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Dimensions of social networks: A taxonomy and operationalization

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Abstract

What are the basic types of social network ties captured by name generators? While there have been several classifications proposed, and a large proliferation of name generators capturing various tie content has emerged, there is no clear way to map a given name generator to a particular tie type. Building on previous research, this paper proposes a framework for doing so in a principled way based on two studies. Study 1 is a dimension reduction of 24 common name generators. We find two dimensions (Valence and Social Distance), three positive tie types (Admiration, Closeness, Socialize), and three negative tie types (Active Conflict, Passive Conflict, Contempt) and use Youden's J statistic as a metric to identify the name generator that best maximizes sensitivity and specificity for detecting our tie types. We find that the most common name generators used by researchers fall within just one tie type (closeness). Study 2 models these six tie types as predictors and outcomes of important sociological variables and finds that each tie type is associated with distinct patterns of emotions, social support, social status, and social roles. Our taxonomy makes a contribution to network theory as well as study design. In particular, it advances our understanding of the nature of signed ties. We find that negative ties are both bipolar and orthogonal, and distinguish between two types of ambivalence. Moreover, the findings contribute to the further refinement and elaboration of a comprehensive taxonomy of network ties.

Keywords: Name Generators, Taxonomy, Tie Types, Multiplex Ties, Dimension Reduction

"There are therefore three kinds of friendship... those who love each other [and] wish well to each other... those who love each other for their utility... those who love [each other] for the sake of pleasure...". [1] *There are three kinds of slighting – contempt, spite, and insolence."* [2]

- Aristotle

1. Introduction

Since the times of the Ancient Greeks, scholars have tried to identify the fundamental kinds of social relationships that entangle human beings, and to build theoretical understanding based on them. Early sociologists have followed this line of inquiry and proposed fundamental distinctions of relations such as Ferdinand Tonnies' ([1887] 1988) *gemeinschaft* and *gesellschaft*, Max Weber's ([1920] 2012) *associative* and *communal*, and Emile Durkheim's ([1893] 2013) *mechanical* and *organic*. With the advent of network science, the precision to measure and analyze social relationships has greatly increased. In tandem with this, there has been a proliferation of questions that aim to measure various kinds of ties, many of which are captured in name generator questions (McCallister and Fischer, 1978; Pescosolido et al., 2018).

This proliferation of name generators has been substantial. In one review, focusing on low and middle-income countries, researchers have found 105 name generators (Perkins et al., 2015). In another review, focusing on negative ties in the work organizations literature specifically, researchers have found 42 papers asking various negative tie name generator questions (Yang et al., 2019). Our own review of the name generator literature, reported in this paper, found 483 papers with 758 unique name generators. But despite the enormous number of different name generators in use, there is no broad agreement about how to classify or organize them vis-à-vis the latent constructs they capture.

The lack of such a classification is a potential problem for both theory development and study design. For theory development, there is the problem that our core categories – the tie types – are dependent on assumptions that largely remain untested. Many theories rely on classifications of ties such as strong ties/weak ties; friendship/advice; positive/negative; affective/instrumental – but these are largely *a priori* theoretical constructions. Our contention is not that these theories are "wrong" to use those classifications but that there is value to better ground the categories empirically as well as make them more precise. In the language of classification, most existing classifications of network ties are typologies (classifications based on conceptual distinctions), but not taxonomies (classifications emerging from empirical data). The risk is that the elaborate categories or distinctions that exist in the realm of ideas may not always map on well to the real world. For study design, there are the twin dangers of redundancy – having multiple name generators that essentially measure the same thing without realizing it – and incomplete data collection – where a missing name generator leaves out a relevant aspect of the social world.

In other fields, such classification issues are tackled using techniques of dimension reduction – cluster analysis, factor analysis, multidimensional scaling, and many other methods. These are widely used to analyze how a large number of items can be better understood as different instances of a small number of categories. But in social network analysis, data-reduction techniques for the purposes of systematic classification of ties are not widely used.

[1] Nicomachean Ethics, Book VIII, Chapter 13 (Aristotle, 2005, p. 100).
[2] Rhetoric, Book II, Part 2.(Aristotle, 2020, p. 55) The exact wording may differ based on the preferred translation from ancient Greek.

This is partly because researchers wanting to conduct dimension reduction of social network ties face a number of challenges. When conducting a survey, name generator questions have a high respondent burden: it takes respondents considerable time and effort to answer them (McCarty et al., 2007). Having many name generators on a survey can increase the cost of respondents and can lead to a decline in data quality[3]. Moreover, dimension reduction of network ties also has the problem that – when choosing analytical models – it is not obvious what types of dimension reduction are appropriate to social network data. This is because assumptions of independence of cases clearly do not hold, with ties being interdependent observations nested within egos, and there being no clear distribution from which the ties are drawn.

In this paper we put forward a methodological framework which, we believe, overcomes many of these constraints on previous research. The framework is based on Vörös & Snijders (2017) and takes advantage of the ability of online crowd-sourced respondents to generate high volumes of high-quality responses. Through designing short surveys – 10 minutes each – and using a factorial design, we are able to compare 24 name generators drawn from the literature, and do so without compromising response quality. We use this method to develop and validate a taxonomy of six tie types based on the 24 name generators. We do this in two studies.

Study 1 is a dimension reduction of 24 common name generators. Cluster analysis and multi-dimensional scaling is used to identify two dimensions (Valence and Social Distance) and six tie types: three positive (Admiration, Closeness, Socialize), and three negative (Active Conflict, Passive Conflict, Contempt). Study 1 ends with a sensitivity/specificity analysis, and the identification of the single best name generator for operationalizing each of the six tie types.

Study 2 takes these operationalized name generators and shows that the six different tie types are "distinctions with a difference" and have distinct correlations with relevant social outcomes such as social support, social influence, emotional distress, and several others. Thus the aim of the second study is to show, using the logic of criterion validity, that if these six tie types are indeed important and distinct categories of ties, then this should be readily apparent through each tie type having distinctly different predictors, and each tie type distinctly predicting different social outcomes of relevance.

The paper makes several contributions to network theory and study design. First, it expands the scope of network theory by showing that existing network research that uses name generators may be focusing on a relatively small part of a much larger terrain. For example, most of the common name generators in use such as "discuss important matters", "close friend", "in whom you confide", and "who you turn to for advice" fall in just one tie type, what we refer to as the Closeness tie type. It is characterized by positive valence, general intimacy, a degree of informality, and relatively low status differential between ego and alter. On the other hand, the taxonomy suggests that a neglected area of focus are the tie types that are differentiated along the social distance dimension. This dimension captures the extent of three mutually reinforcing characteristics of (in)formality, status difference, and friendship/acquaintanceship. For example, tie types that involve formal relations with high status differences are Admiration (positive) and Contempt (negative). Furthermore, our

[3] Name interpreters are a poor substitute because they do not allow one to add new alters, as they are restricted to the alters captured by the name generator.

taxonomy offers a distinction between three types of negative ties, whereas almost every other taxonomy focuses on positive ties. The tie types offer fruitful avenues to refine and expand network theory. The paper also makes a methodological contribution to study design by developing a framework to compare a very large number of name generators using a factorial design and to select among them using the Youden's J/Informedness metric.

In addition, the paper makes a contribution to several questions in the signed ties literature. Are positive/negative ties part of a single continuum (bipolar) or are they best conceptualized as independent of each other but not opposite (orthogonal)? We present evidence that supports both perspectives and explain how the two perspectives can be reconciled using our taxonomic model. Furthermore, we speak to the recent interest in ambivalent ties. Our taxonomy suggests that there are in fact two types of ambivalence – "strong tie ambivalence" and "weak tie ambivalence", each with their own implications for network research.

2. Literature Review

We begin by reviewing other research which has highlighted the need for a more systematic and empirically verified classification of ties. We then explain the difference between a typology and a taxonomy, and review previously published research on the typologies and taxonomies of ties. We end with a brief discussion of the characteristics of a good taxonomy, and briefly overview our analytical approach.

2.1 Name generators

Social tie data can be gathered in multiple ways - from qualitative techniques to unobtrusive data collection such as direct observation, archival coding, and digital tracing (Robins, 2015). Newer methods involve wearable sensors (Choudhury and Pentland, 2002) and smartphone apps that record interactions (Boonstra et al., 2017). However, one of the most common methods of tie collection is via survey instruments that contain a name generator question (Burt, 1984; Campbell and Lee, 1991; Marsden, 1990; McCallister and Fischer, 1978). This question asks the respondent to provide or select[4] the name(s) of persons to which the respondent has some relation or orientation. It has been called "the oldest, most frequently used, and best understood" tie generator tool (Pescolido et al 2018:68). Name generators can be used for both sociocentric and egocentric data collection (Robins, 2015, p96). However, they are more common in egocentric research, where they are considered "the standard method to enumerate networks and delineate network characteristics and structure" (Marin & Hampton 2007:163). Nonetheless, name generators are one of several ways to collect tie information and they have certain biases in terms of the ties they fail to capture such as weak ties or less frequent interactions (Bidart and Charbonneau, 2011; Marin, 2004). We discuss this further in the Limitations section (Section 7.6).

But despite its weaknesses, one of the advantages of the name generator approach, and a major reason we are interested in this particular method, is that it allows the researcher to control the kind of tie content that they are interested in capturing. Archival coding and digital tracing may be more comprehensive but the researcher is limited to what is available.

[4] For sociocentric (whole network) studies, where the researcher possesses a roster containing the members of the community or organization to be studied, the respondent is asked to select the names from the roster.

Data captured by wearable sensors that measure interactions are harder to disaggregate as a particular interaction may actually involve multiplex ties. And while the grist for our mill are the name generator questions, what we are interested in are the latent constructs that they capture.

2.2 What do name generators capture? The demand for a systematic classification of ties

In recent decades there has been a large proliferation of different name generator questions. Researchers focusing on network research in low and middle-income countries identified 105 distinct name generators used in just that literature (Perkins et al., 2015). While another research team reviewing the literature on negative ties in the work organizations context found 42 papers asking various negative tie name generator questions (Yang et al., 2019). Yet, despite this embarrassment of riches, there have been relatively few efforts to try to understand what latent construct of a tie type is being captured by the various name generators and how do they relate to one another. There are several theoretical and methodological advantages for developing such a systematic classification. From a theory building perspective, the key question is what set of properties does one type of tie have vis-à-vis another type of tie and what connects it to a given mechanism. So it is important to relate the tie types based on some dimension that explains how they differ. Some of the recent debates in the social network literature may also stem from a lack of clarity on what type of ties is fundamentally being captured by a particular name generator. For example, debates about the "important matters" name generator - one of the most prominent in the literature – shows that there is not a settled agreement about what type of ties our most established name generator captures, or even which alters it reaches and who it misses (Bearman & Parigi, 2004; Brashears, 2014; Small, 2013). Similarly, debates about whether signed ties are orthogonal (Offer, 2021; Yang et al., 2019) and the nature of ambivalent ties (Fingerman et al., 2004; Methot et al., 2017; Rothman et al., 2017) show that even questions of the most basic categorical distinctions - such as distinctions between positive ties and negative ties are not fully resolved.

For researchers designing studies, selecting the appropriate tie type can be tricky. Burt (1990, 1983) as well as Burt and Schott (1985) cautioned against making distinctions among tie content on an ad hoc manner as this makes equivocal research conclusions more likely. Borgatti et al (2014) advise the researcher to avoid theorizing tie types based on specific tie content, such as for example “friendship”, “gossip”, or “advise”, as that will make network theory overly complex (ibid:11).

Moreover, many primers on network research advise researchers to carefully think about the types of ties they want to collect given their research question, before they select a name generator (see for example, Agneessens and Labianca, 2022; Borgatti et al., 2018; Crossley et al., 2015; Robins, 2015). However, the psychometric properties of name generators are often not available, particularly ones used in sociocentric research; and in practice it is far from clear what criteria will select a good name generator(s). Other researchers have pointed out how the selection of appropriate name generators has received “surprisingly little systematic study” (Burt et al., 2012, p. 1). A systematic empirical classification of ties would help with such decisions.[5]

[5] For our paper we are interested in reducing many different name generators to identify ones that best capture a particular underlying tie. However there are some circumstances where the goal might be to identify many name generators to capture the same underlying tie. For example, small team research in which the network is small and respondent fatigue is not an issue, asking multiple name generator questions can serve the purpose of

2.3 Typologies and taxonomies

The literature on classification draws a distinction between two broad approaches to creating categories: typologies and taxonomies. Typologies are classifications derived analytically and conceptually. They are based on theoretical distinctions drawn deductively from the realm of ideas. Archetypical examples include strong ties and weak ties, or positive and negative ties. By contrast, taxonomies are inductive classifications derived empirically. In a taxonomy, the relevant categories and dimensions emerge from the data, and in modern research they are derived using dimension reduction techniques such as hierarchical clustering, factor analysis, multi-dimensional scaling, and latent-class analysis (Bailey, 1994). While the terms are often used interchangeably, and in practice typologies are informed by data, and taxonomies by theory, the core distinction between a typology and taxonomy is that taxonomies are constrained by the data in a more systematic manner (Bailey, 1994).

We present a review of typologies and taxonomies of ties in Tables 1a and 1b. The classifications in Tables 1a and 1b distinguish between a dimension, a type, and a sub-type. Dimension, in the sense used here, is a composite indicator variable across which items (e.g. name generators) differ. Type is a conceptual grouping of items that share one or more characteristics on a dimension(s) in common (typology) or that have a short distance from one another across one or more dimensions or items (taxonomy). Subtypes are simply further distinctions within a type and are usually present within typologies. And while all taxonomies have implicit dimensions and types, not all researchers choose to interpret and name both.

2.4 Typologies of ties

Within the network literature there are numerous different typologies of ties.[6] One of the most widely used typologies is the distinction between weak and strong ties (Granovetter, 1973). This distinction has been elaborated to take account of shared third parties (Simmelian ties in Krackhardt (1998) and to introduce additional dimensions of strength such as frequency, capacity, and redundancy (Brashears and Quintane, 2018). Another basic dichotomy is between positive (attraction) and negative (aversion) ties (Cartwright and Harary, 1956; Heider, 1946).[7] More detailed typologies of ties also exist, but they are not easily grouped: Borgatti et al. (2018) distinguish relationship ties into relational cognitions, relational roles, and similarities; Labianca (2014) distinguishes between cognitive, affective, and behavioral ties; Kitts (2014) typologies sentiments, access, interactions, and role relations. While egocentric studies commonly distinguish between emotional/affective, instrumental, informational, and companionship ties (van der Poel, 1993; Wellman and Wortley, 1990); and Ibarra (1993) distinguished between prescribed (by third-parties) and emergent ties in addition to expressive and instrumental ties. It is notable that, beyond the broadest dichotomies (strong/weak; positive/negative), these typologies show tremendous diversity and few common categories. Additional examples are provided in Table 1a.

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capturing the same underlying tie type more precisely by collapsing the responses into a single valued type of tie (Agneessens and Labianca, 2022).

[6] To be clear we review typologies of network ties, not of actors based on their networks (Agneessens et al., 2006) or of the networks themselves (Bidart et al., 2018; Giannella and Fischer, 2016; Vacca, 2020).

[7] These typologies are not necessarily claimed to be comprehensive and hence mutually exclusive of one another. So it is possible, for example, to think of tie strength as being orthogonal to tie valence.

Table 1a: Examples of tie typologies in the academic literature

Studies	Tie Dimension/s	Tie Types	Tie Sub-Types
Heider, 1946.	Valence	Positive Ties Negative Ties	
Burt, 1984. Marsden & Cambell, 1984.	Strength	Weak Ties Strong Ties	
Wellman and Wortley, 1990. van der Poel, 1993.	Social Support	Affective Instrumental Informational Companionship	
Fischer, 1982.	Social Context	Kin	Close Kin Extended Kin
		Non-Kin	Work Neighbor Voluntary Assoc. Friends
Ibarra, 1992, 1993.	Control over Tie	Prescribed (Formal) Emergent (Informal)	
	Exchanged Resource	Expressive Instrumental	
Labianca 2014; Yang et al, 2019.		Affective Behavioral Cognitive	
Kitts 2014; Kitts & Quintaine 2020		Sentiments Access Interaction Role Relation	
Borgatti, Everett, & Johnson, 2013.	Relational States	Roles	Kinship, Other Roles
		Cognitions	Affective, Perceptual
		Similarities	Location, Participation, Attribute
	Relational Events	Interactions	Flows
Podolny & Baron, 1997.	Type of Tie	1. Position-to-Position (job interdependence) 2. Person-to-Person (interpersonal attraction, trust)	Task Advice [1,3] (workflow inputs/outputs) Strategic Information [2,3] (gossip)
	Type of Content	3. Material Resources 4. Organizational Identity	Buy-in [1,4] (fate control over job) Social Support [2,4] (friendship)

2.5 Taxonomies[8] of ties

An alternative is to identify types and dimensions based on the data itself: the taxonomic approach. Taxonomies in social network research are rarer than typologies. This rarity is likely a product of logistics and cost of multiple name generator studies: they consume considerable respondent time and researcher budget. Ron Burt has been using dimension reduction taxonomic techniques in several of his works. He identified categories of friendship, acquaintanceship, and work ties (Burt 1983) and also distinguished between personal discussion and corporate authority ties along the intimacy (corresponding to strength of tie) and activity (corresponding to frequency of contact) dimensions. De Lange et al. (2004) identified three factors of network ties: friendship, advice, and companionship. Shakya et al. (2017) found seven clusters within a set of 12 name generators: discussion, domestic interactions, spiritual interactions, domestic resource exchange, instrumental exchange, advice exchange, and relations. Vörös (2015) and Vörös and Snijders (2017) identified three clusters of ties within a set of 21 ties: positive ties (e.g., pretty, kind, clever), social role attributions (e.g., help, trust, look up), and negative ties (e.g, smug, look down, gossipy). Other researchers have developed taxonomies in respect to social capital (Gaarg, 2005) and friendship (Kitts & Leal, 2021). Additional examples are provided in Table 1b. Like typologies, it is notable that the different taxonomies are highly diverse, with only a few similar categories of ties (advice, positive/negative). While many typologies and taxonomies distinguish between different types of positive or neutral ties, few attempt to distinguish between negative ties.

Our paper builds on much of this work. We consider a much larger number of name generators – 24 and our framework using a factorial design could be extended to even more. Previous research has considered usually a handful of negative tie name generators and systematic taxonomies have at most one negative tie type. In contrast, we consider 12 conceptually different negative tie name generators, and identify three tie types. We also present strong evidence for a second major dimension of network ties – social distance.

[8] Many researchers who do various kinds of dimension reduction do not necessarily use the term "taxonomy". For our purposes we term any effort that attempts to identify latent categories of ties using some form of data reduction as a taxonomy. The researchers need not attempt to be comprehensive and aim to identify all possible social ties in existence in order for us to count their work as taxonomic. Our focus is distinguishing efforts that aim to identify tie types conceptually (typologies) and empirically (taxonomies). It is based on Bailey (1994).

Table 1b: Examples of tie taxonomies in the academic literature

Studies	Tie Dimensions	Tie Types
Wish, 1976.	Competitive-Cooperative Equal-Unequal Informal - Formal Superficial-Intense	
Marwell & Hage, 1970.	Intimacy Visibility Regulation	Uncontrolled Gemeinschaft Regulated Gemeinschaft Mixed Gemeinschaft Visible Gemeinschaft Uncontrolled Gesellschaft Regulated Gesellschaft Mixed Gesellschaft Visible Gesellschaft
Haslam & Fiske, 1992.		Equality Matching Market Pricing Authority Ranking Communal Sharing
Burt, 1983.		Kinship Work Acquaintance Friendship
De Lange et al, 2004.		Friendship Advice Companionship
Vörös, 2015; Vörös & Snijders, 2017.		Positive Attributions Negative Attributions Social Role Attributions
Koehly and Marcum, 2016.		Cohesion Conflict
Gaag, 2005.		High Prestige Social Capital Low Prestige Social Capital Network Extensity Social Capital Network Diversity Social Capital Resource Social Capital
Shakya et al, 2017.		Discussion Domestic interactions Spiritual interactions Domestic resource exchange Instrumental exchange Advice exchange Relations
Moolenaar et al 2012	Instrumental - Expressive Mutual In(ter)dependence	
Burt, 1997	Intimacy Activity	Personal Discussion Corporate Authority
Kitts & Leal, 2021.	Behavioral - Structural (Role Expectations) Behavioral Norms - Mutual Sentiments Instrumental - Expressive Interaction	Friendship Around Role Relational Norms Friendship Around Structural Expectations as Self Friendship Around Sentiments

2.6 The goals of this paper

This paper aims to build on this past research and identify and validate a taxonomy of ties. When designing the study we had the following goals: (1) to classify a significant number of commonly used name generators, (2) to extract clusters and dimensions using widely accepted methods, (3) to identify name generators that best operationalized the tie types, (4) to show that the tie types we found were meaningful (distinctions with a difference) by showing that they explain variations in outcomes of interest, and (5) to do all of this with a relatively small budget. The sections that follow explain how we accomplished this, with Study 1 focusing on identifying dimensions and types, and optimal operationalization; and Study 2 focusing on showing how the tie types correlate with outcomes of interest.

3. Study 1: Method

3.1 Selecting Name Generators

Our goal was to select name generators that covered as many conceptually distinct tie types as possible, with a preference for name generators which were widely used in the literature. Given that there are hundreds of name generators it is important to have a framework to organize them. There are two relevant dimensions when it comes to distinguishing name generators.

The first is between general and context-specific name generators (Perkins et al., 2015). Specific generators are used particularly in applied or domain-specific studies and ask for specific characteristics, topics, or interactions (e.g. “With whom do you discuss important matters related to health?”; “If you need to borrow kerosene or rice, to whom would you go?”). General name generators are broader in scope (e.g. “With whom do you discuss important matters?”; “Whom can you rely on to complete a task?”). Given our interest in identifying basic tie types we focused on general name generators.

The second dimension often used to distinguish name generators is between the four approaches: role-relation, interaction, affective, and exchange approach (Marin and Hampton, 2007; Milardo, 1988). The role-relations approach tries to elicit alters that have specific relationships to the ego such as kinship, being a neighbor, co-worker, or sexual partner. The interaction approach aims to elicit alters with whom the ego interacts over a specific time, such as people you have spoken to regularly over the last six months. The exchange approach aims to capture alters with whom the ego engages in some sort of resource exchange or provision. This could include informational exchange such as gossip, provision of instrumental help such as borrowing money or helping when the person is sick. The affective approach aims to capture alters toward which the ego has some emotional evaluation (positive or negative) such as liking the person, feeling close or (dis)energized by the person. Given our interest in identifying basic tie types we did not use role-relation name generators because a specific role can have multiple types of ties. We also did not use the interaction name generators for the same reason as they do not necessarily capture tie content[9]. We thus focused our attention on affective and instrumental name generators.

[9] There are two name generators on our list of 24 that may appear to contradict this, which are the “friend” and “avoid” name generators, which appear as a role-relation and interaction type respectively. However, at close inspection of the full text of the name generator it is apparent that they fall under the affective approach. The first asks about close friends and is used in the literature to identify persons with whom one has a strong tie or

We reviewed the literature in sociology, management/business, and health as well as consulted with experts to identify our initial list. Given that existing taxonomies focus on positive tie name generators we have tried to balance our list with an equal number of positive and negative name generators. Our list of 24 name generators and sources is provided in Table 2.We conducted a post-hoc review based on a sample of 781 articles in the Scopus and Web of Science databases, which contained the phrase “name generator”. After excluding duplicates and irrelevant articles we identified 483 articles that contained 758 unique operationalizations of name generators. Out of those, 75% were either identical, conceptually close, or conceptually related to our list of 24. The remaining 25% tended to be either role-based or interaction based or highly context-specific. A summary of our review of these 758 name generators, vis-à-vis our own, is provided in the Online Appendix in Table A1.

emotional connection. The second question is prefaced by “Sometimes people make us feel uncomfortable or uneasy and therefore we try to avoid interacting with them”. So the question is asking not simply people you avoid but people who make you feel a certain way – uneasy and uncomfortable. It is used in the literature to capture persons that are disliked and is phrased in terms of avoidance because respondents don’t feel comfortable listing persons who they dislike.

Table 2a: 12 negative tie name generators and sources

Summary Text	ID	Short label	Exact Question	Source
Adversarial relationship	1	Adversary	Amongst the people with whom you regularly interact, whom do you have an adversarial relationship with?	Baldwin, Bedell, and Johnson, 1997.
Avoid interaction	2	Avoid	Sometimes people make us feel uncomfortable or uneasy and, therefore, we try to avoid interacting with them. Who do you avoid interacting with?	Venkataramani, Labianca, and Grosser, 2013.
Cannot share personal problems	3	NotShare	Amongst the people you regularly interact with, whom do you feel least comfortable with sharing personal problems or difficulties?	Chua, Ingram, and Morris, 2008.
Could not rely on	4	NotRely	Amongst the people you regularly interact with, who could you not rely on to complete a task they had agreed to do?	Chua, Ingram, and Morris, 2008.
De-energises you	5	Deenergize	Interacting with some people can leave you feeling drained or de-energised. Among the people you regularly interact with please name the people who drain or de-energise you.	Gerbasi, et al., 2015.
Find demanding or difficult	6	Demanding	Who do you sometimes find demanding or difficult?	Offer and Fisher, 2017.
Gossip about	7	GospAbt	We sometimes share information about other people in our lives when they are not present. We might discuss or evaluate them. Name the people you discuss when they are absent. For example you might talk about John with Mary. Please name people like John in your life.	Grosser, et al., 2010.
Had disagreements with	8	Disagree	In the past six months, who have you had disagreements or arguments with?	Herz, 2015.
Look down upon	9	LookDown	Amongst the people you regularly interact with, whom do you look down upon or disdain?	Gervais and Fessler, 2017.
Makes you angry or upset	10	Angry	Who are the people you regularly interact with, that at times, make you feel angry or upset?	Leffer, Krannich, and Gillespie, 1986.
Most dislike	11	Dislike	Thinking about people you regularly interact with, who are the people you most dislike?	Fujimoto, Snijders, and Valente, 2017.
Victimized you	12	HarmYou	Name the people who have in the last six months victimised you, such as people who have mistreated you, communicated with you harshly, or accused you of a wrongdoing?	Huitsing, et al., 2014.

Table 2b: 12 positive tie name generators and sources

SummaryText	ID	Short Label	Exact Question	Source
Ask advice	13	Advice	When you have to make important decisions, for example, about taking a job, family issues, or health problems, whose advice do you or would you seek out? They can be family, friends, or professional advisors. (These can be different people for different matters.)	Offer and Fisher, 2017.
Confide personal matters	14	Confide	Sometimes personal matters come up that concern people, like issues about relationships, important things in their lives, or difficult experiences. Whom do you confide about these sorts of	Herz, 2015.
Consider close friend	15	Friend	Who do you consider to be a close friend?	Brass, 1985.
Could rely on	16	RelyOn	Amongst the people you regularly interact with, whom could you rely on to complete a task they had agreed to do?	Chua, Ingram, and Morris, 2008.
Defends you	17	Defends	Name the people who have in the last six months defended you when you were victimised, such as standing up for you when you were mistreated, protect you when someone was harsh, or defended you when you were accused of wrongdoing.	Huitsing, et al., 2014.
Discuss important matters	18	ImpMatters	From time to time, most people discuss important matters with other people. Looking back over the last 6 months, who are the people with whom you discussed matters important to you?	Burt, 1984.
Energises you	19	Energize	Interacting with some people can leave you feeling enthused about possibilities and energised. Among the people you regularly interact with please name the people who enthuse you about possibilities or energise you.	Gerbasi, et al., 2015.
Gossip to	20	GospTo	We sometimes share information about other people in our lives when they are not present. We might discuss or evaluate them. Name the people with whom you share (discuss) such information about absent others. For example you might talk about John with Mary. Please name people like Mary in your life	Grosser, et al., 2010.
Help if seriously sick	21	HelpYou	If you were seriously injured or sick and needed some help for a couple of weeks with things such as preparing meals and getting around, who would you ask?	Offer and Fisher, 2017.
Look up to	22	LookUp	Amongst the people you regularly interact with, whom do you look up to or admire?	Lusher and Robins, 2010.
Socialize with	23	Socialize	Please think about friends and relatives you typically socialize with - such as people you get together with at someone's house for a meal, you go out to a restaurant with, you go out to concerts, plays, clubs, sports, or other events with friends or relatives, going shopping, out for drinks, to the park, or just hanging out. Who are the people you usually do these sorts of things with?	Offer and Fisher, 2017.
You help them	24	YouHelp	Who are the people that you help out practically, or with advice, or in other kinds of ways at least occasionally?	Offer and Fisher, 2017.

3.2 Data

The surveys were designed and deployed in Qualtrics. Participants were recruited through Mechanical Turk (MTurk). Data using MTurk has been shown to be reliable and high quality (Berinsky et al., 2012; Buhrmester et al., 2011; Hauser and Schwarz, 2016; Shank, 2016). Surveys took 10 minutes to complete. Participants were remunerated USD$2/survey.

The participant sample was limited to the United States. The demographics were 52% female, 79% White, and the median age was 36[10].

To prevent respondent burden, each participant only received six name generators (from the pool of 24). Participants were randomly assigned by Qualtrics to one of 28 conditions, each containing six name generators. At least 50 respondents received each pair of name generators. The study was an 8 x 8 factorial design (minus the redundant conditions represented by the diagonal and the lower half of the matrix in Figure 1).

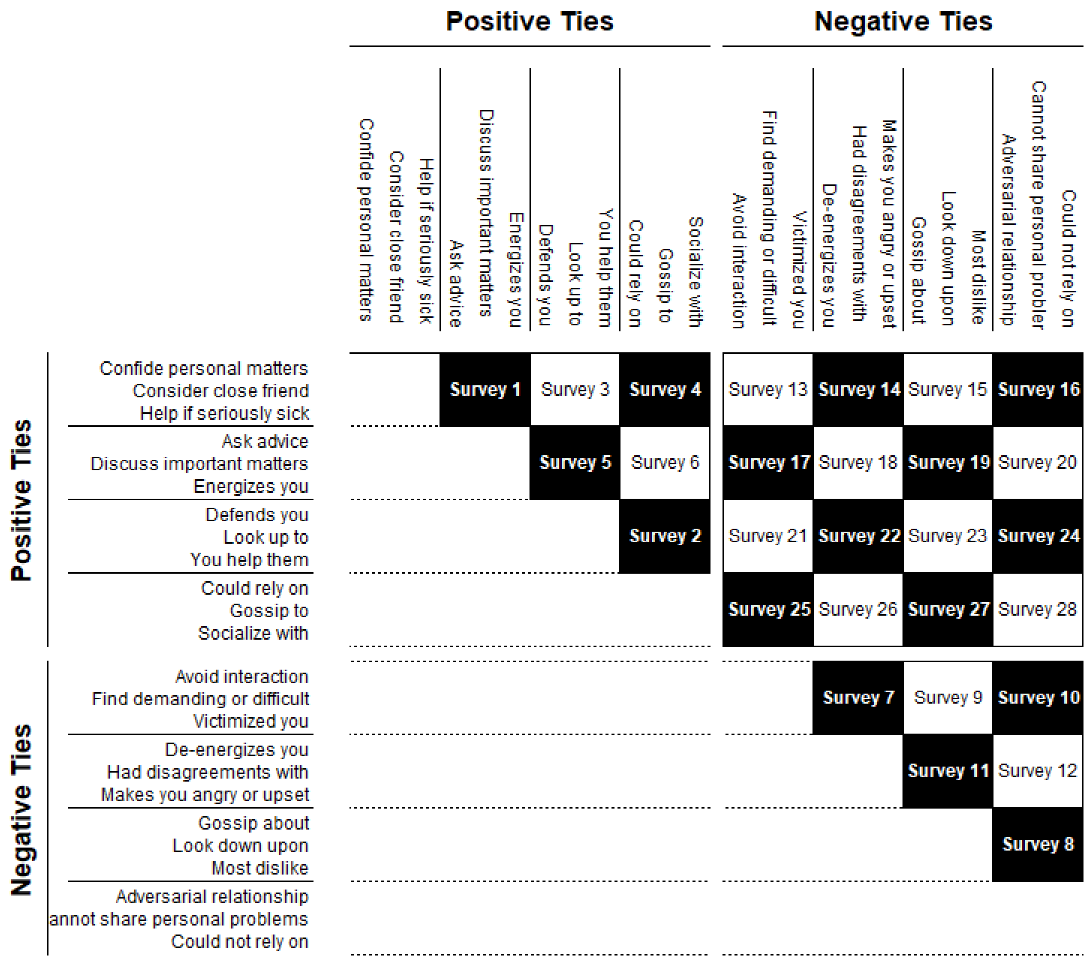

Figure 1: The factorial design of Study 1 showing 28 conditions, each with six name generators

Note: The 24 name generators were randomly assigned to each of the 28 conditions, and their order within each condition was also randomly generated.

[10] Our goal is not to generalize the results to the US Population but according to the key demographics the sample appears relatively close to the population parameters in respect go gender, race, and age. In 2019 the US was 51% female, 76% White, and the median age was 38.5 (U.S. Census Bureau, 2020)

To reduce question ordering influencing the results, the order of presentation of the name generators was randomized in each of the 28 conditions[11]. Participants could name up to 10 alters in response to the first name generator (providing first name, initials, or pseudonym for anonymity). For the second name generator, alters from the first question were "piped" (carried forward) as potential alters that could be selected as tie partners, and space for up to 10 more alters was provided. This was repeated for each of the six name generators, with respondents ultimately able to nominate up to 60 alters. As a further attempt to reduce ordering effects and increase validity, after the six name generators, the participants were presented again with all the alter names (on average 6.5 alters out of a theoretical maximum of 60) and the six networks as a matrix and asked to select again all ties that existed. Participants were then asked about alter characteristics, such as the roles of alters (spouse, parent, friend, neighbor, etc.), and ego characteristics, such as their own income, gender, education, and ethnicity.

3.3 Analysis

Step 1: Measure Similarity with Conditional Probability. The analytical approach broadly followed that of Vörös & Snijders, (2017). To measure network similarity, we used conditional probability: the probability that alter j would be nominated by participant (ego) i for name generator A, given that alter j has also been nominated by participant i for name generator B.[12]

Step 2: Identify cluster structure (Hierarchical clustering). We then identify the cluster structure using hierarchical clustering of a distance matrix generated from the conditional probability matrix. Given that the conditional probabilities matrix is asymmetric, the (Euclidean) distance matrix was calculated from the 48 x 24 matrix created by stacking the conditional probability matrix and its transpose. Hierarchical clustering was conducted using Ward's minimum variance method (ward.D2 in R) (R Core Team, 2020; Ward Jr, 1963).

Step 3: Identify dimensions (Multidimensional Scaling). We used multidimensional scaling (MDS) to visualize the similarity structure of 24 name generators, and the clusters identified in Step 2, in a low dimensional space (in our case two dimensions). This analysis allowed us to identify the major dimensions on which our name generators and clusters vary. We also conducted supplementary analysis (presented in the Online Appendix) using non-metric MDS, and also principal component analysis to check that the results are not dependent on the method of dimension reduction, and to also check the optimal dimensions (using a scree plot, parallel analysis, optimal coordinates, and acceleration factor).

[11] The specific randomized sequence of the name generators in the 28 surveys can be found in the Online Appendix A8. Furthermore, tables A9a-d contain tests that show that there was no significant correlation between the shared survey group and the conditional probability of one tie being entrained with another tie from the same group.

[12] Conditional probability was chosen over the Jaccard index because conditional probability better captured the potentially highly asymmetric nature of intersections between sets of ties of different sizes. For example, in Figure 2, we can see that while 10% of alters "socialized with" were also nominated as someone who "harms you", 70% of those who "harm you" were nominated as alters who were "socialized with". A visual inspection of the conditional probability shows how important the distinction between conditional probability and Jaccard index can be, particularly for "socialize" ties. Participants tended to socialize with the majority of the people they sent negative ties to (bottom row), but these people represented only a small fraction of the total number of persons the participants socialized with (far left column).

Step 4: Identify best operationalization of tie types (Youden's J). Dimension reduction can help future researchers better focus limited resources by identifying a small number of measures that best capture the concept being measured. To facilitate choice of name generators by future researchers, we identified which single name generators (from our set of 24) best operationalize each tie type (tie cluster in Step 2). We used Youden's J (also called Bookmaker Informedness – a measure for measuring the combined true positive and true negative rate) to calculate which name generators best measures each tie type (Youden, 1950).

4. Results: Study 1

4.1 Descriptive Statistics

Table 3 and two tables in the Online Appendix (Tables A2a and A2b) show the descriptive statistics for Study 1 (and Study 2, which is discussed later). In Table A2a we can see that Study 1 had 1,406 respondents (egos), 8,602 alters, and 21,560 ties. Each ego nominated on average 6.1 alters, and 10.0 positive ties, and 5.4 negative ties. In Table A2b we can see that alters came from a wide variety of social roles. Note that a single alter could be nominated as fulfilling multiple roles. Table 3 shows the number of ties and the average indegree and outdegree for each of the 24 name generators. For ease of reference, these are organized by the tie clusters found in step 2 (below). The least common negative ties are "Look down upon", while the most common negative ties are "Had disagreements with". For positive ties, the least common ties are "Look up to", while the most common are "Socialize".

Table 3: Descriptive Statistics: Name Generators

Valence of tie[i] Tie type (Study 1 Cluster)[ii] Name Generator[iii]	Study 1			Study 2		
	Average Outdegree[1]	Average Indegree[2]	Ties[3]	Average Outdegree[1]	Average Indegree[2]	Ties[3]
Negative ties						
Contempt						
Most dislike[iv]	1.57	0.25	559	1.53	0.22	812
Look down upon	1.35	0.22	481			
Passive conflict						
Avoid interaction[iv]	1.78	0.30	624	1.78	0.25	942
Adversarial relationship	1.20	0.22	424			
Cannot share personal problems	1.81	0.33	636			
Could not rely on	1.82	0.33	639			
Victimized you	1.16	0.19	408			
Active conflict						
Makes you angry or upset[iv]	2.05	0.35	684	1.70	0.24	899
Deenergizes you	1.82	0.31	607			
Find demanding or difficult	2.17	0.36	760			
Gossip about	2.37	0.38	840			
Had disagreements with	2.61	0.45	872			
Average/negative name gen.	1.81	0.31	628	1.67	0.23	884
Positive ties						
Social						
Socialize with[iv]	4.67	0.72	1643	4.35	0.61	2307
Closeness						
Confide personal matters[iv]	2.98	0.47	1061	2.97	0.42	1574
Ask advice	3.44	0.53	1226			
Consider close friend	3.32	0.53	1182			
Could rely on	3.81	0.59	1342			
Discuss important matters	3.44	0.53	1224			
Gossip to	2.93	0.46	1033			
Help if seriously sick	2.90	0.46	1032			
You help them	3.68	0.60	1317			
Admiration						
Defends you[iv]	2.73	0.44	976	2.38	0.33	1259
Energizes you	3.14	0.48	1119			
Look up to	2.43	0.39	871			
Average/positive name gen.	3.29	0.52	1169	3.23	0.45	1713

Notes:

[i] Valence: In general terms, does the name generator (tie) measure 'positive' or 'negative' sentiment towards the alter?

[ii] Study 1 Cluster (tie type): Descriptive statistics for name generators are classified by tie types (clusters) found in Study 1, Steps 2 and 3 (see Figure 2 dendrogram and Figure 3 MDS plot). This is done for ease of reference of readers. Note that these clusters (tie types) were found *a posterior* i (after study 1 was conducted), and did not influence study 1's design.

[iii] Name generator full text is provided in Tables 1a and 1b.

[iv] Name generators used in Study 2 were those name generators identified in Study 1 as best operationalisations of their cluster (tie type).

[1] Av. Outdegree (Egos): Average number of ties of this type sent by respondant (ego) if respondant was asked this name generator.

[2] Av. Indegree (Alters): Probability alter receives tie if ego was asked this name generator.

[3] Total ties for this name generator in study.

4.2 Analysis

Step 1: Similarity Matrix (Conditional Probability). The matrix of conditional probabilities is present in Table 4. Visual inspection of this shows at least four trends: (1) bipolarity (positive ties predict further positive ties, and less negative ties, and vice versa); (2) negative ties involving conflict (such as anger and demanding) coexist with some types of positive ties (like confide); (3) Disdain/contempt (Look Down, Dislike) have almost no intersection with positive ties; (4) Socializing often does coexist with negative ties (except look down and dislike).

Table 4: Conditional probability of ego sending a tie (row tie) to an alter if ego has sent a tie (column tie) to that same alter

	Socialize	LookUp	Defends	Energize	HelpYou	Confide	Friend	GospTo	YouHelp	RelyOn	Advice	ImpMatters	GospAbt	Disagree	Demanding	Deenergize	Angry	LookDown	Dislike	NotRely	Avoid	NotShare	Adversary	HarmYou
HarmYou	0.1	0.1	0.1	0	0.1	0.1	0.1	0.1	0.1	0.1	0	0	0.2	0.3	0.3	0.4	0.4	0.3	0.4	0.5	0.4	0.5	0.6	1
Adversary	0.1	0	0	0.1	0	0	0	0.1	0.1	0	0.1	0.1	0.3	0.3	0.5	0.3	0.4	0.5	0.5	0.3	0.6	0.4	1	0.6
NotShare	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.2	0.1	0.1	0.1	0.5	0.4	0.5	0.6	0.6	0.7	0.6	0.5	0.6	1	0.6	0.5
Avoid	0.1	0	0.1	0.1	0	0	0	0.1	0.1	0.1	0.1	0.1	0.4	0.4	0.5	0.5	0.5	0.6	0.7	0.6	1	0.6	0.7	0.6
NotRely	0.1	0	0.1	0.1	0.1	0.1	0.1	0.1	0.2	0	0.1	0.1	0.5	0.4	0.5	0.6	0.5	0.6	0.6	1	0.6	0.5	0.5	0.5
Dislike	0	0	0	0	0	0	0	0	0	0	0	0	0.3	0.2	0.3	0.3	0.4	0.7	1	0.5	0.4	0.5	0.7	0.6
LookDown	0.1	0	0	0	0	0	0	0	0	0	0	0	0.3	0.2	0.3	0.3	0.4	1	0.6	0.4	0.3	0.4	0.6	0.4
Angry	0.3	0.1	0.2	0.2	0.3	0.3	0.3	0.3	0.3	0.3	0.2	0.3	0.4	0.6	0.6	0.6	1	0.6	0.6	0.4	0.6	0.4	0.6	0.6
Deenergize	0.2	0.1	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.2	0.1	0.2	0.3	0.4	0.5	1	0.6	0.5	0.5	0.5	0.6	0.5	0.5	0.6
Demanding	0.3	0.2	0.2	0.2	0.2	0.2	0.2	0.3	0.3	0.3	0.2	0.2	0.4	0.6	1	0.6	0.6	0.5	0.5	0.6	0.6	0.6	0.7	0.6
Disagree	0.4	0.3	0.4	0.3	0.3	0.4	0.3	0.5	0.4	0.4	0.3	0.4	0.6	1	0.7	0.6	0.7	0.5	0.5	0.4	0.6	0.4	0.7	0.7
GospAbt	0.2	0.1	0.2	0.2	0.2	0.1	0.1	0.3	0.2	0.2	0.2	0.3	1	0.5	0.4	0.5	0.6	0.6	0.5	0.5	0.3	0.5	0.6	0.5
ImpMatters	0.5	0.7	0.8	0.7	0.9	0.9	0.7	0.7	0.7	0.7	0.8	1	0.4	0.5	0.2	0.3	0.4	0.1	0.1	0.3	0.2	0.3	0.2	0.1
Advice	0.5	0.8	0.8	0.7	0.7	0.7	0.7	0.7	0.7	0.7	1	0.8	0.3	0.4	0.4	0.1	0.3	0	0	0.2	0.2	0.3	0.3	0.2
RelyOn	0.7	0.9	0.9	0.8	0.9	0.9	0.8	0.7	0.7	1	0.9	0.8	0.2	0.5	0.5	0.3	0.4	0.1	0	0	0.2	0.3	0.2	0.3
YouHelp	0.7	0.7	0.8	0.7	0.9	0.8	0.8	0.7	1	0.7	0.7	0.7	0.4	0.5	0.4	0.4	0.5	0.1	0.1	0.5	0.2	0.4	0.2	0.3
GospTo	0.5	0.6	0.6	0.6	0.6	0.7	0.6	1	0.6	0.5	0.7	0.7	0.3	0.4	0.5	0.3	0.3	0.1	0	0.2	0.3	0.2	0.2	0.4
Friend	0.6	0.7	0.6	0.7	0.7	0.8	1	0.6	0.7	0.6	0.7	0.6	0.2	0.4	0.3	0.3	0.5	0	0	0.2	0.1	0.1	0	0.2
Confide	0.6	0.8	0.7	0.7	0.7	1	0.7	0.7	0.8	0.6	0.7	0.8	0.1	0.5	0.2	0.3	0.4	0	0	0.1	0	0.1	0	0.1
HelpYou	0.5	0.6	0.6	0.5	1	0.7	0.6	0.6	0.6	0.6	0.5	0.6	0.2	0.6	0.2	0.3	0.5	0	0	0.1	0.1	0.1	0	0.2
Energize	0.6	0.6	0.6	1	0.5	0.5	0.6	0.6	0.6	0.7	0.6	0.6	0.4	0.3	0.2	0.2	0.3	0	0	0.2	0.1	0.2	0.1	0.1
Defends	0.5	0.6	1	0.6	0.7	0.7	0.7	0.6	0.6	0.6	0.6	0.6	0.1	0.3	0.3	0.2	0.2	0	0	0.2	0.1	0.2	0	0.2
LookUp	0.4	1	0.6	0.6	0.5	0.5	0.5	0.4	0.5	0.5	0.6	0.6	0.2	0.3	0.2	0.1	0.2	0	0	0.1	0	0.1	0	0.1
Socialize	1	0.8	0.8	0.9	0.8	0.9	0.9	0.8	0.8	0.8	0.8	0.8	0.4	0.6	0.8	0.4	0.4	0.1	0	0.6	0.5	0.8	0.6	0.7

Step 2: Cluster structure (Hierarchical clustering). To inform our identification of the main types of ties, we used Ward's minimum variance method to identify clusters within the conditional probability matrix (step 1). The results of this can be seen in Figure 2.

We identified three main clusters of positive ties, and three main clusters of negative ties. We named the three negative tie clusters: *Contempt* (Dislike, Look Down), *Passive Conflict* (Not Share, Avoid, Not Rely, Adversary, Harm You), *Active Conflict* (Disagree, Demanding, Angry, Deenergize, Gossip About); and the three positive tie clusters: *Socialize* (Socialize); *Closeness* (You Help, Rely On, Gossip To, Important Matters, Advice, Friend, Help You, Confide); and *Admire* (Defends, Energize, Look Up).

To determine this six-cluster structure we constrained our choice of clusters to those identified in the hierarchical clustering dendrogram in Figure 2. However, there remained a choice about the number of clusters in our final model. To make the choice of the number of clusters, we avoid relying on just one method, and instead identified a cluster structure which incorporated the insights of multiple analytic tools, including visual inspection of the conditional probability matrix, hierarchical clustering, multidimensional scaling, and principle component analysis.

We settled on a six-cluster solution for the following reasons. First, while all methods of analysis found the largest difference within the dataset was between positive and negative ties, a two-cluster solution (i.e. one positive tie cluster, and one negative tie cluster) would have had to completely ignore the second (Social Distance) dimension of our MDS and PCA analysis. Leaving out one entire dimension was not acceptable. Second, for negative ties, a two negative tie clusters solution provided by the dendrogram in Figure 2 would have grouped the Passive Conflict ties (e.g. Avoid) with the Contempt ties (e.g. Look Down). But it is clear from the conditional probability matrix that these two types are distinct. A visual inspection of the conditional probability matrix shows two white strips where there are almost no ties between the Contempt cluster (i.e. Look Down and Dislike) and all positive ties. To ignore this distinction would be to leave out a major difference within the set of negative ties. Based on this logic we converged on a three-cluster solution for negative ties.

Third, for positive ties, a two positive clusters solution of the dendrogram in Figure 2 would have grouped eleven of the ties into one cluster, and in the other cluster placed Socialize by itself. While this finding is useful – it tells us that most positive ties capture very similar alters – it somewhat defeats the purpose of attempting to identify a taxonomy of ties. In addition, the three positive cluster solution of the dendrogram, identified a third cluster (Admiration), which was largely differentiated by the fact that it contained ties that were at one extreme end (formal/acquaintanceship) of our second dimension of the MDS analysis. In addition, this third cluster (Admiration) was distinguished from other positive ties by its consistently lower intersection with any alters with negative ties.

Fourth, while we think it is potentially arguable – especially with a larger dataset than ours – that a fourth or fifth negative tie cluster and fourth or fifth positive tie cluster could have been identified and a plausible empirical and theoretical argument made for their utility, we felt that such differentiation would push beyond the limits of a credible and conservative analysis that contains just 24 ties.

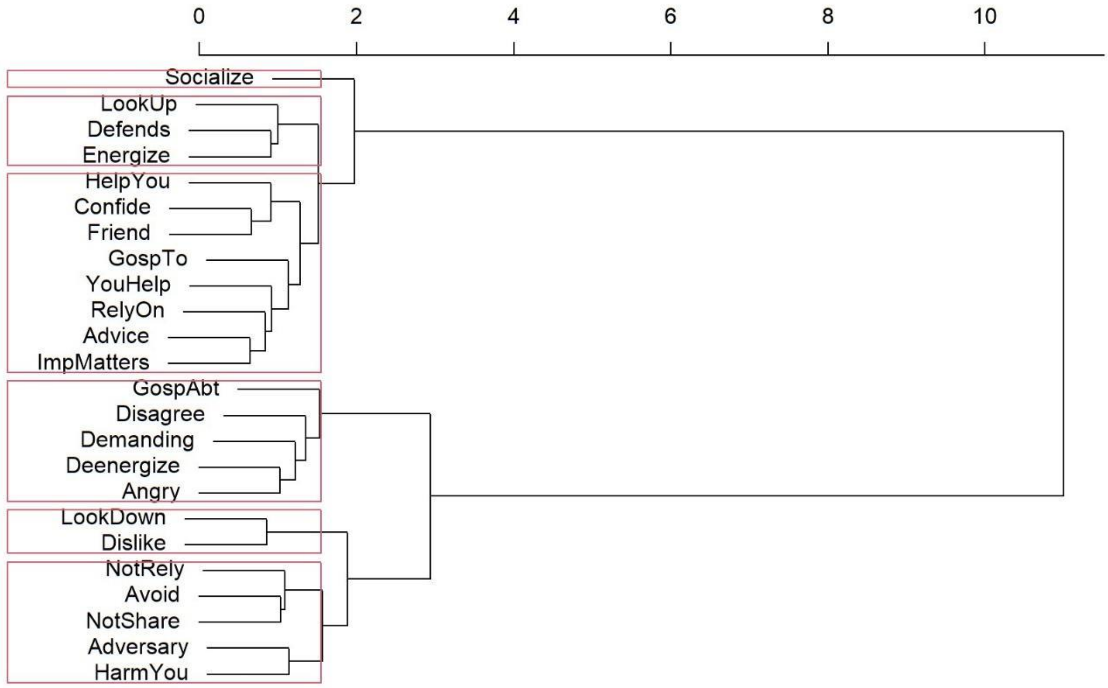

Figure 2: Hierarchical clustering of 24 signed ties (Distance: conditional probability. Cluster method: Ward's)

Table 4 and Figure 2 contain important insights into the nature of ambivalent relationships. Ambivalent relationships are "multiplex relationships with co-existing positive and negative elements" (Methot and Rosado-Solomon, 2019, p. 90). Table 4 suggest that there are at least two distinct types of ambivalent relationships: "strong tie ambivalence" and "weak tie ambivalence". Figure 2 helps us understand this ambivalence in terms of our clusters. Strong tie ambivalence combines the positive ties of the Closeness and Admiration cluster with one of the five negative ties (Angry, Deenergize, Demanding, Disagree, Gossip About) of the Active Conflict cluster. For example, strong tie ambivalence can be seen in the fact that egos Rely On 50% of alters they Disagree with or find Demanding. Weak tie ambivalence, in contrast, combines the Socialize positive tie with the five negative ties (Not Rely, Avoid, Not Share, Adversary, Harm You) of the Passive Conflict cluster. An example of Weak tie ambivalence can be seen when egos Socialize with 60-70% of alters who Harm them or are an Adversary. The negative ties involved in Strong tie ambivalence (Active Conflict ties) and Weak tie ambivalence (Passive Conflict ties) starkly contrast with the two ties of the Contempt cluster (Look Down and Dislike). Contempt ties almost never coexist with positive ties. This is shown in the distinct white colored rows of 0s and 0.1s in Table 4.

In summary, the existence of these combinations, and the absence of other configurations suggests that there is a unique logic by which positive and negative ties tend to combine to create ambivalence, as shown in Table 5. The Active Conflict cluster (e.g. Anger and Disagreement) can coexist with any positive ties, and so makes Strong tie ambivalence possible. The Passive Conflict cluster (e.g. avoid) tends to only coexist with Socialize, and when this occurs we call it Weak tie ambivalence. The Contempt cluster (Dislike and Look Down) cannot coexist with positive ties, and hence Contempt ties are not found in ambivalent relationships.

Table 5: Tie clusters that characterise Strong tie and Weak tie ambivalence

		NEGATIVE		
		Active Conflict	*Passive Conflict*	*Contempt*
POSITIVE	***Admiration***	Strong tie ambivalence	X	X
POSITIVE	***Closeness***	Strong tie ambivalence	X	X
	Socialize	✓[1]	Weak Tie ambivalence	X

[1] We don't give a specific name to this combination, as it generally co-exists within a relationship characterised by either Strong or Weak tie ambivalence.

Step 3: Dimensions (MDS). The next step in our analysis was to identify the main characteristics - also called dimensions (or components or factors) - on which our types of ties differ.

To identify these dimensions we used classical multidimensional scaling. This method uses the distances between each name generator (as measured by conditional probability of intersection with other name generators), and then attempts to "fit" the 24 name generators into a two-dimensional space. We can imagine having a table of distances between cities (which exist on a globe), and then trying to find the best two-dimensional map/model of the relative position of the cities. This is effectively what we are doing with our name generators, but instead of distance in kilometers, distances between name generators are based on the intersection in the conditional probability matrix. For example, lower intersection implies greater distance.

An important question when conducting MDS is to determine how many dimensions to use. In the Online Appendix we show that several different methods of identifying the optimal dimensions (scree plot, parallel analysis, and others) all suggest that a two dimensional solution is optimal. We have also confirmed that the two dimensions (valence and social distance) exist independent of any specific name generators. To test this we generated a series of MDS plots based on different random draws of 12 of our 24 name generators. All MDS plots preserved both the first dimension of valance and the second dimension of social distance. The results of the multidimensional scaling are visualized in Figure 3.[13]

[13] The stress associated with these MDS plots was between 0.02 and 0.03, depending on the method used. According to Kruskal (1964) they are between good (0.05) and excellent (0.02) fit.

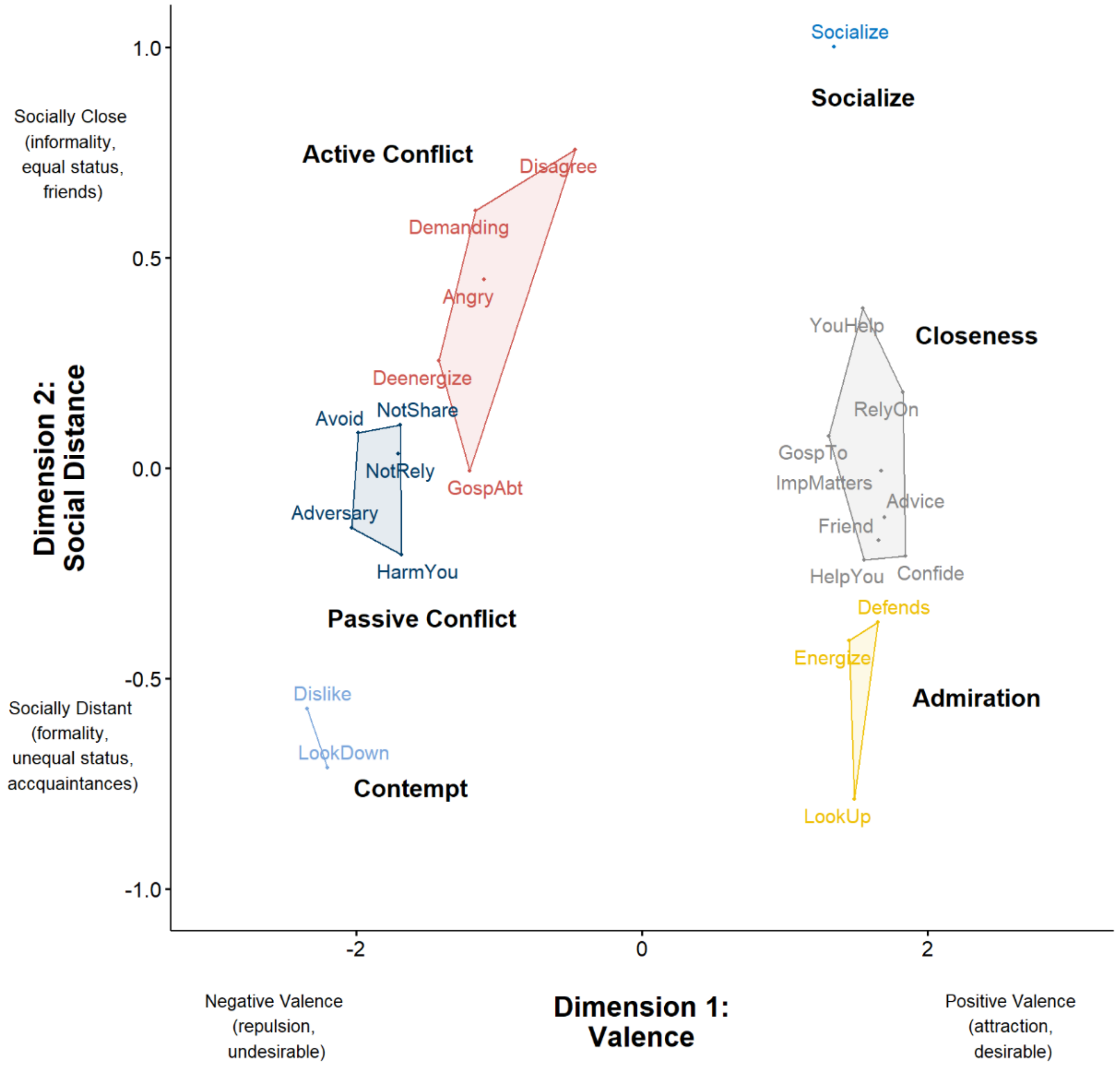

Figure 3: Multidimensional Scaling (MDS) of 24 Signed Ties.
Distance: Conditional Probability.
Method: Classical MDS (principal coordinates analysis)

Six aspects of Figure 3 can be clearly observed:

1. ***Valence.*** Most variation between our ties (and tie clusters) occurs along the dimension (or axis) of valence. In essence, the main characteristic which differentiates our different name generators is their relative positive or negative character. Principal component analysis in the Online Appendix shows that this first dimension explains around 75% of all explainable variation.
2. ***Social distance.*** The second main way our ties and tie clusters differ is with respect to something we call “social distance”. In this context we define "social distance" as a property of relationships that captures the extent of three mutually reinforcing characteristics of informality, status difference, and friendship. It partly corresponds to Wish’s dimension of formal-informality (Wish et al 1976). On one end of the spectrum are relationships with equal status, informality, and friendship, and the other end are relationships with status

difference, formal relations, and acquaintanceship. This can be seen in both Look Down and Look Up being at one end of the dimension, and ties that involve more equal status (such as Socialize and Disagree) at the other end. Subsequent analysis in Study 2 shows the "socially close" end of this dimension is associated with companionship, friendship, siblings, and children, while the "socially distant" end of this dimension is associated with acquaintances, work seniors, and parents.

3. ***Ambivalence of Active Conflict.*** The cluster of Active Conflict ties show considerably less negativity, and also considerably lower social distance (higher interaction) than the other negative tie types, suggesting that these are genuinely ambivalent ties which occur regularly in otherwise positive relationships (such as close interdependent relationships of spouses, parents-children, housemates, interdependent co-workers).

4. ***Uniqueness of Socializing ties.*** Socializing ties are very different from other positive ties, as they appear to show low social distance. In contrast, the Contempt cluster, and the Admire cluster are characterized by high social distances/less interaction.

5. ***Most positive ties are in one cluster.*** Most positive ties – eight of the 12 ties included in our study – are within the single Closeness cluster. This cluster includes the bulk of the most popular social network ties in the research literature, including "important matters", "close friend", "in whom you confide", and "who you turn to for advice".

6. ***Prevalence of moderate valence/low social distance ties:*** If we examine the MDS plot alongside the count of ties for each of the types in Table A2b, we can observe that moderate valence, low social distance ties (such as Socialize, and Active Conflict) are more common, while high valence, high social distance ties (such as the Contempt cluster, and the Admire cluster) are relatively scarce.

Step 4: Operationalization of Taxonomy (Youden's J). The respondent burden of large social network surveys prevents network researchers from using indexes to operationalize clusters or dimensions (such as done in personality psychology). Instead, researchers ideally would like to select the best single name generator to operationalize each major type of tie. In light of this, we attempted to identify the best name generator to operationalize each tie type. Table 6 shows the results of our analysis.

We calculate three measures of performance for each name generator: sensitivity (true positive rate), specificity (true negative rate), and Youden's J (also called Bookmaker's Informedness). For these tests, the items to be detected are alters who are nominated for one or more ties within the cluster. So, for example, within the Contempt cluster, an item to be detected would be any alter in the dataset who receives either a Dislike or a Look Down tie (or both). The true positive rate (sensitivity) is the proportion of alters receiving ties correctly identified as such by a single name generator (such as Dislike), divided by the total number of alters nominated for a Dislike and/or Look Down tie. The true negative rate (specificity) is the proportion of alters who do not receive a Contempt tie that are correctly identified by the name generator being tested, divided by the total number of alters not nominated for a Contempt tie. A good name generator will, therefore, correctly identify as many recipients of a tie from the cluster as possible, while not identifying any alters outside the cluster.

Youden's J (Bookmaker's Informedness) is a measure that attempts to optimize the highest combined sensitivity and specificity. It is simply the sensitivity plus specificity, minus 1. This means that a Youden's J of around 0.5 is associated with an average sensitivity and specificity of 0.75. Table 6 shows which of the single name generators best operationalizes each cluster, based on the Youden's J (J). We can see that the Dislike name generator is the best operationalization of the Contempt cluster (J = 0.76); the Avoid name generator is the best operationalization of the Passive Conflict cluster (J = 0.48); the Angry name generator is the best operationalization of the Active Conflict cluster (J= 0.43); the Socialize name generator is the only candidate for operationalization of the Socialize cluster; the Confide name generator is the best operationalization of the Closeness cluster (J = 0.47); and the Defends name generator is the best operationalization of the Admiration cluster (J = 0.53). We can also see that the Angry, Avoid, and Confide name generators appear to be substantially better operationalizations of their respective clusters than most other name generators. There is little difference between the quality of the name generators in the Contempt and Admiration clusters.

Table 6: Identification of best operationalization of tie types using sensitivity and specificity analysis, and Bookmaker Informedness (Youden's J).

Type	Name Generator	TPR (Sensitivity)	TNR (Specificity)	Bookmaker Informedness (BM) (TPR + TNR - 1)
Negative				
Contempt				
	Dislike	**0.83**	0.93	**0.76**
	LookDown	0.79	**0.95**	0.74
Passive Conflict				
	Avoid	**0.71**	0.77	**0.48**
	Adversary	0.59	**0.83**	0.42
	NotRely	0.63	0.76	0.39
	NotShare	0.65	0.75	0.39
	HarmYou	0.57	0.76	0.34
Active Conflict				
	Angry	0.64	**0.79**	**0.43**
	Deenergize	0.57	0.78	0.35
	Disagree	**0.72**	0.63	0.35
	Demanding	0.64	0.67	0.32
	GospAbt	0.59	0.60	0.20
Positive				
Socialize				
	Socialize	**1.00**	**1.00**	**1.00**
Closeness				
	Confide	0.74	0.73	**0.47**
	HelpYou	0.65	**0.76**	0.41
	Advice	0.76	0.65	0.41
	ImpMatters	0.79	0.62	0.41
	RelyOn	**0.85**	0.57	0.41
	GospTo	0.67	0.70	0.37
	Friend	0.70	0.66	0.35
	YouHelp	0.80	0.53	0.33
Admiration				
	Defends	**0.76**	**0.77**	**0.53**
	LookUp	0.72	**0.77**	0.50
	Energize	0.74	0.75	0.49

Note:
TPR: True Positive Rate. Proportion of alters receiving a tie from name generators in this type, who are also sent a tie by this name generator. For example, TPR for Defends is the proportion of alters who receive 'Defends', 'Look Up' and 'Energize' ties (ties within the 'Admiration' type) who also receive a 'Defends' tie. By analogy, when screening for a disease, TPR is the positive cases identified by the test, as a proportion of all positive cases.

TNR: True Negative Rate. Proportion of alters NOT receiving a tie from name generators in this type, who are also NOT sent a tie by this name generator. For example, TPR for Defends is the proportion of alters who DO NOT receive 'Defends', 'Look Up', or 'Energize' ties (ties within the 'Admiration' type) who also DO NOT receive a 'Defends' tie. By analogy, when screening for a disease, TNR is the negative cases identified by the test, as a proportion of all negative cases.

Bookmakers Informedness (Youden's J): Combines TPR and TNR is a single measure (TPR + TNR -1) to account for the inherent trade-off between sensitivity and specificity. Higher informedness for a name generator indicates a better measure for the tie type.

5. Study 2: Methods

5.1 Data

The goal of Study 2 is to test whether our six dimensions identified and operationalized in Study 1 have significant correlations with real world predictors and outcomes of broad interest to social scientists. In short, do these tie types matter?

As with Study 1, the surveys were designed and deployed in Qualtrics. Participants were recruited through Mechanical Turk (MTurk). Surveys took 10 minutes to complete. Participants were remunerated USD$2/survey.

Each participant received the six name generators identified as the best operationalization of each tie type (in Study 1), and participants were randomly assigned by Qualtrics to one of six random orderings of the name generators.

Participants could name up to 10 new alters for each of the six name generators, with alters from earlier name generators "piped" (carried forward). As with Study 1, after the six name generators, the participants were presented again with all the names and the six networks as a matrix, and asked to confirm (or change) their choices.

Alongside ego and alter demographic characteristics (gender, age, race), a variety of other questions were asked about each alter, including: social status (above, equal, or below ego) (Adler et al., 2000), types of social support the alter would be approached for (Agneessens et al., 2006), emotions evoked by alter (Watson and Clark, 1994), interdependence of ego and alter (Rossi, 2008; Van den Broucke et al., 1995), influence of alter on ego (Seufert et al., 2016), social role of alter (e.g. parent, work senior), and strength of tie (Marsden and Campbell, 1984).

5.2 Analytic approach

Our analytical approach had three main characteristics. First, to control for the nested nature of alters within egos, we used multilevel modelling with random effects for egos (respondents). Second, we started by running bivariate models, with just the main outcome, and each individual predictor. This allowed us to understand the non-controlled correlations in our data, and also to give us a baseline to compare the final controlled results. Third, after the bivariate models, we ran multivariate models, treating our six tie types as both predictors of important outcomes (like emotions evoked by alters, social support potentially provided by alters, and other outcomes like causing emotional distress), and six tie types as outcomes themselves (i.e. assuming each tie type as an outcome of a complex social process).

6. Results: Study 2

6.1 Descriptive statistics

We again refer to Table 3 and the two tables, A2a and A2b, in the Online Appendix for the descriptive statistics of Study 2. There were 530 respondents to Study 2, but all respondents received the same survey (with the order of name generators randomized). The descriptive statistics for Study 2 are remarkable for their similarity to Study 1 in key measures (despite being collected on a completely different sample with almost no overlapping respondents and collected about a year after Study 1). Study 1 and Study 2 have relatively similar statistics for key measures like average ties per ego, ties per alter, proportion of alters in each role, and ties per name generator.

6.2 Analysis

We present the analysis of our six tie types on various emotions, social support, and other outcomes. We show both bivariate and multivariate tables that describe how the outcomes are related. Because we are taking validated measures of outcomes from the literature we analyze how all the outcomes relate to all our tie types. One consequence of this is that some pairs of outcomes and tie types are logically linked because they tap the same conceptual domain and their correlations are expected and are not particularly interesting. For example, the Active Conflict tie type is measured using the Anger name generator. As one would expect, it is correlated very highly with the Anger emotion. The Closeness tie type is measured using the Confide name generator. As one would expect, it is highly correlated with one of the social support measures, involving “who do you talk to”. These cases are

6.2.1 Emotions

Table 7a shows a summary of the bivariate and multivariate models of 13 different emotions – seven negative and six positive. For negative emotions, there is significant differentiation between tie types. Active Conflict ties are particularly associated with anger[14] and sadness. Passive Conflict ties are associated with boredom, fear, guilt, and shyness. Contempt ties strongly predict the emotion of disgust. For positive emotions, the differentiation between tie types is much less than for negative emotions. Closeness ties are predictive of all positive emotions, while Socialize ties are more associated with calmness and joy. Lastly, Admiration ties are associated with gratitude (but not calmness).

6.2.2 Social Support

The first six models in Table 7b show a summary of the bivariate and multivariate models of social support. For negative emotions, the multivariate models of social support are notable for the lack of statistically significant correlations, suggesting that negative ties, in and of themselves, are not a substantive barrier to social support. We may find people difficult, we may avoid them, we may even despise them, but negative ties, in themselves, are not a barrier to various forms of practical support. For positive ties, the main trends are that, firstly, Closeness ties are the best predictor of almost all forms of social support[15], except companionship, which is best predicted by Socialize ties. Comparing Socialize ties and Admiration ties, we can see a bifurcation of ties and social support: Socialize ties are

[14] The correlation of Active Conflict with Anger is strongly expected, given that this tie type is measured using the Anger name generator and is tapping the same conceptual domain.

[15] The correlation of Closeness with the talk form of social support is strongly expected, given that this tie type is measured using the Confide name generator and is tapping the same conceptual domain.

somewhat stronger predictors of talk and companionship support (more “superficial” types of support), and Admiration ties are slightly better at predicting sickness, comfort, and financial support (i.e. more “weighty” forms of support).

6.2.3 Other Outcomes

The right-hand side of Table 7b shows a summary of the bivariate and multivariate models of five other outcomes of interest to social scientists. The models show that positive ties to alters tend to predict an alter with whom one: (1) discusses important matters[16]; (2) is influential on ego; (3) is in an interdependent relationship with ego; (4) does not cause ego distress; and (5) is a person ego socializes with out of choice, not obligation. For negative ties, there is almost no effect of negative ties on the first three outcomes (important matters, influences me, and interdependence), with the exception that Contempt appears to predict interdependence (2.4). Negative ties, however, are very strong predictors of cause distress, and significant predictors of obligatory socializing.

6.2.4 Predictors of Ties

Table 8 shows a reduced multivariate model (only variables significant in one model are included in this table; the full model is available in an Online Appendix) of the predictors of each tie type. We see that negative ties are associated with lower status, with low emotional closeness, and are not sent to friends. Active Conflict ties clearly behave very differently to the other two negative ties and seem to - at least in some cases - be associated with “strong ties”: Active Conflict ties are significantly more likely to be sent to spouses, parents, siblings, and people ego has relatively more frequent contact with[17]. Within positive ties, it is notable that Socialize ties are strongly positively correlated with alters who are friends (and not with work colleagues); Closeness ties with spouses and romantic partners (and not with work colleagues); and Admiration ties with both spouses and work colleagues, particularly senior work colleagues.

[16] The correlation of Closeness with “discusses important matters” is strongly expected, given that this tie type is measured using the Confide name generator and is tapping the same conceptual domain.

[17] Active Conflict ties are measured with the Makes You Angry name generator that already restricts the alters to “people you regularly interact with”. However, the frequency of contact variable ranges from “Daily; Several times a week; About once a week; Several times a month; Once a month; At least once a year; Less than once a year”[reverse coded]. Therefore the statement is to be interpreted in relative terms – that is out of the people ego regularly interacts with, active conflict ties are more likely to be sent to the most frequently interacted alters.

**Table 7a: Multi-level logistic regression models of emotions evoked by alter as outcome.
Tie types are predictors. (Summary table. Full table in the Online Appendix)**

	Negative Emotions[3]							Positive Emotions[3]					
	Angry Irritable	Sad Blue	Bored Tired	Afraid Scared	Guilty Ashamed	Shy Timid	Disgust Loathing	Calm Relaxed	Attentive Determined	Excited Interested	Happy Joyful	Proud Confident	Grateful Appreciativ
	(Odds Ratios)							(Odds Ratios)					
Bivariate models (no controls)[1]													
Anger [Active Conflict]	21.02 ***	5.97 ***	5.34 ***	3.97 ***	1.74 **	1.78 ***	9.19 ***	0.11 ***	0.36 ***	0.15 ***	0.08 ***	0.18 ***	0.15 ***
Avoid [Passive Conflic	19.96 ***	4.12 ***	14.52 ***	13.24 ***	4.54 ***	5.78 ***	20.22 ***	0.01 ***	0.19 ***	0.04 ***	0.01 ***	0.03 ***	0.02 ***
Dislike [Contempt]	37.35 ***	3.72 ***	11.88 ***	5.61 ***	2.49 ***	2.71 ***	42.01 ***	0.01 ***	0.14 ***	0.02 ***	0.01 ***	0.02 ***	0.01 ***
Social [Socialize]	0.04 ***	0.28 ***	0.09 ***	0.13 ***	0.32 ***	0.24 ***	0.03 ***	26.86 ***	4.71 ***	13.80 ***	35.32 ***	12.06 ***	13.89 ***
Confide [Closeness]	0.07 ***	0.38 ***	0.11 ***	0.06 ***	0.47 ***	0.24 ***	0.03 ***	19.56 ***	4.69 ***	10.58 ***	24.63 ***	12.63 ***	21.73 ***
Defends [Admiration]	0.10 ***	0.28 ***	0.13 ***	0.22 ***	0.54 **	0.36 ***	0.05 ***	9.98 ***	4.22 ***	7.13 ***	11.88 ***	9.07 ***	15.33 ***
Multivariate models (with controls)[2]													
Anger [Active Conflict]	11.81 ***	3.23 ***	1.59 ***	1.51	0.88	0.94	2.04 ***	0.34 ***	0.96	0.64 **	0.21 ***	0.62 *	0.54 **
Avoid [Passive Conflic	2.01 ***	1.74 *	2.31 ***	6.33 ***	4.33 ***	2.93 ***	1.91 ***	0.21 ***	1.17	0.60 *	0.25 ***	0.85	0.49 **
Dislike [Contempt]	3.74 ***	1.04	1.45 *	1.02	1.12	0.65 *	5.07 ***	0.46 **	0.55 ***	0.35 ***	0.33 **	0.71	0.37 ***
Social [Socialize]	0.47 ***	0.80	0.68 *	0.65	0.59	0.75	0.63	2.09 ***	1.55 **	1.74 ***	2.69 ***	1.52 *	1.53 *
Confide [Closeness]	0.55 **	1.21	0.64 *	0.16 ***	0.78	0.68	0.74	2.25 ***	1.48 **	2.10 ***	2.57 ***	2.10 ***	2.58 ***
Defends [Admiration]	0.79	0.55 *	0.61 **	1.09	0.94	0.98	0.83	1.09	1.24	1.75 ***	1.65 **	1.78 ***	2.75 ***
Marginal R^2	0.63	0.17	0.39	0.30	0.13	0.27	0.75	0.62	0.25	0.50	0.73	0.54	0.62
Conditional R^2	0.76	0.58	0.61	0.75	0.65	0.54	0.83	0.82	0.50	0.73	0.88	0.76	0.81

* $p < .05$ ** $p < .01$ *** $p < .001$

[1] Bivariate models: Each coefficient presented here is a separate multilevel model, with random effects for each ego. Bivariate models for all variables available in the Online Appendix.

[2] Multilevel models: Each column presented here is a separate multilevel model, with random effects for each ego. All multivariate models include controls. Full models available in the Online Appendix. Controls in multivariate models are:
- Alter Roles: Spouse, Romantic, Parent, Child, Sibling, Other Family, Housemate, Neighbor, Work Senior, Work Equal or Jnr, School, Religious, Voluntary, Friend, Acquaintance
- Ego Attributes: Age, Male, Education, Income, White, Hispanic, Black, Asian
- Alter Attributes: Age, Same Race, Male, Status
- Strength of Tie: Emotional Closeness, Frequency of contact, Length of relationship

[3] Question asked "Indicate most common feeling(s) you have when around this person." Emotions were presented as 13 word pairs, such as "Angry/Irritable".

Table 7b: Multi-level logistic regression models of social support and other outcomes. Tie types are predictors. (Summary table. Full table in the Online Appendix)

	Social Support						Other Outcomes				
	Talk Support	Sick Support	Companion Support	Comfort Support	Money Support	Job Support	Important Matters	Influence Me	Inter-dependence	Cause Distress	Obligatory Social
	Odds Ratios						Odds Ratios				
Bivariate models (no controls)[1]											
Anger [Active Conflict]	0.14 ***	0.33 ***	0.17 ***	0.23 ***	0.64 ***	0.65 ***	0.27 ***	0.25 ***	0.44 ***	20.64 ***	5.09 ***
Avoid [Passive Conflict]	0.02 ***	0.04 ***	0.02 ***	0.03 ***	0.19 ***	0.37 ***	0.05 ***	0.05 ***	0.09 ***	13.02 ***	14.52 ***
Dislike [Contempt]	0.02 ***	0.04 ***	0.01 ***	0.02 ***	0.14 ***	0.35 ***	0.04 ***	0.04 ***	0.10 ***	20.47 ***	12.55 ***
Social [Socialize]	28.49 ***	8.67 ***	32.45 ***	9.49 ***	4.01 ***	2.53 ***	8.47 ***	9.01 ***	6.07 ***	0.09 ***	0.08 ***
Confide [Closeness]	40.88 ***	19.96 ***	16.70 ***	37.08 ***	7.86 ***	2.85 ***	57.87 ***	18.19 ***	11.61 ***	0.15 ***	0.06 ***
Defends [Admiration]	14.21 ***	10.66 ***	7.66 ***	13.04 ***	4.97 ***	2.73 ***	15.95 ***	9.28 ***	8.75 ***	0.23 ***	0.10 ***
Multivariate models (with controls)[2]											
Anger [Active Conflict]	0.86	1.02	0.83	0.82	1.21	1.22	0.96	0.93	1.18	8.93 ***	1.54 ***
Avoid [Passive Conflict]	0.51 **	0.61	0.61	0.67	1.77 *	1.13	1.38	0.68	0.88	2.66 ***	2.11 ***
Dislike [Contempt]	0.49 **	0.80	0.34 ***	0.79	1.00	0.93	0.66	0.71	2.42 **	4.09 ***	1.50 **
Social [Socialize]	2.47 ***	1.61 *	4.43 ***	0.99	1.34	1.73 ***	1.20	1.20	1.65 **	0.65 *	0.60 **
Confide [Closeness]	4.27 ***	3.43 ***	2.31 ***	5.60 ***	2.41 ***	1.64 ***	13.70 ***	3.38 ***	2.67 ***	0.53 ***	0.37 ***
Defends [Admiration]	1.83 ***	2.09 ***	1.22	2.43 ***	1.53 **	1.36 *	3.57 ***	1.75 ***	2.07 ***	0.88	0.65 *
Marginal R^2	0.64	0.68	0.69	0.73	0.48	0.29	0.71	0.58	0.64	0.51	0.47
Conditional R^2	0.83	0.83	0.81	0.84	0.62	0.48	0.82	0.73	0.79	0.68	0.59

* $p < .05$ ** $p < .01$ *** $p < .001$

[1] Bivariate models: Each coefficient presented here is a separate multilevel model, with random effects for each ego. Bivariate models for all variables are available in the Online Appendix.

[2] Multilevel models: Each column presented here is a separate multilevel model, with random effects for each ego. All multivariate models include controls. Full models available in the Online Appendix. Controls in multivariate models are:

- Alter Roles: Spouse, Romantic, Parent, Child, Sibling, Other Family, Housemate, Neighbor, Work Senior, Work Equal or Jnr, School, Religious, Voluntary, Friend, Acquaintance
- Ego Attributes: Age, Male, Education, Income, White, Hispanic, Black, Asian
- Alter Attributes: Age, Same Race, Male, Status
- Strength of Tie: Emotional Closeness, Frequency of contact, Length of relationship

Note: Tie type abbreviations: AC:Active conflict; PC: Passive conflict; CT: Contempt; S: Socialize; CL: Closeness; A: Admiration

Table 8: Multi-level logistic regression models of tie types as outcome.

Operationalisation [tie type]	Anger [Active conflict]	Avoid [Passive conflict]	Dislike [Contempt]	Social [Socialize]	Confide [Closeness]	Defends [Admiration]
			(Odds Ratios)			
Alter Role						
Spouse	2.54 ***	1.33	0.59	1.37	6.73 ***	2.81 ***
Romantic	1.56	1.31	1.03	1.10	3.34 **	1.95 *
Parent	4.32 ***	1.56	1.08	0.57 *	1.17	1.52
Child	1.57	0.31	0.08 **	0.84	0.54 *	0.86
Sibling	2.46 ***	1.14	1.11	1.23	1.11	1.12
Other Family	1.75 **	1.53	1.12	1.18	0.78	0.85
Housemate	1.75 *	0.93	2.01	1.61	0.88	1.11
Neighbor	0.76	1.42	1.10	1.08	0.55 *	0.90
Work Senior	1.47	1.47	1.50	0.28 ***	0.38 ***	3.91 ***
Work Equal or Jnr	1.11	1.40	1.59 *	0.46 ***	1.02	2.09 ***
School	1.15	2.56 *	1.94	0.53	0.36 *	1.04
Voluntary	0.86	0.43	2.15	0.48	2.79 *	2.26
Friend	0.63 **	0.35 ***	0.29 ***	4.72 ***	1.66 **	1.68 **
Ego Attributes						
Male	0.85	0.94	1.05	0.67 *	0.84	0.81
Asian	0.83	0.78	0.35 *	0.86	2.80 *	1.15
Alter Attributes						
Age	1.03	1.00	1.19	1.38 **	1.54 ***	1.04
Same Gender	1.30 **	0.98	1.24	1.20	0.54 ***	0.76 **
Status	0.75 ***	0.81 *	0.69 ***	1.04	1.54 ***	1.14
Strength of Tie						
Closeness	0.49 ***	0.33 ***	0.31 ***	2.79 ***	3.82 ***	2.85 ***
Frequency of contact	1.24 ***	0.92	1.04	1.07	1.18 **	1.27 ***
Length of relationship	1.10	1.05	1.11	1.06	1.16 *	0.99
Marginal R^2	0.32	0.59	0.62	0.58	0.69	0.53
Conditional R^2	0.47	0.72	0.74	0.72	0.79	0.70

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

7. Discussion

7.1 Motivation

Name generators are survey questions that ask for the names of people with whom a participant has some sort of a relationship. A typical example is "Whom do you consider a close friend?" Name generators are both a key innovation and a central tool of social network analysis.

The social networks literature has accumulated a very large number of name generators. Different name generators are used to operationalize important theoretical concepts (e.g. strong/weak ties, positive/negative ties), and the networks literature on study design contains many warnings about the need to choose name generators carefully.

However, it remains unclear how a researcher should choose name generators. There are clearly more than one type of tie in almost any network, but there are also not as many types of ties as there are name generators as many name generators effectively measure the same type of tie.

A review of the existing literature on typologies and taxonomies shows little consensus about what are the main categories of name generators. This appears to be the product of the frequent reliance on secondary data, made necessary by the high temporal and financial cost of collecting multiple name generators on the same actors.

In light of this situation, this paper set itself the primary goal of providing a more empirically grounded and systematic categorization of widely used name generators. As secondary goals it aimed to identify optimal name generators to operationalize the main “types” of ties (making comprehensive name generator selection easier for future researchers), and to show that the tie types are meaningfully different in respect to important sociological variables (i.e. the tie types are “distinctions with a difference”).

7.2 Main findings

The core findings of this paper were that 24 common name generators are characterized by two dimensions (Valence and Social Distance), and six main types of ties: three positive tie types (Admiration, Closeness, Socialize), and three negative tie types (Active Conflict, Passive Conflict, Contempt).

Using a trade-off/optimization of sensitivity and specificity (Youden's J/Informedness), we identified the name generators which best operationalize each tie type [Tie/type in square brackets]: Dislike [Contempt], Avoid [Passive Conflict], Angry [Active Conflict], Socialize [Socialize], Confide [Closeness], and Defends [Admiration].

Through modelling the relationship of each tie type with important sociological predictors and outcomes, we show these types are meaningfully distinct. For negative ties, we find that: (1) Contempt ties are associated with very low status alters as well as the emotion of disgust. They also appear to forbid positive ties to that alter; (2) Passive Conflict ties evoke fear, shame/guilt, shyness, and appear to forbid all positive ties except Socialize; (3) Active

Conflict ties evoke anger and sadness, but are often (but not always) sent to some of the strongest positive tie partners, such as spouses and parents. For positive ties, we find that: (1) Socialize ties tend to evoke calmness and joy, are sent to others of similar social status, tend to be sources of more “light” forms of social support (e.g. companionship, talking), and coexist with many negative ties (but not Contempt); (2) Closeness ties, the core strong ties often measured in the networks literature, are associated with calmness, joy, and gratitude as well as with all forms of social support. They often coexists with Active Conflict ties; (3) Admiration ties are associated with the emotion of gratitude, and tend to provide “heavy” forms of social support (e.g. money, comfort while grieving), but not “light” forms (e.g. companionship).

Our findings are theoretically intuitive and broadly consistent with the findings in the existing literature. Moreover, our taxonomy of six tie types allows one to approach issues from a different angle by involving a greater elaboration of the categories of existing tie classifications (e.g. the positive/negative ties dichotomy becomes six tie types with three kinds of positive and three kinds of negative ties); the grouping together of similar ties (e.g. advice, confide, friend, important matters fall within the Closeness tie type); or an alternative division of categories (e.g. the distinction between affective, behavioral, and cognitive ties fall within each our six tie types).

While there are many nuanced insights that can be gleaned from the models presented, we want to draw attention to what we see as three of the most important theoretical contributions: one general, and two specific.

7.3 Contribution 1: Expanding the scope of network study design and theory

A considerable number of the most widely used name generators in network research fall into just one cluster of name generators: the Closeness tie type. This suggests that this kind of network research could be exploring a relatively small part of the larger network terrain and unintentionally constraining its scope. Furthermore, the clustering of many common name generators also points towards unintended redundancy of name generators used in some studies, with considerable time and budget spent collecting name generators, which ultimately are within the same cluster/type, and potentially carry little new information.

Theoretically, the existence of multiple tie types that are frequently not collected is not only an opportunity for improved study design, but also for improved and more elaborated theory development. In particular, the three different kinds of negative tie types, distinguished by the social distance dimension, offer a particularly fruitful avenue of research. Our taxonomy could provide an opportunity to extend many important network theories and concepts (e.g. balance, strong/weak ties, small worlds, preferential attachment), and also explore and elaborate on these existing theories with more detailed predictors, mediators, and outcomes constructed with the six tie types.

Lastly, the taxonomy could also be used to select name generators and to understand particular results depending on the name generator that a researcher is using and which cluster it falls under in the multidimensional space. The paper’s framework for using a factorial design could be used on comparing a very large number of name generators and then assessing the one that optimizes the sensitivity/specificity tradeoff. Thus, researchers who propose a tie type or name generator not considered here can use the framework to compare and refine our taxonomy.

7.4 Contribution 2: Positive/negative ties are bipolar and orthogonal

There is much discussion in the existing signed ties and negative ties literature about whether it is safe to assume positive and negative ties are opposites – two ends of a single spectrum ("bipolar") – or if they are better conceptualized as different, but not opposite – they are two independent concepts, akin to the X and Y axis of a Cartesian plot ("orthogonal").

Our study provides evidence for both perspectives. Our dimension reduction provides support for the "bipolar" perspective in the finding that the first dimension of the 24 name generators in study 1 is "valence" (i.e. positive/negative), and this first dimension explains about 75% of the variation that is explainable by our model. Based on this, we think we can safely claim that, at a first approximation, positive and negative ties are opposites.

However, the second dimension ("social distance") of our dimension reduction provides evidence for the "orthogonal" perspective. In this dimension we see that "love" and "hate" (Admire and Contempt) are not opposites, but at the same end of a spectrum (both have high social distance). And the opposite of "love and hate" appears to be "socializing" and "disagreement" (low social distance). While the meaning of this second dimension is open to debate and interpretation, the existence of this dimension appears to provide evidence for the importance of "orthogonal" conceptions of signed ties. We discuss this in more detail in the next section on ambivalent ties.

7.5 Contribution 3: Two types of ambivalence

Ambivalent relationships - those which contain both positive and negative ties - are an important type of a network relationship. Yet, they are difficult to conceptualize and understand. To the extent that ambivalent relationships exist, they challenge a pure "bipolar" conception of signed ties. Ambivalent relationships are often analyzed by considering one sort of positive and negative tie. But by considering multiple positive and negative ties we are able to consider the property of ambivalence in a richer way by looking at which kinds of positive and negative ties tend to coexist.

Our results suggest at least two distinct types of ambivalent relationships: "strong tie ambivalence" and "weak tie ambivalence". Strong tie ambivalence combines Closeness or Admiration with Active Conflict, while weak tie ambivalence combines Socialize and Passive Conflict. Weak tie ambivalence can be seen in Passive Conflict's ability to exist with Socialize, but not other positive ties. Strong tie ambivalence can be seen in correlations between Active Conflict and strong tie roles (spouse, parent), some social support, and most positive tie types.[18] The existence of these combinations, and the absence of other

[18] One could further argue that there is some evidence for a third type of ambivalence which we could call a "dependent contempt". This can be seen in the correlations between interdependence and Contempt, and also work senior and interdependence (Online Appendix). This could be thought of as the person in a prescribed (imposed) relationship - such as deep interdependence in a workplace - where the ego feels contempt. In our data, such a relationship (because it would not involve positive ties) would only show up as a Contempt tie, but

configurations suggests that there is a unique logic by which positive and negative ties tend to combine to create ambivalence. Certain ties rule out the presence of others: Passive Conflict appears to rule out Closeness and Admiration, while Contempt is incompatible with almost any type of positive tie. In contrast, Active Conflict can and does coexist with many positive ties.

7.6 Limitations and Future Directions Section

While our study makes a number of contributions it also has several limitations that we wish to acknowledge. We have used 24 common name generators from the literature to identify our six tie types. But we do not mean to claim that these six types are exhaustive to all social network ties. The space of social network ties that we considered is limited by three parameters: 1) the kind of tie measurement approach used – name generator; 2) the kind of name-generator approach used – general and content-focused; 3) the qualifiers of the name generator question used. Below, we discuss each one and the kinds of ties our analysis did not consequently include.

First, name generators represent one way to collect tie data. However, there are certain types of ties that are not well-captured by the name generator approach. Name generators rely on memory and recall, particularly in ego-centric studies where the roster of possible respondents is not available. Forgetting a substantial portion of close contacts has been shown to be a persistent phenomenon (Bell et al., 2007; Brewer, 2000). This creates a bias for capturing stronger ties and ties that are more connected, particularly when a single name generator is used (Marin, 2004). In addition, many name generators explicitly ask the respondent to think of people with whom they frequently interact. Consequently, the approach has been criticized for failing to capture persons who one may rarely interact with but who nonetheless play an important role in people's lives (Bidart and Charbonneau, 2011). It is also likely to miss casual contacts or "familiar strangers", which are important for processes such as disease diffusion (Sun et al., 2013). Lastly, social network ties not usually captured with name generators, such as relational event ties or multi-modal ties, are also not ones that are included. While this study focused on name generators, it is not inherently tied to this type of network data collection. One future direction is to apply our framework – of identifying the alters captured, performing a data reduction technique, and then using Youden's J to select the tie measurement that maximizes sensitivity and specificity – to other network measures.

Second, as mentioned earlier in section 3.1, name generators themselves can be distinguished along two dimensions. The extent to which a given name generator is general as opposed to context or domain specific (Perkins et al., 2015) and the extent to which it captures one of four kinds of relationships: role-relation, interaction, affective, and exchange (Marin and Hampton 2007; Milardo, 1988). Given our interest in basic tie types that capture tie content, we focus on general, affective and exchange type of name generators. We therefore do not include ties that are specific to a particular domain or task such as, for example, criminal networks or micro-lending networks. Nor do we focus on ties based on roles such as co-worker or interaction such as what a pandemic contact-tracer might ask. One important consequence of this is that our taxonomy would not be relevant to theories whose scope conditions require ties based on interaction such as theories about diffusion or information

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the fact that the ego remains in the relationship and needs the alter, suggests it could be classified as ambivalent in some theories (the ego is attracted to alter and stays in relationship because of various benefits, like a job).

flow. See Kitts (2014) for the necessity to pay attention to the scope conditions of a network theory.

Third, the name generators that we did use were taken from published studies because they have undergone some level of validation and pre-testing. However, any general name generator that is content-based, has two components. There is the specific tie-content that is being captured (e.g. confiding, helping, disliking) and the qualifiers that contextualize or narrow the boundary of the alters further. The qualifier can be in terms of directionality (e.g. "who do you ____" vs "who ____ 's you"), recency of contact (e.g. "in the last six months"), or frequency of contact (e.g. "out of the people you regularly interact with"). The qualifiers are especially prominent in egocentric negative tie questions because not including them causes respondents to list persons whom they are not personally close to. For example, "who de-energizes you" may elicit responses that include politicians, celebrities, or other persons outside the interpersonal context. However, including qualifiers such as "people you regularly interact with", creates a kind of compound question that excludes persons who may be part of the interpersonal context but who are not ones an alter regularly interacts with. We have 10 such name generators (7 negative and 3 positive). While this is an unavoidable limitation of using published name generators, we have nonetheless performed some analysis comparing the simple and compound name generators in respect to our overall analysis. The results can be seen in the Online Appendix (10.15). In summary, we found that compound name generators have no greater or lesser indegree or outdegree than simple name generators, when we control for the two dimensions identified in our paper (Valence and Social Distance). Similarly, when we split the name generators into simple and compound, and then separately conducted both hierarchical clustering and MDS plot analysis, the results were not substantively different from the results of our main study.

However, this compound/simple analysis is post-hoc and not decisive. It future studies it will be useful to systematically manipulate qualifiers when comparing name generators. For example, one possible pattern that emerged in the Youden's J analysis to identify the optimal name generator to operationalize each tie type is that in four clusters where simple and compound name generators co-existed, it appears that three name generators that had the highest Youden's J score were simple in terms of not restricting the alter set to partners that the ego regularly interacts with. However, this needs to be tested more systematically.

Our study is not based on a nationally representative sample and we do not claim to generalize the results to the US population as this was not our goal. Moreover, while our study is based on an American sample, it is possible that the number of tie types will be different if the sample was taken from a different cultural context. But while there may be differences there may also be commonalities across contexts. This remains a very interesting research question.

We therefore do not wish to claim that the tie types that we uncovered are complete. We encourage other researchers to use our framework to continue to refine the taxonomy developed here.

Lastly, a validated taxonomy of ties could provide a measure against which any one particular name generator is evaluated against. While in many studies we may not exactly be sure what a name generator is actually measuring, a validated taxonomy and standardized set of measures of that taxonomy could be used to quantitatively and comprehensively describe any name generator of interest. There is also scope for a comprehensive comparison of existing name generators against a validated taxonomy. The results of such a study could provide an elaborate, but systematic, description of major name generators and the extent to which each captures various tie types and dimensions.

8. Conclusion

This paper found that 24 common name generators cluster into six tie types, three negative – Contempt, Passive Conflict, Active Conflict; and three positive – Socialize, Closeness, Admiration. It also found that these 24 name generators largely vary along two dimensions: Valence (i.e., positivity/attraction to negativity/repulsion) and Social Distance (i.e., frequency of contact and status differential). We found six name generators – one for each tie type – that best operationalized each tie cluster, and then, in the second study, showed how these name generators predict and are predicted by, important social variables, such as emotions, social support, social role, and status.

One contribution of this study is to show that there is a broad range of ties that may be underexplored in existing studies – both in study design and theory. The nature of social network ties – what is their content and how should they be classified and characterized – is an assumption made by every network research design and network theory. We show in our study that some of the most popular name generators fall into just one tie type - Closeness - suggesting data collection and theory development may be currently exploring a relatively small part of the larger network terrain.

Our study also points to important opportunities and open questions on the nature of ambivalent relationships – relationships with both positive and negative ties. Our data does suggest that at a first approximation, negative and positive ties are opposites of each other – they are bipolar. However, our data also suggests that ambivalence is present and plays an important, secondary, role. We also see evidence that ambivalence takes at least two very different forms – a strong tie ambivalence (Active Conflict and Closeness/Admiration) and a weak tie ambivalence (Passive Conflict and Socialize).

We hope this study will show the substantial terrain available for network researchers to explore, particularly those who use name generators. Much of this terrain involves core, fundamental questions – particularly the nature, measurement, and consequences of types of ties, and the nature and role of ambivalent relationships. As fundamental questions, with practical application to education, business, health and politics, such research is of considerable importance, and we hope will have substantial impact.

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10. Online Appendix

10.1 Principal Components Analysis

One alternative method for finding and plotting the main dimensions of the 24 name generators is to conduct Principal Components Analysis. As can be seen in Figure A1, the results are similar to the metric-MDS present in the body of this paper.

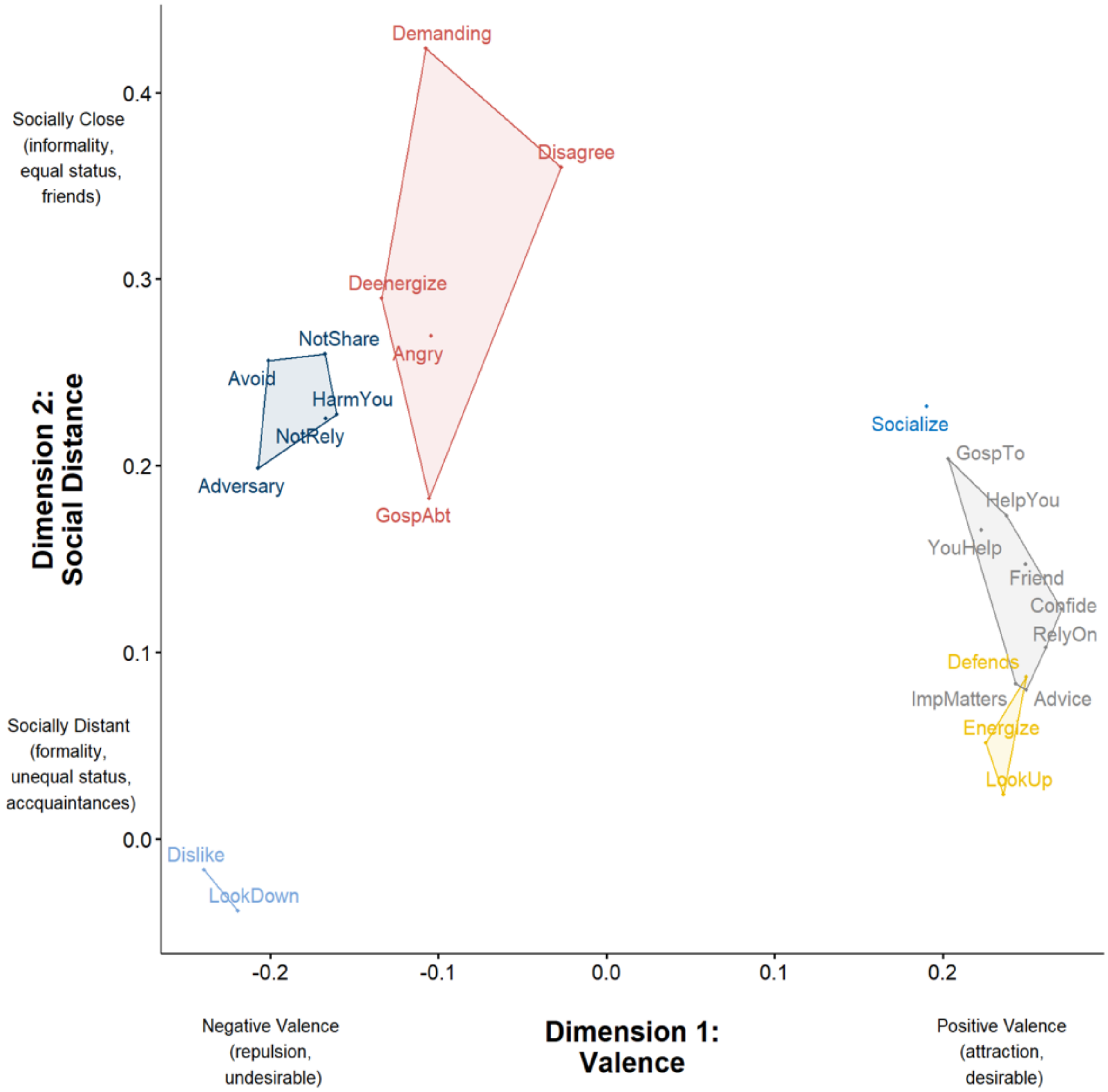

Figure A1: Principal Components Analysis (PCA) of 24 Signed Ties. (Data: Conditional Probability. Method: singular value decomposition of the (centered) matrix.)

10.2 Non-Metric MDS

Another alternative method for finding and plotting the main dimensions of the 24 name generators is to conduct non-metric MDS (as recommended by Vörös and Snidjers, 2017). As can be seen in Figure A2, the results are similar to the metric-MDS present in the body of this paper.

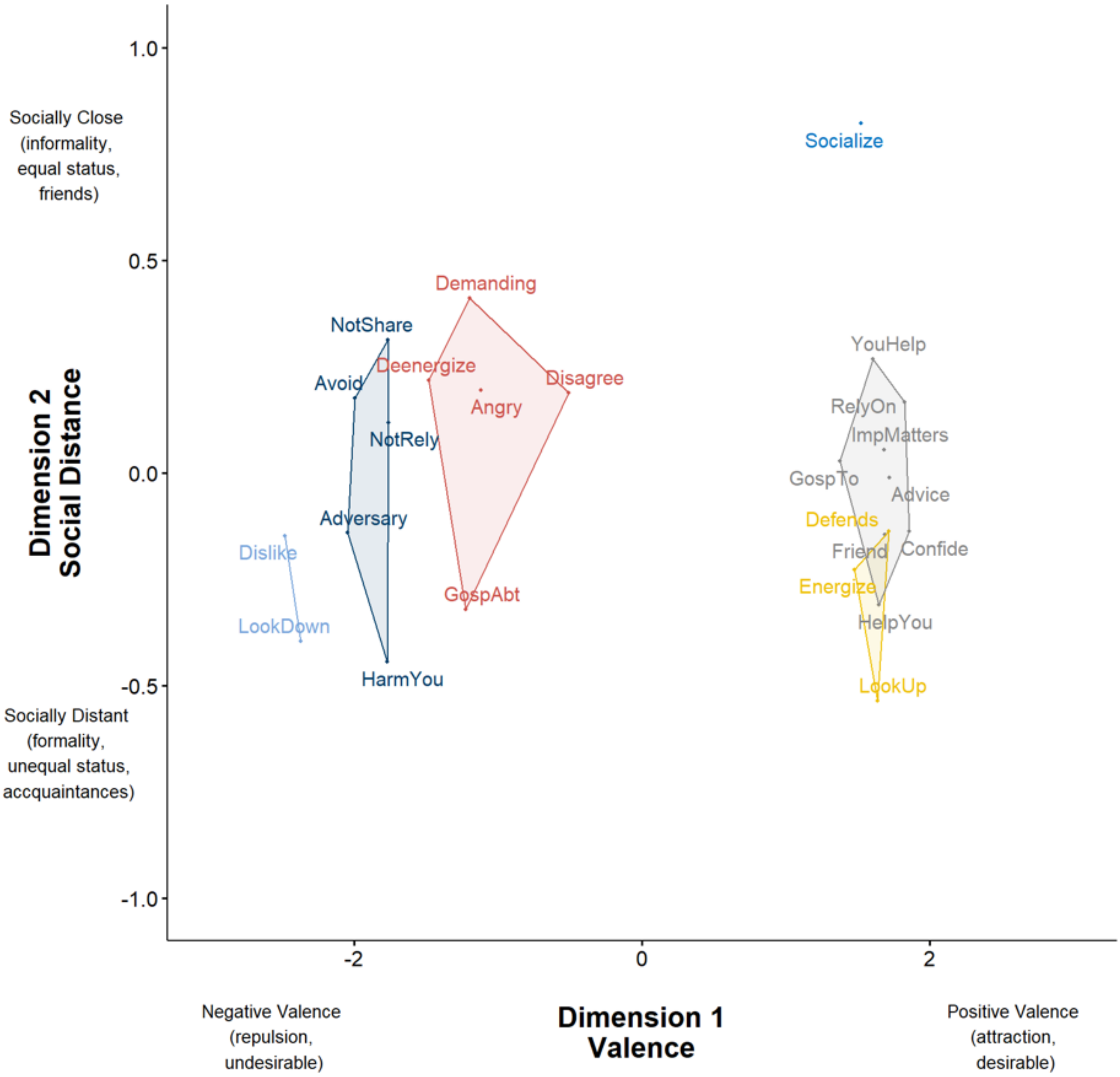

Figure A2: Non-Metric Multidimensional Scaling (MDS) of 24 Signed Ties. (Distance: Conditional Probability. Method: Non-metric MDS (Kruskal's))

10.3 Estimate of optimal dimensions: Scree Plot

One way to estimate the optimal number of dimensions to extract in dimension reduction is to visualize the scree plot of the explained variance (in this case from the PCA analysis). The y-axis in this plot is the proportion of variance explained by each component. These scree plots tend to approximate the shape of a cliff (and the “scree” at the base of the cliff – the boulders and rocks of the crumbled cliff face).

The question to consider when looking at a scree plot is when does the proportion of variance explained, level out and become almost horizontal, or at least shows a constant linear decrease with each component. Generally the optimal number of dimensions (components) to extract is all the components which explain more variance than predicted by this line of constant linear decrease. In the language of a cliff’s face and scree, we include those components/dimensions that are part of the cliff face, and part of the scree slope, but not those components in the base that are after the scree plot.

In our case, we can see that there are two dimensions/components which should be included in the model.

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10
	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10
Variance Explained	77.1%	6.9%	2.6%	2.3%	1.9%	1.6%	1.2%	1.0%	0.9%	0.7%

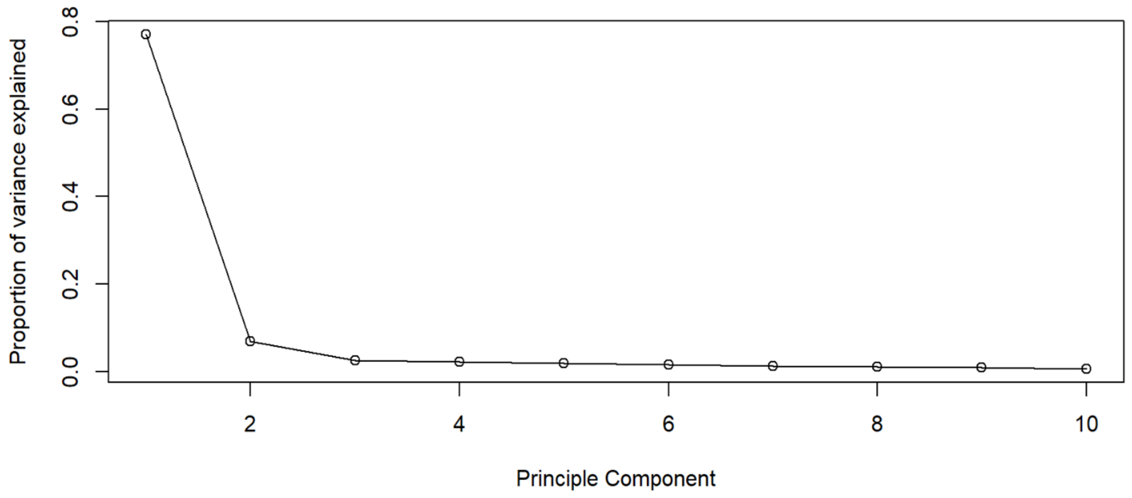

Figure A3: Scree Plot of Principal Components Analysis (PCA) of 24 Signed Ties. (Data: Conditional Probability. Method: singular value decomposition of the (centered) matrix.)

10.4 Estimate of optimal dimensions: Parallel Analysis

Another method for estimating the optimal number of dimensions or components, to include in a dimension reduction, is called parallel analysis. This method generates random simulations of our dataset, using data without any underlying components/dimensions. The dimensions/components of these random datasets are then extracted, and the average eigenvalues for each component (eigenvalues being one measure of the explained variance) in the random data are calculated. The eigenvalues from the simulated data then act as a baseline set of eigenvalues for a dataset where "nothing is happening" (i.e. the null hypothesis is true, and there are no components/dimensions).

By comparing the eigenvalues of our real dataset with the simulated data, we can identify those components which have eigenvalues above that which would be expected at random. It is these components that should be extracted and interpreted.

Again, using this parallel analysis (and also other methods such as optimal coordinates, and acceleration factor) we can see that the optimal number of dimensions/components to extract and interpret is two.

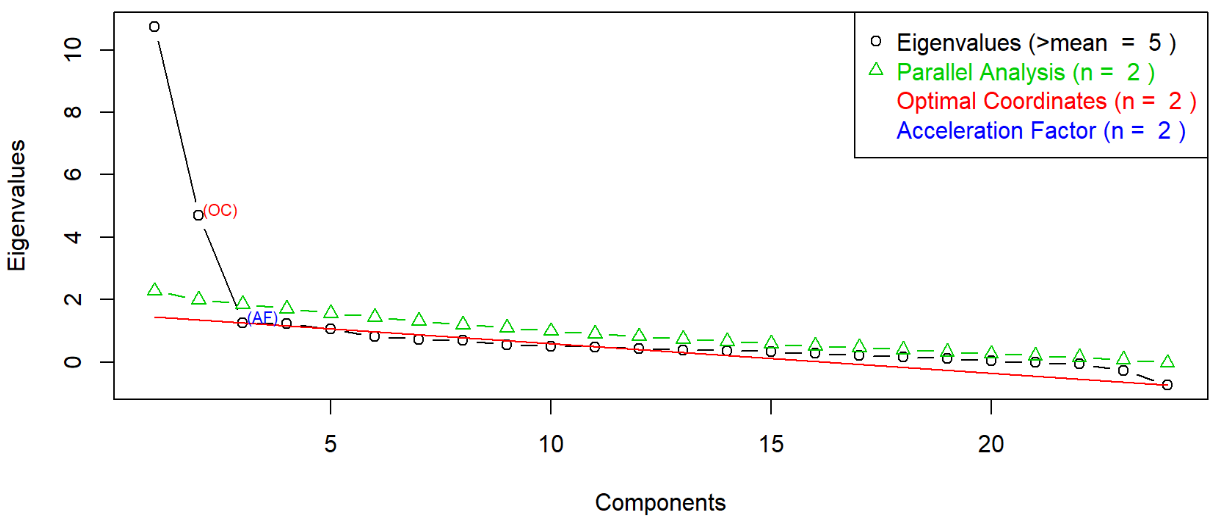

Figure A4: Parallel Analysis and other non-graphical estimates of optimal number of components (Data: Conditional Probability of 24 Ties. Package: nFactors (in R).)

10.5 Radar diagrams of types of ties received by alters in different roles.

Figure A5: Radar diagrams of types of ties received by alters in different roles.

10.6 Name generators in the literature: Overview and comparison

Table A1: Name generators in the literature: Overview and comparison

Similarity (to our name generators)	Name generator	Type	count	%	E.g. of name generator in this category
1. Identical or very similar operationalisation			328	23%	
	Discuss important matters	Closeness	141	10%	"persons with whom they could discuss important matters"
	Consider close friend	Closeness	92	6%	"Who are your best and closest friends?"
	Socialize with	Socialize	60	4%	"Individuals were asked who they ... engage socially with"
	Ask advice	Closeness	29	2%	"persons who advised them on problems"
	Help if seriously sick	Closeness	25	2%	"if they were seriously injured or sick and needed help for a couple of weeks"
	Confide personal matters	Closeness	17	1%	"list the people with whom they are engaged in ... as ... confidant"
2. Conceptually close, but different setting or operationalisation			363	25%	
	Ask advice	Closeness	83	6%	"Individuals were asked who they ... obtain medical advice from"
	Consider close friend	Closeness	64	4%	"subjects were asked to identify their relatives, "close friends,""
	Socialize with	Socialize	57	4%	"discusses hobbies"
	Confide personal matters	Closeness	53	4%	"Asked to name people who provide emotional support."
	Help if seriously sick	Closeness	34	2%	"... [to name] social contacts who provided instrumental aid"
	Discuss important matters	Closeness	29	2%	"list the initials of up to five other individuals they considered important in their lives."
	You help them	Closeness	12	1%	"Which of your classmates would ask you to lend your study materials?"
	Find demanding or difficult	Active Conflict	11	1%	"who ... has made it the most difficult for you to carry out your job responsibilities?"
	Could rely on	Closeness	8	1%	"Who [do] you turn to ... in order to best accomplish your goals and objectives ...?"
3. Conceptually related, but not closely related			390	27%	
	Help if seriously sick	Closeness	125	9%	"whom would you ask for external agricultural inputs such as chemical fertiliser, ...?"
	Discuss important matters	Closeness	79	5%	"whom you have discussed your intention to start a business"
	Ask advice	Closeness	59	4%	"If you have any legal ... questions about your possible migration ... whom would you ask?"
	Could rely on	Closeness	34	2%	"which individuals at your university have been your closest research collaborators"
	Consider close friend	Closeness	26	2%	"We therefore invited our participants to name up to 7 people they consider central to their lives..."
	You help them	Closeness	26	2%	"Who might want to talk to you if they are having that kind of problem ?"
	Socialize with	Socialize	21	1%	"go to temple with"
	Confide personal matters	Closeness	20	1%	"... all people available for validation or positive feedback (e.g. tell good things about yourself)"
4. Conceptually distinct (no parallel in our study)			361	25%	
	Contacts/Frequent contact		67	5%	"asked for a list of 45 people with whom he has a relationship during the week,"
	Role (spouse, boss, dating seriously, kin)		49	3%	"individuals were asked who they are related to."
	Drug use partner		26	2%	"describe their 30-day drug injection, ... and cocaine use partners, drug supplier contacts ..."
	Sexual partner		25	2%	"provide the names of other people with whom they had sex in the last 30 days"
	Anyone else?' prompt at end of survey		16	1%	"any other people who are important to you that you haven't named yet ?"
	Borrow large sum		14	1%	"Whom would you ask for a large sum of money as a credit?"
	Other name generators not classified		162	11%	"Assisted you while you were involved in improving the delivery of your products"
Total			1442	100%	

Note: Sample was 781 articles returned by a search for "name generator/s" in Scopus and Web of Science. Of these, 483 articles contained name generators. We found 1442 instances of name generators, including 758 unique operationalizations of name generators. Table includes all name generators which appeared six or more times. 'Type' is the cluster membership identified in Study 1.

10.7 Descriptive statistics for Studies 1 and 2

Table A2a: Descriptive Statistics:
Study design and counts of egos, alters, and ties.

	Study 1	Study 2
Study design		
Name generators in whole study	24	6
Conditions (i.e. versions of survey)	28	1
Name generators in each condition	6	6
Egos (survey respondants)		
Egos	1,406	530
Av. egos/condition	50	530
Av. egos/name generator	352	530
Av. alters/ego	6.1	7.1
Av. ties/ego	15.3	14.7
Av. negative ties/ego	5.4	5.0
Av. positive ties/ego	10.0	9.7
Alters (tie recipients)		
Alters	8,602	3,769
Av. alters/condition	307	3,769
Av. alters/name generator	2,151	3,769
Av. ties/alter	2.5	2.1
Av. negative ties/alter	0.9	0.7
Av. positive ties/alter	1.6	1.4
Ties (name generator nominations)		
Negative ties	7,534	2,653
Positive ties	14,026	5,140
All ties	21,560	7,793

Table A2b: Descriptive Statistics: Alter Roles.

Role of alter	Study 1		Study 2	
	Alters in role	Proportion of alters	Alters in role	Proportion of alters
Family				
Spouse	520	0.06	215	0.06
Romantic	399	0.05	157	0.04
Parent	734	0.09	303	0.08
Child	396	0.05	175	0.05
Sibling	770	0.09	242	0.06
OtherFamily	1091	0.13	384	0.10
Work				
WorkSenior	700	0.08	287	0.08
WorkEqualJnr	1193	0.14	536	0.14
Friend/Acquaintance				
Friend	3451	0.40	1491	0.40
Acquaintance	781	0.09	383	0.10
Other roles				
Housemate	662	0.08	221	0.06
Neighbor	671	0.08	269	0.07
School	300	0.03	82	0.02
Religious	395	0.05	111	0.03
Voluntary	271	0.03	75	0.02

10.8 Proportion of unique ties (ties not sent to alters receiving ties of other types) for each name generator

Table A3: Proportion of unique ties (ties not sent to alters receiving ties of other types) for each name generator

Type	Name Generator	Total Ties	Unique Ties[1]	Uniqueness[2] (Uniq)	Entrained with ties of type[3]
Positive					
Contempt					
	Dislike	559	181	<u>**0.32**</u>	Other negative ties (strong)
	LookDown	481	119	0.25	
Passive Conflict					
	NotRely	639	299	<u>**0.47**</u>	Other negative ties (strong) Social (moderate)
	Adversary	424	198	<u>**0.47**</u>	
	NotShare	636	289	0.45	
	Avoid	624	207	0.33	
	HarmYou	408	107	0.26	
Active Conflict					
	Deenergize	607	284	<u>**0.47**</u>	Other negative ties (strong) Socialize (moderate) Positive ties (moderate to weak)
	Disagree	872	393	0.45	
	Angry	684	288	0.42	
	GospAbt	840	266	0.32	
	Demanding	760	155	0.20	
Negative					
Social					
	Socialize	1643	182	<u>**0.11**</u>	Everything except Contempt (strong to moderate)
Closeness					
	Friend	1182	665	<u>**0.56**</u>	Other positive ties (strong) Active conflict (moderate)
	HelpYou	1032	565	0.55	
	Confide	1061	553	0.52	
	Advice	1226	314	0.26	
	ImpMatters	1224	294	0.24	
	YouHelp	1317	240	0.18	
	RelyOn	1342	175	0.13	
	GospTo	1033	117	0.11	
Admiration					
	LookUp	871	146	<u>**0.17**</u>	Other positive ties (strong) Active conflict (moderate)
	Energize	1119	176	0.16	
	Defends	976	119	0.12	

Note:
[1] *Uniqueness* = Unique ties/Total ties
[2] *Unique Ties:* Count of ties by this name generator to alters who only receive ties of this type.

For example, 17% of Look Up ties (or 0.17 as a proportion) are sent to alters who only receive ties from one or more the three 'Admiration' ties (Look Up, Energize, Defends). In otherwords, 83% of Look Up ties are 'not unique' because they are sent to alters who are also sent one of the other 21 name generators.

[3] 'Entrained' in this context means that if ties of one type are sent, ties of the other type are also sent. For example, we tend to admire those we are intimate friends with. Admiration and Intimacy (or name generators 'Confide' and 'Defend') are entrained.

Strength of entrainment is read from the conditional probability table earlier in the paper, the conditional probability associated with each descriptor are as follows: strong (0.4+), moderate (0.2-0.3), weak (0.1 or less).

10.9 Complete multi-level logistic regression models of emotions evoked by alter as outcome. Tie types are predictors.

Table A4a: Complete multi-level logistic regression models of emotions evoked by alter as outcome. Tie types are predictors.

	Negative Emotions[1]							Positive Emotions[1]					
	Angry Irritable	Sad Blue	Bored Tired	Afraid Scared	Guilty Ashamed	Shy Timid	Disgust Loathing	Calm Relaxed	Attentive Determin	Excited Intereste	Happy Joyful	Proud Confiden	Grateful Apprecia
	(Odds Ratios)							(Odds Ratios)					
Ties [type]													
Anger [Active Conflict]	11.81 ***	3.23 ***	1.59 ***	1.51	0.88	0.94	2.04 ***	0.34 ***	0.96	0.64 **	0.21 ***	0.62 *	0.54 **
Avoid [Passive Conflict]	2.01 ***	1.74 *	2.31 ***	6.33 ***	4.33 ***	2.93 ***	1.91 ***	0.21 ***	1.17	0.60 *	0.25 ***	0.85	0.49 **
Dislike [Contempt]	3.74 ***	1.04	1.45 *	1.02	1.12	0.65 *	5.07 ***	0.46 **	0.55 ***	0.35 ***	0.33 **	0.71	0.37 ***
Social [Socialize]	0.47 ***	0.8	0.68 *	0.65	0.59	0.75	0.63	2.09 ***	1.55 **	1.74 ***	2.69 ***	1.52 *	1.53 *
Confide [Closeness]	0.55 **	1.21	0.64 *	0.16 ***	0.78	0.68	0.74	2.25 ***	1.48 **	2.10 ***	2.57 ***	2.10 ***	2.58 ***
Defends [Admiration]	0.79	0.55 *	0.61 **	1.09	0.94	0.98	0.83	1.09	1.24	1.75 ***	1.65 **	1.78 ***	2.75 ***
Alter Role													
Spouse	1.93	1.2	1.72	3.18	2.01	0.68	0.55	0.68	1.47	1.22	3.21 **	3.96 ***	1.27
Romantic	1.07	2.01	0.8	6.64 *	1.08	5.25 ***	8.00 ***	0.55	1.88 *	3.49 ***	1.32	1.89 *	1.47
Parent	1.34	2.49 *	2.52 ***	4.70 **	3.78 **	1.01	1.84	1.12	0.86	0.22 ***	0.46 *	1.27	2.11 *
Child	1.52	0.85	0.45	2.16	2.71	0.23	0	0.73	3.28 ***	1.45	4.12 **	27.57 ***	1.93
Sibling	1.82	1.31	1.6	2.06	1.11	0.9	1.38	0.75	1.01	0.62	1.14	1.35	1.14
Other Family	1.26	0.91	1.69 *	1.08	2.20 *	2.15 **	1.67	1.37	1.03	0.81	1.04	3.30 ***	1.79 *
Housemate	2.00 *	1.34	1.6	1.82	0.97	0.95	2.36	0.99	0.81	0.9	0.67	0.76	1.02
Neighbor	0.98	0.98	1.59 *	1.09	1.02	1.86 *	1.84 *	0.93	1.49 *	1.09	0.77	0.74	1.25
Work Senior	0.89	0.98	1.36	1.54	1.23	2.85 ***	1.53	1.13	2.44 ***	0.85	0.51	1.35	1.29
Work Equal or Jnr	1.22	0.67	1.66 *	0.95	1.79	1.27	1.48	1.23	1.96 ***	0.7	0.56 *	1.23	0.98
School	1.17	2.48	1.34	0.23	1.11	1.78	3.02 *	0.33 *	2.98 **	1.27	0.52	1.49	0.89
Religious	3.39 **	0.61	1.03	0.15 *	0.94	2.2	1.29	0.59	1.43	1.77	2.4	2.15 *	1.04
Voluntary	0.24 *	0.78	1.2	0.85	1.39	1.66	1.09	0.86	2.32 *	1.02	1.68	5.51 ***	0.89
Friend	0.53 **	0.76	0.59 **	1.4	1.13	1.41	0.77	1.72 *	0.99	2.00 ***	3.44 ***	2.16 ***	0.93
Acquaintance	1.29	0.88	1.84 **	0.65	1.16	0.83	1.05	0.71	1.2	0.9	0.51	0.76	1.38
Ego Attributes													
Age	0.98	0.98	0.99	0.95 **	0.96 **	0.96 ***	0.98 *	1.01	1	0.98	0.97 *	0.97 **	1
Male	1.1	0.75	1.26	1.07	1.61	0.82	1.12	0.81	1.22	1.03	0.63	1.11	1.01
Education	0.83	0.83	0.85	1.39	0.91	1	1.02	0.77	1.08	1.01	1.11	0.8	1.12
Income	1.02	0.89	1.08	1.01	0.88	0.93	0.94	0.99	0.97	1	1.06	1	0.99
White	0.28 **	1.82	0.53	3.22	1.41	0.95	0.7	1.22	1.11	1.02	1.31	1.66	0.46
Hispanic	0.13 ***	0.85	0.49	1.14	0.44	0.62	1.16	1.45	0.74	0.27 *	2.69	0.71	0.41
Black	0.17 ***	1.11	0.76	0.41	1.27	0.57	0.48	1.64	1.24	1.29	0.9	1.66	0.77
Asian	0.41	0.94	1.11	0.39	1.13	0.71	0.89	3.96 *	1.4	1.22	1.13	1.09	1.19
Alter Attributes													
Age	0.98	1.09	1.02	0.79	1.18	0.84	1.04	0.97	0.97	0.94	0.83	1.07	0.92
Same Race	0.82	1.14	1.25	0.64	1.65	0.76	1.45	1.12	1.01	0.82	0.95	0.87	1.26
Male	1.05	0.77	1	1.13	0.86	0.89	1.61 **	1.28	1.06	0.97	0.75	0.91	0.91
Status	0.78 *	0.9	0.68 ***	1.32	1.51 **	1.78 ***	0.61 ***	0.72 **	1.37 ***	1.37 **	1.25	1.11	1.89 ***
Strength of Tie													
Strength:Close	0.61 ***	0.88	0.74 ***	0.93	1.11	0.81 **	0.61 ***	2.45 ***	1.34 ***	1.67 ***	2.90 ***	2.01 ***	2.32 ***
Strength:Freq	1.14 *	0.99	1.04	0.80 *	0.91	0.89 *	0.90 *	1.12 *	1.16 ***	0.99	0.92	1.1	1.14 *
Strength:Length	0.94	1.05	1.02	0.87	1.02	0.98	0.97	0.93	1.01	0.94	0.85 *	0.94	0.9
(Intercept)	11.59 **	0.15	0.77	0.02 *	0.03 *	1.64	0.71	0.02 ***	0.02 ***	0.04 ***	0.01 ***	0.01 ***	0.00 ***
Random Effects													
σ2	3.29	3.29	3.29	3.29	3.29	3.29	3.29	3.29	3.29	3.29	3.29	3.29	3.29
τ00	1.84	3.12	1.83	6.04	4.85	1.92	1.44	3.71	1.67	2.92	4.25	2.83	3.30
ICC	0.36	0.49	0.36	0.65	0.60	0.37	0.30	0.53	0.34	0.47	0.56	0.46	0.50
N (Egos)	514	514	514	514	514	514	514	514	514	514	514	514	514
N (Alters)	3679	3679	3679	3679	3679	3679	3679	3679	3679	3679	3679	3679	3679
Marginal R^2	0.63	0.17	0.39	0.30	0.13	0.27	0.75	0.62	0.25	0.50	0.73	0.54	0.62
Conditional R^2	0.76	0.58	0.61	0.75	0.65	0.54	0.83	0.82	0.50	0.73	0.88	0.76	0.81

* $p < .05$ ** $p < .01$ *** $p < .001$

[1] The question asked "Indicate most common feeling(s) you have when around this person." Emotions were presented as 13 word pairs, such as "Angry/Irritable".

10.10 Complete multi-level logistic regression models of social support and other outcomes. Tie types are predictors.

Table A4b: Complete multi-level logistic regression models of social support and other outcomes. Tie types are predictors.

	Social Support						Other Outcomes				
	Talk Support	Sick Support	Companion Support	Comfort Support	Money Support	Job Support	Important Matters	Influence Me	Inter-dependenc	Cause Distress	Obligatory Social
	(Odds Ratios)						(Odds Ratios)				
Ties [type]											
Anger [Active Conflict]	0.86	1.02	0.83	0.82	1.21	1.22	0.96	0.93	1.18	8.93***	1.54***
Avoid [Passive Conflict]	0.51**	0.61	0.61	0.67	1.77*	1.13	1.38	0.68	0.88	2.66***	2.11***
Dislike [Contempt]	0.49**	0.80	0.34***	0.79	1.00	0.93	0.66	0.71	2.42**	4.09***	1.50**
Social [Socialize]	2.47***	1.61*	4.43***	0.99	1.34	1.73***	1.20	1.20	1.65**	0.65*	0.60**
Confide [Closeness]	4.27***	3.43***	2.31***	5.60***	2.41***	1.64***	13.70***	3.38***	2.67***	0.53***	0.37***
Defends [Admiration]	1.83***	2.09***	1.22	2.43***	1.53**	1.36*	3.57***	1.75***	2.07***	0.88	0.65*
Alter Role											
Spouse	0.86	7.15***	5.77***	5.10***	6.50***	0.67	7.09***	2.11*	23.15***	2.84***	0.49
Romantic	1.27	4.56***	4.41**	4.71***	1.69*	0.93	1.66	2.03*	9.47***	4.49***	0.30
Parent	0.75	6.88***	0.46**	2.80**	11.44***	0.50**	2.14*	0.95	0.73	2.74***	1.54
Child	0.66	1.12	1.88	1.36	0.73	0.24***	0.51	1.07	2.51**	3.50***	0.66
Sibling	1.53	1.45	1.39	1.54	2.10**	0.43**	1.52	1.35	0.72	1.58	0.85
Other Family	0.64	1.18	0.80	1.34	1.96**	0.44***	1.13	0.64	1.54	0.81	1.80**
Housemate	1.98	2.07*	1.47	0.81	1.31	0.71	3.02**	1.55	1.89*	1.81*	1.26
Neighbor	0.90	1.25	1.36	0.57	1.04	0.79	1.08	1.06	1.06	0.92	0.80
Work Senior	0.65	0.87	0.19***	0.32**	0.92	7.54***	1.78*	1.58	4.10***	1.24	1.12
Work Equal or Jnr	0.98	0.52*	0.81	0.51**	1.12	2.12***	0.57*	0.73	1.40	0.53**	0.91
School	0.77	0.84	1.08	0.84	0.95	1.10	1.32	0.67	1.23	0.63	1.68
Religious	0.97	0.74	0.70	2.30*	1.03	1.53	1.30	1.34	1.51	1.36	1.57
Voluntary	1.35	1.90	1.83	2.28	0.40	2.32*	0.73	1.25	2.60*	0.85	0.53
Friend	3.02***	0.88	1.95**	1.41	0.80	0.73	1.71*	1.41	0.44***	0.47***	0.54***
Acquaintance	0.91	1.12	0.63	1.09	0.75	0.75	1.04	0.83	1.25	1.04	1.77**
Ego Attributes											
Age	0.99	1.02*	1.00	1.00	1.00	0.97***	1.01	0.99	1.00	0.99	0.99
Male	1.03	1.14	0.98	0.89	1.20	1.09	1.33	1.33	1.32	0.84	0.92
Education	0.87	1.33*	1.29*	1.06	1.00	1.05	0.93	0.96	1.18	0.89	0.98
Income	0.94	0.98	0.98	1.04	0.88**	0.94	0.91	1.02	0.84**	1.00	1.03
White	1.64	0.78	2.02	0.73	0.86	0.59	0.35*	0.78	0.54	0.59	1.26
Hispanic	2.53	1.19	1.20	1.16	1.13	0.51	0.31*	0.94	1.07	0.90	1.21
Black	1.76	0.75	1.20	0.94	1.25	0.86	0.43	0.76	1.12	0.57	0.79
Asian	0.97	1.10	1.84	1.21	1.03	0.79	0.34*	1.36	0.92	0.54	1.64
Alter Attributes											
Age	1.04	0.84	1.09	1.00	1.12	1.11	0.89	1.21*	0.93	0.94	1.07
Same Race	0.94	1.02	0.67*	0.86	1.46*	1.17	0.94	0.88	1.18	1.01	0.97
Male	0.68**	0.49***	1.25	0.50***	1.73***	1.63***	0.72*	1.12	1.19	0.83	0.96
Status	0.96	1.36*	1.04	1.26*	1.93***	1.94***	1.43**	1.83***	1.02	0.81*	0.96
Strength of Tie											
Strength:Close	2.37***	2.11***	2.05***	2.96***	1.57***	1.32***	2.04***	1.97***	2.40***	0.84**	0.78***
Strength:Freq	1.04	1.73***	1.12*	1.17*	1.22***	1.05	1.38***	1.12*	1.60***	0.97	1.06
Strength:Length	1.19*	1.14	1.07	0.92	1.05	1.27***	0.94	1.01	0.97	1.06	0.92
(Intercept)	0.01***	0.00***	0.00***	0.00***	0.00***	0.02***	0.00***	0.01***	0.00***	1.31	1.45
Random Effects											
$\sigma2$	3.29	3.29	3.29	3.29	3.29	3.29	3.29	3.29	3.29	3.29	3.29
$\tau00$	3.91	3.01	2.26	2.25	1.27	1.22	2.04	1.81	2.26	1.78	0.92
ICC	0.54	0.48	0.41	0.41	0.28	0.27	0.38	0.35	0.41	0.35	0.22
N (Egos)	514	514	514	514	514	514	514	514	514	514	514
N (Alters)	3679	3679	3679	3679	3679	3679	3679	3679	3679	3679	3679
Marginal R^2	0.64	0.68	0.69	0.73	0.48	0.29	0.71	0.58	0.64	0.51	0.47
Conditional R^2	0.83	0.83	0.81	0.84	0.62	0.48	0.82	0.73	0.79	0.68	0.59

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

10.11 Complete bivariate correlation (Pearson's) of tie types as outcome with range of predictors. Predictors are range of variables including alter role, alter characteristics, ego characteristics, and strength of tie.

Table A5: Complete bivariate correlation (Pearson's) of tie types as outcome with range of predictors. Predictors are range of variables including alter role, alter characteristics, ego characteristics, and strength of tie.

	Bivariate					
Operationalisation [tie type]	Anger [Active conflict]	Avoid [Passive conflict]	Dislike [Contempt]	Social [Socialize]	Confide [Closeness]	Defends [Admiration]
	(Odds Ratios)					
Alter Role						
Spouse	0.89	0.12 ***	0.10 ***	6.67 ***	22.70 ***	10.06 ***
Romantic	0.69	0.11 ***	0.09 ***	6.74 ***	15.97 ***	10.11 ***
Parent	1.45 **	0.43 ***	0.41 ***	1.45 **	2.81 ***	2.41 ***
Child	0.53 **	0.08 ***	0.04 ***	3.68 ***	1.90 ***	2.21 ***
Sibling	1.14	0.60 **	0.64 *	1.54 **	1.34 *	1.09
Other Family	1.40 **	1.66 ***	1.43 **	0.72 **	0.51 ***	0.45 ***
Housemate	1.33	0.27 ***	0.40 ***	3.80 ***	3.90 ***	4.36 ***
Neighbor	1.05	2.03 ***	1.83 ***	0.53 ***	0.32 ***	0.41 ***
Work Senior	2.48 ***	3.38 ***	3.37 ***	0.15 ***	0.17 ***	0.59 ***
Work Equal or Jnr	1.79 ***	2.47 ***	2.78 ***	0.31 ***	0.46 ***	0.68 **
School	0.88	1.45	1.24	0.76	0.50 *	0.67
Religious	0.59	0.87	0.67	1.69 *	1.11	0.97
Voluntary	0.56	0.66	1.22	0.74	1.6	1.71
Friend	0.20 ***	0.12 ***	0.10 ***	9.48 ***	2.61 ***	2.05 ***
Acquaintance	2.21 ***	7.74 ***	6.22 ***	0.11 ***	0.11 ***	0.17 ***
Ego Attributes						
Age	1	1	1	1	0.99	0.99
Male	0.84	0.89	0.94	0.92	0.9	0.95
Education	0.83 **	1.03	0.99	1.02	1.13 *	1.04
Income	0.95	0.96	0.97	1.08 **	1.06 *	1.02
White	1.22	0.73 **	0.95	1.54 ***	1	1.08
Hispanic	1.1	0.99	1.32	0.98	0.86	1.48
Black	0.68 *	1.09	0.84	0.78	0.93	0.75
Asian	0.95	1.47 *	1	0.59 **	1.36	0.88
Alter Attributes						
Age	0.88 *	1.03	0.97	1.01	1.11 *	1
Same Race	1.04	0.68 ***	0.79 *	1.42 ***	1.2	1.25 *
Male	1.28 **	1.15	1.33 ***	0.89	0.62 ***	0.70 ***
Same Gender	1	1.30 **	1.38 ***	0.87	0.71 ***	0.61 ***
Status	0.71 ***	0.65 ***	0.60 ***	1.35 ***	1.48 ***	1.35 ***
Strength of Tie						
Closeness	0.59 ***	0.29 ***	0.27 ***	3.19 ***	4.55 ***	3.11 ***
Frequency of contact	0.88 ***	0.60 ***	0.65 ***	1.62 ***	1.85 ***	2.06 ***
Length of relationship	0.85 ***	0.69 ***	0.69 ***	1.61 ***	1.69 ***	1.49 ***

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

10.12 Complete multi-level logistic regression models of tie types as outcome. Predictors are range of variables including alter role, alter characteristics, ego characteristics, and strength of tie.

Table A6: Complete multi-level logistic regression models of tie types as outcome. Predictors are range of variables including alter role, alter characteristics, ego characteristics, and strength of tie.

	Multivariate					
Operationalisation [tie type]	Anger [Active conflict]	Avoid [Passive conflict]	Dislike [Contempt]	Social [Socialize]	Confide [Closeness]	Defends [Admiration]
	(Odds Ratios)					
Alter Role						
Spouse	2.54 ***	1.33	0.6	1.37	6.73 ***	2.81 ***
Romantic	1.6	1.31	1	1.1	3.34 **	1.95 *
Parent	4.32 ***	1.56	1.1	0.57 *	1.17	1.52
Child	1.6	0.31	0.08 **	0.84	0.54 *	0.86
Sibling	2.46 ***	1.14	1.1	1.23	1.11	1.12
Other Family	1.75 **	1.53	1.1	1.18	0.78	0.85
Housemate	1.75 *	0.93	2	1.61	0.88	1.11
Neighbor	0.8	1.42	1.1	1.08	0.55 *	0.9
Work Senior	1.5	1.47	1.5	0.28 ***	0.38 ***	3.91 ***
Work Equal or Jnr	1.1	1.4	1.59 *	0.46 ***	1.02	2.09 ***
School	1.2	2.56 *	1.9	0.53	0.36 *	1.04
Religious	0.7	1.28	0.9	1.71	1.06	0.63
Voluntary	0.9	0.43	2.2	0.48	2.79 *	2.26
Friend	0.63 **	0.35 ***	0.29 ***	4.72 ***	1.66 **	1.68 **
Acquaintance	0.9	1.53	1.2	1.06	1.06	1.69
Ego Attributes						
Age	1	0.99	1	0.99	0.99	0.99
Male	0.9	0.94	1.1	0.67 *	0.84	0.81
Education	0.9	1.18	1.1	1.01	1.19	1.05
Income	1	1.02	1	1.04	0.99	0.92
White	1.3	0.69	0.9	1.63	1.18	0.93
Hispanic	1	0.89	1.3	1.16	0.78	1.72
Black	0.7	0.61	0.4	1.12	1.12	0.61
Asian	0.8	0.78	0.35 *	0.86	2.80 *	1.15
Alter Attributes						
Age	1	1	1.2	1.38 **	1.54 ***	1.04
Same Race	0.9	1.08	0.9	0.93	1.14	0.98
Male	1.2	1.11	1.3	0.92	0.76	1.06
Same Gender	1.30 **	0.98	1.2	1.2	0.54 ***	0.76 **
Status	0.75 ***	0.81 *	0.69 ***	1.04	1.54 ***	1.14
Strength of Tie						
Closeness	0.49 ***	0.33 ***	0.31 ***	2.79 ***	3.82 ***	2.85 ***
Frequency of contact	1.24 ***	0.92	1	1.07	1.18 **	1.27 ***
Length of relationship	1.1	1.05	1.1	1.06	1.16 *	0.99
(Intercept)	2.5	30.41 ***	11.89 **	0.00 ***	0.00 ***	0.00 ***
Random Effects						
σ2	3.3	3.29	3.3	3.29	3.29	3.29
τ00	1	1.52	1.5	1.73	1.61	1.89
ICC	0.2	0.32	0.3	0.34	0.33	0.37
N (Egos)	514	514	514	514	514	514
N (Alters)	###	3679	###	3679	3679	3679
Marginal R^2	0.3	0.59	0.6	0.58	0.69	0.532
Conditional R^2	0.5	0.72	0.7	0.73	0.79	0.703

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

10.13 Selected survey questions

Table A7: Selected Survey Questions

Variable Name	Question Answer options
Intro Message	We would like to ask you some questions about your social interactions with people in your life. Think about people in all different parts of your life including school, family, work, volunteering or religious organizations. Please fill-in the names of people who you know (and they know you) on a first name basis. Please only write either first names, initials, or nicknames to protect their privacy. Please make sure we are able to distinguish between different people by giving them unique names. (Eg. Mike G and Mike from school or MG and Mscl). Please note that you do not need to fill out all of the boxes below. For each question, you may provide between 0 and 10 nominations. Name 1; Name 2; Name 3; Name 4; …
Recategorizer Question	PLEASE REVIEW AND CONFIRM YOUR CHOICES. Many people find that as they are asked about different ties, their memory is jogged. In addition, we often find that people belong to multiple categories. Below is a list of all the people you have selected previously. Note that you must allocate each person to at least one category. You may select more than one category if applicable. If someone does not belong in any category, you can select "This person belongs in no category/I accidentally selected this person."
Role	People can be connected to each other in a few different ways, even family members. Here is a list of the ways people can be connected. What are all the ways that you are connected nowadays to ___________ : [Participants are given a list of the nominated alters and are asked to assign them to appropriate roles within a category] FAMILY; Spouse/partner; Romantic partner; My parent; My child; Brother/sister; Other family/relatives; RESIDENCE; Housemate; Neighbor; WORK/SCHOOL; Work: More senior than me; Work: My equal or junior; School; VOLUNTARY GROUPS; Religious organization; Voluntary organization; FRIENDS; Friend; Acquaintance; OTHER; Please specify;
Ego gender	What is your gender?
Ego age	What year were you born in?
Ego race	Which categories describe you? White; Hispanic Latino, or Spanish Origin; Black or African American; Asian; American Indian or Alaska Native; Middle Eastern or North African; Native Hawaiian or Pacific Islander; Some other race, ethncity or origin; Prefer not to answer
Ego education	What is your highest level of completed education? Less than a high school diploma; High school degree or equivalent (e.g. GED); Some college, no degree; Associate degree (e.g. AA, AS); Bachelor's degree (e.g. BA, BS); Master's degree (e.g. MA, MS, MEd); Professional degree (e.g. MD, DDS, DVM); Doctorate (e.g. PhD, EdD);
Ego income	What is your approximate yearly household income? Less than \$15,000; \$15,000 to \$24,999; \$25,000 to \$34,999; \$35,000 to \$49,999; \$50,000 to \$74,999; \$75,000 to \$99,999; \$100,000 to \$149,999; \$150,000 to \$199,999; \$200,000 and over

Variable Name	Question Answer options
Influence	Which, if any, of the following people influence you? For example, they sometimes help you form an opinion or change an existing opinion on various topics such as food, fashion, sports, relationships, news, and other people.
Interdependence	For which people below is the following statement TRUE: "This person and I depend on each other to achieve one or more important goals in our lives."
Distress	Which of the following people, if any, cause you emotional distress?
Obligatory Socializing	Some people we socialize with because we feel an obligation. Others we socialize with because we enjoy it. Which, if any, of these people do you socialize with because of an obligation (not enjoyment)?
Emotions	These are some words that describe different feelings and emotions. Please indicate the most common feeling(s) - if any - that you have when around each person below. Afraid/Scared; Angry/Irritable; Disgusted/Loathing; Guilty/Ashamed; Sad/Blue; Happy/Joyful; Proud/Confident; Attentive/Determined; Grateful/Appreciative; Around this person I feel...; Calm/Relaxed; Bored/Tired; Excited/Interested; Shy/Timid
Closeness	How close/distant do you feel to this person? Very close; Close; Somewhat close; Neither close/distant; Somewhat distant; Distant; Very distant
Frequency	How often are you in contact with this person? Daily; Several times a week; About once a week; Several times a month; Once a month; At least ones a year; Less than once a year
Duration	How long have you known this person? Less than 6 months; 6 months - 1 year; 1-2 years; 2-3 years; 3-4 years; 4+ years;
Status	Think of this ladder as representing where people stand in their communities. [Picture of Ladder] People define community in different ways; please define it in whatever way is most meaningful to you. At the top of the ladder are people who have the highest standing in their community. At the bottom are the people who have the lowest standing in their community. Think about where each person below stands in the community RELATIVE TO YOU. Where would you say they stand? ... above me; ... about equal; ... below me
Social Support	Which, if any, of these people would you consider contacting for the following support: If you need to talk to someone [TALK] For aid when you are sick [SICK] For companionship to go out for a day [TRIP] For comfort when someone close dies [COMFORT] For financial problems [MONEY] For getting a job [JOB]
Alter age	11. What is the age of each person? Younger than me; About same age as me; Older than me
Alter race	12. What is the race of each person relative to you? Same race as me; Different race than me
Alter gender	13. What is the gender of each person Male; Female; Other

10.14 Order of name generators

Table A8: Randomized sequence of name generators in 28 surveys

Table TA8a: Name generator IDs and groupings

Name Generator	ID number	Survey grouping
Adversarial relationship	1	1
Avoid interaction	2	2
Cannot share personal problems	3	1
Could not rely on	4	1
De-energizes you	5	3
Find demanding or difficult	6	2
Gossip about	7	4
Had disagreements with	8	3
Look down upon	9	4
Makes you angry or upset	10	3
Most dislike	11	4
Victimized you	12	2
Ask advice	13	5
Confide personal matters	14	6
Consider close friend	15	6
Could rely on	16	8
Defends you	17	7
Discuss important matters	18	5
Energizes you	19	5
Gossip to	20	8
Help if seriously sick	21	6
Look up to	22	7
Socialize with	23	8
You help them	24	7

Table TA8b: Name generator sequence

	1st NG	2nd NG	3rd NG	4th NG	5th NG	6th NG
Survey 1	18	14	19	21	13	15
Survey 2	20	17	16	23	22	24
Survey 3	17	14	24	21	15	22
Survey 4	16	23	21	14	15	20
Survey 5	13	17	19	18	24	22
Survey 6	19	16	23	20	18	13
Survey 7	12	10	5	8	6	2
Survey 8	11	4	7	9	3	1
Survey 9	2	9	12	11	7	6
Survey 10	12	1	2	3	6	4
Survey 11	8	11	9	7	5	10
Survey 12	4	3	8	5	10	1
Survey 13	15	2	6	12	21	14
Survey 14	21	10	5	14	8	15
Survey 15	11	9	7	21	14	15
Survey 16	4	1	15	21	14	3
Survey 17	19	13	6	2	12	18
Survey 18	10	5	19	8	18	13
Survey 19	19	7	13	11	18	9
Survey 20	18	3	4	1	13	19
Survey 21	17	22	2	12	6	24
Survey 22	8	10	22	24	17	5
Survey 23	24	11	7	9	17	22
Survey 24	3	1	4	24	17	22
Survey 25	23	16	20	6	12	2
Survey 26	10	8	16	23	5	20
Survey 27	11	7	23	20	9	16
Survey 28	23	4	1	16	3	20

Table A9a & b: Peasons correlation of conditional probability and shared survey group

Table A9a: Conditional Probabilitiy Matrix

	Advice	Confide	CloseFriend	RelyOn	Defends	ImpMatters	Energize	GospTo	HelpYou	LookUp	Socialize	YouHelp
Advice		0.73	0.72	0.72	0.82	0.77	0.66	0.67	0.72	0.76	0.54	0.73
Confide	0.73		0.70	0.58	0.73	0.76	0.66	0.69	0.70	0.80	0.56	0.76
CloseFriend	0.68	0.77		0.57	0.61	0.59	0.66	0.64	0.66	0.70	0.58	0.66
RelyOn	0.86	0.88	0.83		0.86	0.85	0.79	0.71	0.92	0.88	0.67	0.74
Defends	0.61	0.68	0.67	0.65		0.63	0.64	0.59	0.70	0.63	0.54	0.58
ImpMatters	0.76	0.87	0.72	0.72	0.81		0.67	0.66	0.86	0.71	0.54	0.74
Energize	0.60	0.54	0.56	0.68	0.63	0.62		0.58	0.53	0.59	0.59	0.57
GospTo	0.70	0.66	0.60	0.54	0.60	0.68	0.59		0.56	0.58	0.53	0.62
HelpYou	0.53	0.68	0.58	0.63	0.58	0.55	0.48	0.60		0.60	0.54	0.63
LookUp	0.58	0.50	0.51	0.51	0.56	0.56	0.61	0.43	0.48		0.40	0.46
Socialize	0.82	0.91	0.91	0.82	0.80	0.80	0.87	0.84	0.85	0.77		0.81
YouHelp	0.68	0.84	0.85	0.69	0.78	0.71	0.72	0.75	0.89	0.69	0.68	

Table A9b: Same Survey Group Matrix (1 = same group)

	Advice	Confide	CloseFriend	RelyOn	Defends	ImpMatters	Energize	GospTo	HelpYou	LookUp	Socialize	YouHelp
Advice		0	0	0	0	1	1	0	0	0	0	0
Confide	0		1	0	0	0	0	0	1	0	0	0
CloseFriend	0	1		0	0	0	0	0	1	0	0	0
RelyOn	0	0	0		0	0	0	1	0	0	1	0
Defends	0	0	0	0		0	0	0	0	1	0	1
ImpMatters	1	0	0	0	0		1	0	0	0	0	0
Energize	1	0	0	0	0	1		0	0	0	0	0
GospTo	0	0	0	1	0	0	0		0	0	1	0
HelpYou	0	1	1	0	0	0	0	0		0	0	0
LookUp	0	0	0	0	1	0	0	0	0		0	1
Socialize	0	0	0	1	0	0	0	1	0	0		0
YouHelp	0	0	0	0	1	0	0	0	0	1	0	

Pearsons correlation of cond prob and same group = -0.04

`	Adversary	Avoid	NotShare	NotRely	Deenergize	Demanding	GospAbt	Disagree	LookDown	Angry	Dislike	HarmYou
Adversary		0.64	0.38	0.35	0.31	0.53	0.34	0.33	0.50	0.40	0.49	0.57
Avoid	0.71		0.63	0.64	0.51	0.45	0.38	0.37	0.63	0.46	0.72	0.55
NotShare	0.57	0.64		0.50	0.56	0.54	0.49	0.37	0.65	0.57	0.62	0.52
NotRely	0.53	0.62	0.50		0.61	0.47	0.45	0.45	0.61	0.55	0.56	0.51
Deenergize	0.54	0.58	0.48	0.47		0.52	0.33	0.44	0.47	0.56	0.53	0.57
Demanding	0.70	0.55	0.63	0.57	0.62		0.41	0.56	0.49	0.62	0.49	0.64
GospAbt	0.63	0.32	0.53	0.48	0.47	0.42		0.48	0.59	0.60	0.51	0.49
Disagree	0.70	0.60	0.38	0.41	0.63	0.68	0.59		0.47	0.72	0.47	0.65
LookDown	0.59	0.34	0.44	0.42	0.29	0.32	0.34	0.17		0.36	0.57	0.40
Angry	0.62	0.58	0.43	0.36	0.63	0.57	0.44	0.56	0.60		0.65	0.57
Dislike	0.74	0.37	0.54	0.49	0.35	0.30	0.34	0.18	0.66	0.42		0.56
HarmYou	0.57	0.36	0.46	0.48	0.38	0.34	0.23	0.30	0.30	0.35	0.45	

	Adversary	Avoid	NotShare	NotRely	Deenergize	Demanding	GospAbt	Disagree	LookDown	Angry	Dislike	HarmYou
Adversary		0	1	1	0	0	0	0	0	0	0	0
Avoid	0		0	0	0	1	0	0	0	0	0	1
NotShare	1	0		1	0	0	0	0	0	0	0	0
NotRely	1	0	1		0	0	0	0	0	0	0	0
Deenergize	0	0	0	0		0	0	1	0	1	0	0
Demanding	0	1	0	0	0		0	0	0	0	0	1
GospAbt	0	0	0	0	0	0		0	1	0	1	0
Disagree	0	0	0	0	1	0	0		0	1	0	0
LookDown	0	0	0	0	0	0	1	0		0	1	0
Angry	0	0	0	0	1	0	0	1	0		0	0
Dislike	0	0	0	0	0	0	1	0	1	0		0
HarmYou	0	1	0	0	0	1	0	0	0	0	0	

Pearsons correlation of cond prob and same group = 0.05

Table A9c & d: Comparision of mean conditional probablity for pairs of name generators that are and are not in same survey group

Table A9c: Conditional Probability of Pairs in same group

	Advice	Confide	CloseFriend	RelyOn	Defends	ImpMatters	Energize	GospTo	HelpYou	LookUp	Socialize	YouHelp
Advice						0.77	0.66					
Confide			0.70						0.70			
CloseFriend		0.77							0.66			
RelyOn								0.71			0.67	
Defends										0.63		0.58
ImpMatters	0.76						0.67					
Energize	0.60					0.62						
GospTo				0.54							0.53	
HelpYou		0.68	0.58									
LookUp					0.56							0.46
Socialize				0.82				0.84				
YouHelp					0.78					0.69		

Mean Cond Prob = 0.67
SD of Mean = 0.10
SE of Mean = 0.02

Table A9d: Conditional Probability of Pairs NOT in same group

	Advice	Confide	CloseFriend	RelyOn	Defends	ImpMatters	Energize	GospTo	HelpYou	LookUp	Socialize	YouHelp
Advice		0.73	0.72	0.72	0.82			0.67	0.72	0.76	0.54	0.73
Confide	0.73			0.58	0.73	0.76	0.66	0.69		0.80	0.56	0.76
CloseFriend	0.68			0.57	0.61	0.59	0.66	0.64		0.70	0.58	0.66
RelyOn	0.86	0.88	0.83		0.86	0.85	0.79		0.92	0.88		0.74
Defends	0.61	0.68	0.67	0.65		0.63	0.64	0.59	0.70		0.54	
ImpMatters		0.87	0.72	0.72	0.81			0.66	0.86	0.71	0.54	0.74
Energize		0.54	0.56	0.68	0.63			0.58	0.53	0.59	0.59	0.57
GospTo	0.70	0.66	0.60		0.60	0.68	0.59		0.56	0.58		0.62
HelpYou	0.53			0.63	0.58	0.55	0.48	0.60		0.60	0.54	0.63
LookUp	0.58	0.50	0.51	0.51		0.56	0.61	0.43	0.48		0.40	
Socialize	0.82	0.91	0.91		0.80	0.80	0.87		0.85	0.77		0.81
YouHelp	0.68	0.84	0.85	0.69		0.71	0.72	0.75	0.89		0.68	

Mean Cond Prob = 0.68
SD of Mean = 0.12
SE of Mean = 0.01

	Adversary	Avoid	NotShare	NotRely	Deenergize	Demanding	GospAbt	Disagree	LookDown	Angry	Dislike	HarmYou
Adversary			0.38	0.35								
Avoid						0.45						0.55
NotShare	0.57			0.50								
NotRely	0.53		0.50									
Deenergize								0.44		0.56		
Demanding		0.55										0.64
GospAbt									0.59		0.51	
Disagree					0.63					0.72		
LookDown							0.34				0.57	
Angry					0.63			0.56				
Dislike							0.34		0.66			
HarmYou		0.36				0.34						

Mean Cond Prob = 0.51
SD of Mean = 0.11
SE of Mean = 0.02

	Adversary	Avoid	NotShare	NotRely	Deenergize	Demanding	GospAbt	Disagree	LookDown	Angry	Dislike	HarmYou
Adversary		0.64			0.31	0.53	0.34	0.33	0.50	0.40	0.49	0.57
Avoid	0.71		0.63	0.64	0.51		0.38	0.37	0.63	0.46	0.72	
NotShare		0.64			0.56	0.54	0.49	0.37	0.65	0.57	0.62	0.52
NotRely		0.62			0.61	0.47	0.45	0.45	0.61	0.55	0.56	0.51
Deenergize	0.54	0.58	0.48	0.47		0.52	0.33		0.47		0.53	0.57
Demanding	0.70		0.63	0.57	0.62		0.41	0.56	0.49	0.62	0.49	
GospAbt	0.63	0.32	0.53	0.48	0.47	0.42		0.48		0.60		0.49
Disagree	0.70	0.60	0.38	0.41		0.68	0.59		0.47		0.47	0.65
LookDown	0.59	0.34	0.44	0.42	0.29	0.32		0.17		0.36		0.40
Angry	0.62	0.58	0.43	0.36		0.57	0.44		0.60		0.65	0.57
Dislike	0.74	0.37	0.54	0.49	0.35	0.30		0.18		0.42		0.56
HarmYou	0.57		0.46	0.48	0.38		0.23	0.30	0.30	0.35	0.45	

Mean Cond Prob = 0.50
SD of Mean = 0.12
SE of Mean = 0.01

10.15 Compound name generators

To assess the impact of compound ties on the results of this paper, we conducted a series of hypothesis tests.

Test 1: Outdegree and Indegree
As Reviewer 3 points out, there is a risk that compound ties reduce the set of potential alters that might be selected for a tie. In our case the part of the question that does this is the phrase "Amongst the people you regularly interact with".

If compound name generators do have the problem of limiting the selected alters, we reason that we should expect that the outdegree of egos and the indegree of alters should be, on average, lower for compound tie name generators, and higher for simple name generators. Egos should rule out certain alters because of the qualification "people you regularly interact with", and the alters should receive fewer ties, since alters that people don't regularly interact with, but which are nominated for one of the other five name generators in the survey, will not be selected for compound name generators.

We test this with a series of linear regression models (though similar results are obtained through other statistical methods). In these models, we treat each name generator type as a case (so they are 24 name generators and therefore 24 cases).

First, we test for the uncontrolled bivariate relationship of compound (vs simple) name generator with average indegree and average outdegree.

Second, we test whether this relationship holds once we control for the two dimensions identified in this paper (valence and social distance). We include these two dimension variables because they reflect the simplest operationalization of the theoretical findings of our paper. In addition, it speaks to Reviewer 3's suggestion that much of the variation we identify is an accidental by-product of the compound/simple nature of our name generators.

In Models 1 and 2, we regress the variable "compound name generator" (1 = compound; 0 = simple) against average outdegree of egos and average indegree of alters.

In Models 3 and 4, we regress our two dimensions - valence and social distance - against outdegree and indegree.

In Models 5 and 6, we put all variables in the one model.

In Models 7 and 8, we include all variables again, but reduce valence and social distance to binary variables with a median split. This makes all our independent variables binary, and gives compound/simple a greater chance at achieving significance. One potential criticism of Models 5 and 6 is that valence and social distance measures show large effect sizes because they are measured on a continuous scale.

Models 1 to 8 are presented in Table A10.

Table A10: Test for the impact of compound and simple name generators on the number of tie sent (outdegree) and received (indegree)

	Model 1 Outdegree (Egos)		Model 2 Indegree (Alters)		Model 3 Outdegree (Egos)		Model 4 Indegree (Alters)		Model 5 Outdegree (Egos)		Model 6 Indegree (Alters)		Model 7 Outdegree (Egos)		Model 8 Indegree (Alters)	
	Coef.	p	Coef.	p	Coef.	p	Coef.	p	Coef.	p	Coef.	p	Coef.	p	Coef.	p
Compound	-0.77	0.039	-0.11	0.041					0.09	0.569	0.02	0.398	-0.26	0.185	-0.04	0.186
Valence[i]					0.47	<0.001	0.07	<0.001	0.49	<0.001	0.07	<0.001				
Social Distance[ii]					0.76	<0.001	0.13	<0.001	0.79	<0.001	0.14	<0.001				
Valence (binary)[iii]													1.49	<0.001	0.21	<0.001
Soc. Dist. (binary)[iii]													0.58	0.004	0.1	0.001
(Intercept)	2.87	<0.001	0.46	<0.001	2.55	<0.001	0.41	<0.001	2.51	<0.001	0.4	<0.001	1.62	<0.001	0.27	<0.001
Observations	24		24		24		24		24		24		24		24	
R2 / R2 adjusted	0.180 / 0.142		0.176 / 0.139		0.879 / 0.867		0.892 / 0.882		0.881 / 0.863		0.896 / 0.880		0.812 / 0.784		0.802 / 0.773	

Notes:
i. Valence is first dimension of MDS plot. Positive values for valence reflect ties of attraction and positive affect.
ii. Social Distances is the second dimension of MDS plot. Positive values reflect friendship, informality, and low status differences.
iii. Median split

Table A10 shows a moderate bivariate/uncontrolled effect for compound (vs simple) name generators in Models 1 and 2. Compound name generators are associated with 0.8 less out-ties of egos, and 0.1 less in-ties of alters. These are significant at the p <0.05 level, and explain around 14 percent of variance in degree (adjusted R-square).

However, Models 5, 6, 7, and 8 show that the effect of compound (vs simple) name generators disappears when we control for the two dimensions of our dimension reduction (Valence and Social Distance).

In Tables 7 and 8 we give compound ties a better chance at remaining significant by operationalising both Valence and Social Distance as binary (median split) variables. However, despite this, compound ties remain non-significant.

We note that around 77 to 88 percent of variation in outdegree and indegree are potentially explainable by the two dimensions identified in our paper (valence and social distance).

Test 2: Dimension Reduction on Compound and Simple Name Generators

We ran a second set of tests. We conducted hierarchical clustering and multi-dimensional scaling (MDS) on the compound and simple name generators separately.

We expected that if compound and simple name generators had a significant effect on our results, then the hierarchical clustering and MDS should show: (1) very different results for the two classes (compound/simple) of name generators; and (2) at least one of them (compound/simple) not having the same dimensions or clusters as the full dataset analysed in our paper.

Results of our analysis are provided in Figures A6, A7, A8, and A9.

Figure A6 shows the hierarchical clustering of simple name generators. We see here that the clusters of the main study are largely reproduced: there is a cluster of all the Active Conflict name generators; a cluster of all the Passive Conflict name generators; Socialize is on its own, and all of the Closeness name generators cluster together. The only deviation from our model is that Defends - the only name generator in the dataset from the Admiration cluster - is clustered within the Closeness cluster. However, some deviation from our model should be expected, especially when only one tie from the cluster is present, and nearly half the data of the study (the compound name generators) is excluded.

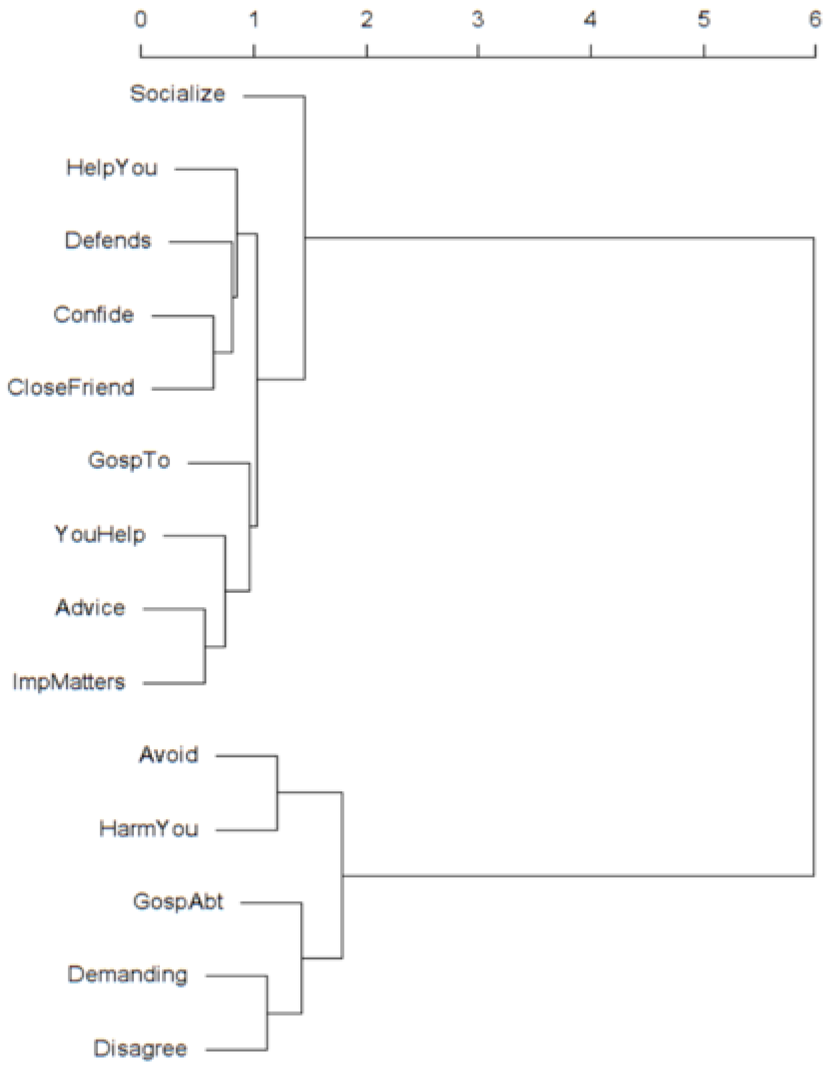

Figure A6: Hierarchical Clustering of Simple Name Generators

Figure A7 shows the MDS plot for simple name generators. We see here that the dimensions identified by the MDS algorithm are almost identical to the dimensions we found on the full dataset, with valence and social distance clearly present. In addition, we can see that the positioning of individual name generators on this MDS plot are, again, almost identical in position to that found in the MDS plot for the full dataset. One way to check this is to count the relative order of name generators on the valence and then the social distance dimensions, and compare this relative order for the full dataset with the simple name generators only dataset. Performing this analysis shows that the relative order of name generators in the simple dataset plot is, again, almost identical to the relative order in the full dataset plot.

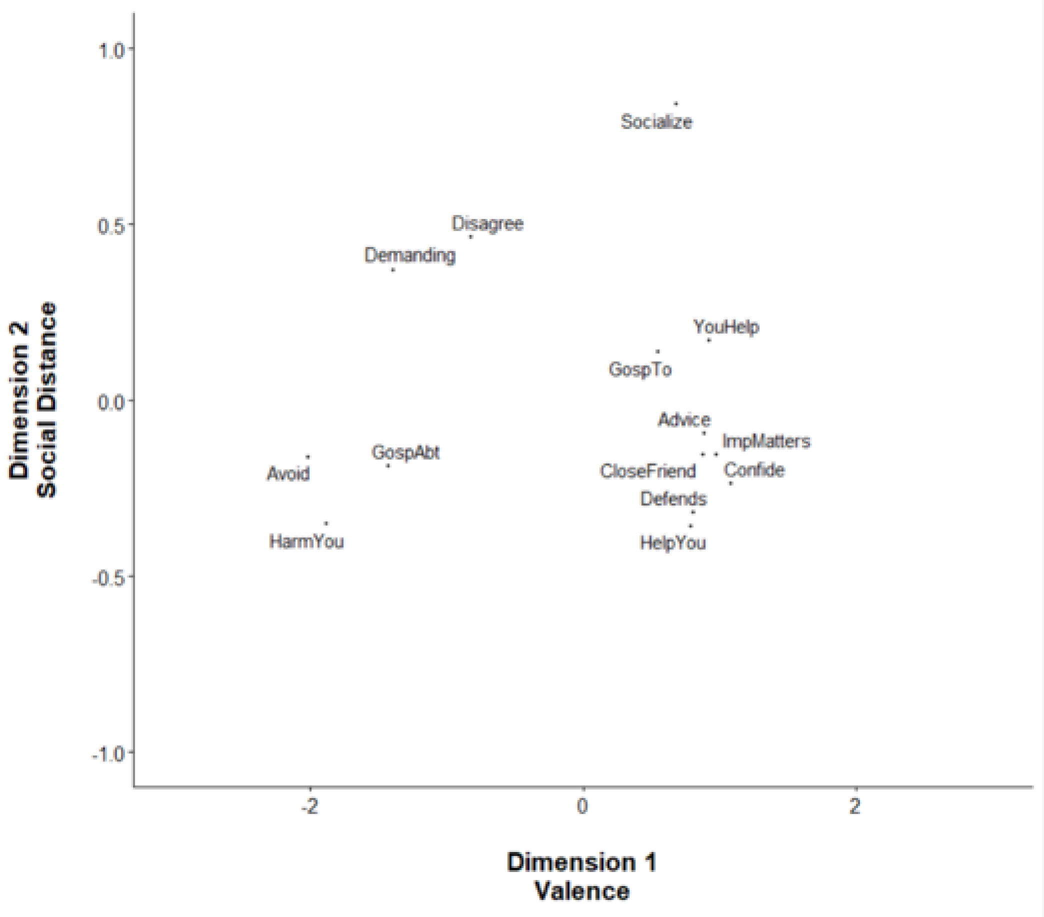

Figure A7: Multi Dimensional Scaling of Simple Name Generators

Figure A8 shows the hierarchical clustering of compound name generators. For negative ties, we see here the clustering of Passive Conflict, Active Conflict, and Contempt name generators, with the one exception being the name generator Adversary, which clusters with the Contempt ties. For the positive ties, the clustering does not quite follow what we expected, with Rely On clustering with Energize, rather than Look Up and Energize clustering together (two Admiration cluster ties). The different findings of our main study and this sample could partly be a product of the small numbers of positive name generators, and the large number of ties excluded from this test.

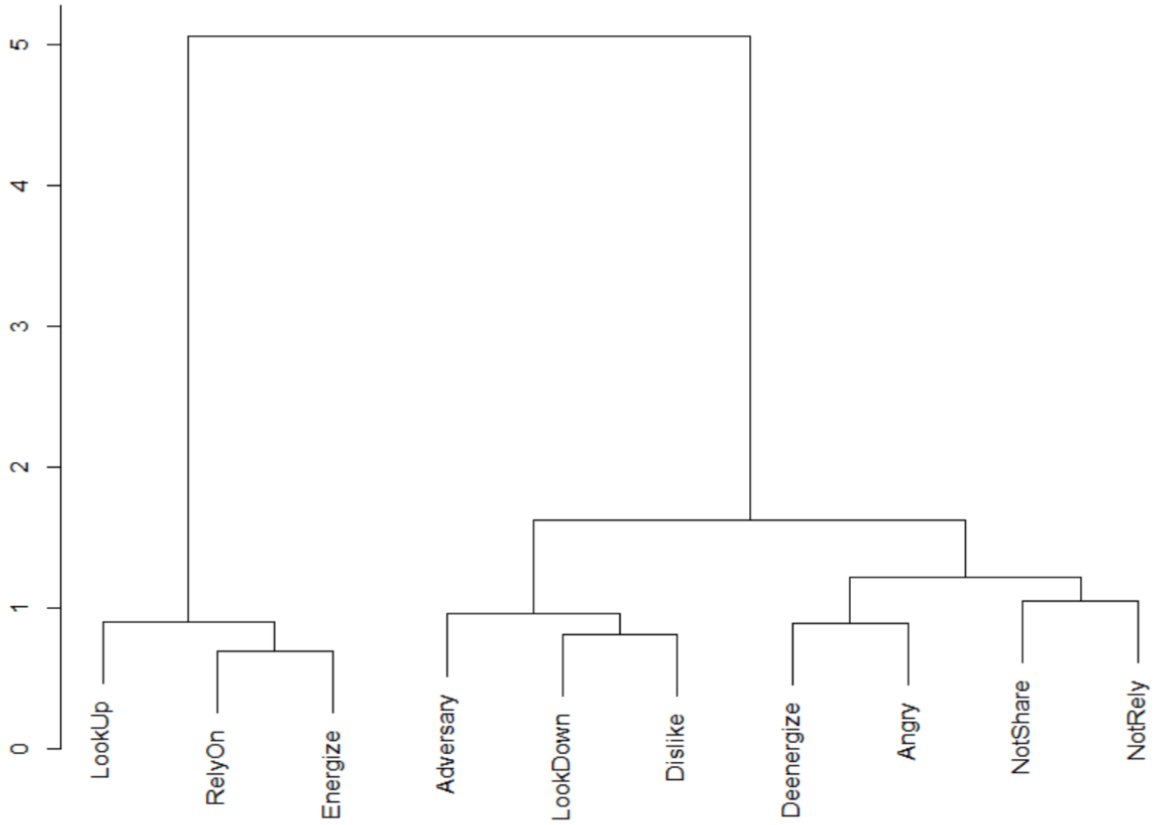

Figure A8: Hierarchical Clustering of Compound Name Generators

Figure A9 shows the MDS plot for compound name generators. We see here, again, that the dimensions are almost identical to those found in the full dataset, and that the positioning of individual name generators on this MDS plot are very similar to their position - both relative and absolute - in the MDS plot for the full dataset.

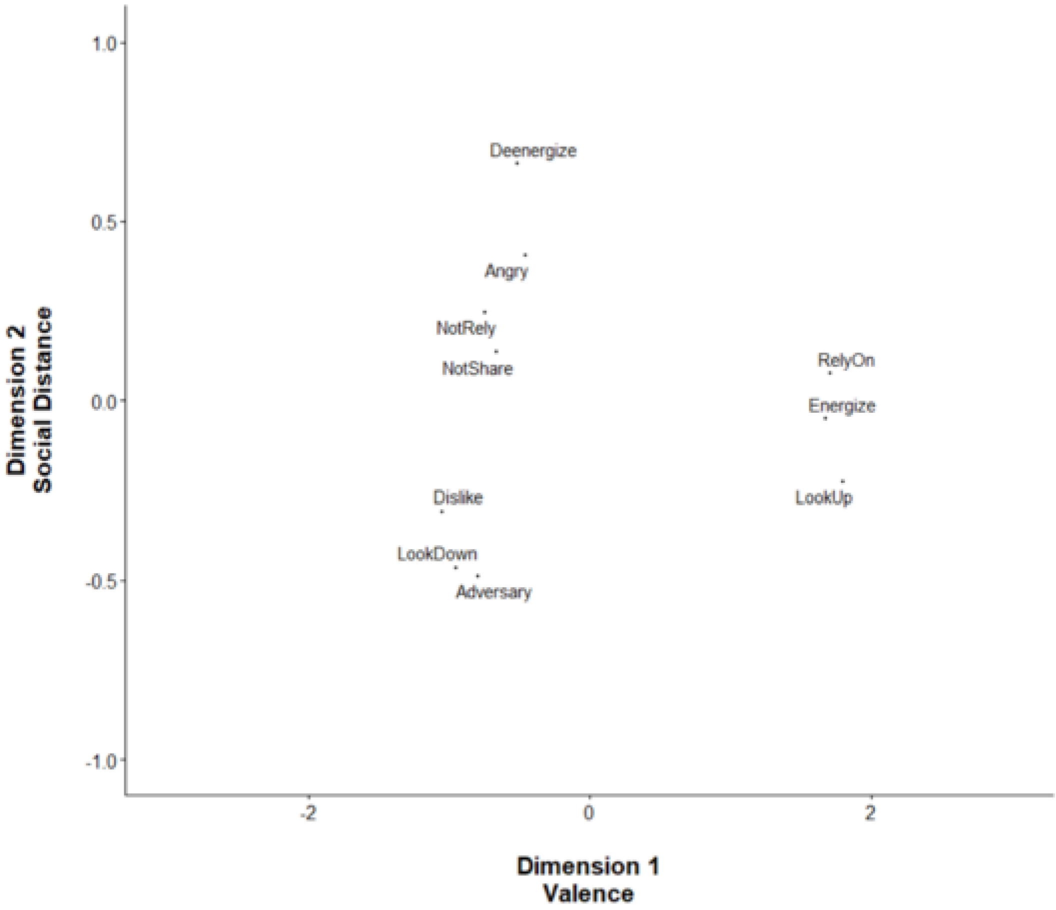

Figure A9: Multi Dimensional Scaling of Compound Name Generators

In summary, while there are differences when we conduct analysis on the compound and simple name generators separately, these differences don't seem to be systematic, and what is most notable is that almost all the features and findings of the main analysis of this paper hold when we conduct the analysis on these two separate datasets.