latent profile analyses) to explore how the tiers of a person's social network have different, or similar, effects on his/her individual and relational perceptions.

Third, HMT only explores a portion of the understanding surrounding the definition and characteristics of the social network. For example, neither reachability nor network overlap (Surra, 1988) is gauged using HMT. Network interdependence (Stein, 2019) is not measured by HMT either. As such, it is necessary to couple HMT with other measures that gauge network makeup, such as duocentric data collection (Kennedy et al., 2015), network overlap (see Stein, 2021), and network interdependence (Stein & Davidson, 2019). Together, these measures can paint a more complete picture of the social network.

3.5 *Conclusion*

This study used HMT to explore the size, density, and clustering of our sample's social networks. We believe that our results are important for informing future relationship research, as well as for aiding in the ongoing definition of what a social network is and is not. In short, relationships do not occur within a vacuum. Our findings highlight the intricacies of the social network and provide a methodology for interpersonal communication scholars to use in data collections focused on exploring how people in close relationships balance their partners and network members. Moreover, HMT can and should be used to expand the scope of existing interpersonal theories, coupling it with extant network-based measures.

In short, this investigation aimed for clarity and specificity in the ongoing effort to define and probe what constitutes a person's social network. Interpersonal communication scholars studying how people in close relationships interact with their social network(s) need to understand who those people are most likely to interact with, and whom they consider closest to them. Solidifying these descriptive features is important for developing measures and theories that articulate how dyads (and the individuals in them) communicate with social networks (and their members).

Conflict of interest

The authors declare no competing interests.

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Appendix A

Full list of relationship types uncovered using HMT.

Relationship Type	*n*	% of *N*
Friend	772	20.57%
Best Friend	523	13.94%
Parent/Caregiver	447	11.91%
Bio-sibling	320	8.53%
Aunt/Uncle	299	7.97%
Cousin	286	7.62%
Co-worker	284	7.57%
Roommate	171	4.56%
Peer	155	4.13%
Acquaintance	89	2.37%
Person of Reverence	86	2.29%
In-law	71	1.89%
Neighbor	68	1.81%
Child	49	1.31%
Patron	45	1.20%
Half-sibling	42	1.12%
Step-sibling	30	0.80%
Adopted Sibling	16	0.43%
Total	3,753	100%

Note: Answers reported by 254 participants, for an average network size of 14.78 people per respondent.