On a Potential New Measurement of the Self-Concept

THESIS

Presented in Partial Fulfillment of the Requirements for the Degree Master of Science in the Graduate School of The Ohio State University

By

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2021

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Abstract

Past measurements of the self-concept fail to adequately capture the full extent of the construct. In an attempt to establish a novel measurement of the self-concept, participants generated a network of self-relevant aspects and described the extent to which they were connected. Researchers then used social network analysis methodologies to quantify these networks. We failed to find any evidence to support the validity of this new measure. These metrics do not correlate significantly with any previous measure that we used. Potential limitations and future directions are discussed.

Dedication

Dedicated to my parents, my friends, and all those who’ve pushed me to do better.

Acknowledgments

I would like to thank members of the OSU Psychology Department, and especially the Social Psychology Area. I would like to specifically thank my advisor Steve Spencer, my secondary advisor Baldwin Way, Russ Fazio for their invaluable advice over the years. I'd like to thank Jonathan Stahl and Nate Haines, as well as Kenny Connor and the rest of my research assistants for their help on this specific project. And finally I'd like to thank Haemi Nam, Allison Londerèe, Shelby Boggs, Joe Siev, Jaroth Lanzalotta, and the rest of the social psychology graduate students for their love and support during my tenure here at Ohio State.

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Introduction

There's a distinct benefit to knowing who you are. Attempts to categorize their social roles, attributes, and other self-relevant information results in the formation of cognitive structures about the self (Markus & Sentis, 1982). These representations of our self-concepts can guide everything from how we process information (Markus, 1977; Bower & Gilligan, 1979) to how we respond to threats to our self-esteem (Jordan et al., 2003; McGregor & Jordan, 2007). We are proposing a new model which both encompasses past work and can make a new set of theoretical and quantitative predictions regarding the ways in which people represent their self-concepts. Drawing from past research, we are proposing a network model of the self-concept in which different self-aspects (social roles, traits, relationships, values, etc.) increase or inhibit accessibility of other self-aspects.

Previous Models of the Self-Concept

Ascribing labels and categories to the varying aspects of the self allows for the world around you to be more easily understood (Markus & Sentis, 1982) and for a sense of self to be more certain (Campbell, 1990).When asked, people can describe themselves in any manner of ways. As such, there have been a number of different models that have attempted to capture this cognitive structure underlying the self, to varying degrees of success.

These models are all based on relatively simplistic models of cognitive structure with a few noteworthy issues that are fairly common. First, none of the models allows for sufficient interplay between different aspects. If the self-concept is a dynamic framework in which relevant information increases the accessibility of other information (DeSteno & Salovey, 1997), then any representation of that framework should allow for easy activation between aspects of the self. Rather, many of these models rely on a sense of hierarchy in which only the more abstract level of one's identity are directly linked. This hierarchy also results in another key failing of these previous models. Under hierarchical models of the self-concept, such as Allen McConnell's work on the Multiple Self-Aspects Framework (McConnell, 2011), attributes are only categorized in terms of the roles they serve. Participants are asked to ascribe attributes to social roles, without consideration that some attributes may be more abstract and not tied to one specific social role. In this way social roles at an abstract level affect one another in the model but attributes do not. Further as Semin & Fiedler (1988) have shown linguistic categories can affect how information is processed in terms of informativeness and temporal stability. In a similar way self-attributes may take on different meaning when used in different ways linguistically. Considering myself "intelligent" is different than "OSU Grad Student". Together these points all suggest that the relation of self-attributes may be more fluid and less structured than previous models has assumed.

Based on these top-down impositions, previous ways to measure the self-concept were static and structured. In Linville's Self-Complexity work, for example, she had participants create self-relevant groups based on a pre-generated list of adjectives

(Linville, 1987). In doing so, this work potentially fails to include vital aspects about an individual. Instead, it may be important to allow participants to freely generate a list of their own most important aspects and use methods that allow a dynamic interplay between those aspects.

Current Model of the Self-Concept

Science works by building upon the research that came before. Markus's work was among the first to take a cognitive approach to the self-concept. McConnell's work expanded upon that by adding a predictable structure under which self-concepts operate. In the current model, we are building upon that that theorizing with a measurement strategy that allows us to make meaningful predictions and quantify the relationship between self-concepts. I am proposing a network model of the self-concept in which different self-aspects (social roles, traits, relationships, values, etc.) increase or inhibit accessibility of other self-aspects. Inherent to this model are a series of tenets that have been established by previous research (Markus, 1977; McConnell, 2011):

1. The self-concept is a network of multiple, interconnected, and context-dependent aspects.
2. Relationships between aspects are defined as the ability of activation of one aspect leading to the activation/inhibition of the other aspects.
3. The self-concept is situationally and temporally defined, but a core set of aspects may be temporally stable.

4. The shape of one’s self-concept defines how one interacts with the world around them.

5. Feedback evaluating one aspect affects the evaluations of surrounding highly connected aspects.

Self-Concepts and Social Network Analysis

The self-concept has often been described as a dynamic and context-dependent framework under which relevant information increases the accessibility of other information (DeSteno & Salovey, 1997). For example, if someone considers being *intelligent, curious,* and *creative* to be important to their self-concept, some of these pairings may be more closely linked than others. If this person has a long experience as a scientist, then *intelligent* and *curious* would be closely linked. Activation of either *intelligent* or *curious* should increase the likelihood, then, of the other aspect being activated, and may actually reduce the likelihood of *creative* being activated. Having individuals elaborate on the interconnectedness of a large number of these relevant self-aspects will result in a visualizable network to which we can ascribe a number of quantifiable metrics. Specifically, we are hypothesizing that social network analysis (Wasserman & Faust, 1994) will allow for more exact quantitative predictions than have been previously possible regarding the aspects of the self-concept that are more central to an individual.

Social network analysis is a widely used set of analytical procedures throughout the social and behavioral science community as a way to investigate political, economic, or social structural environments (Wasserman & Faust, 1994). In these past procedures, social networks are measured as the graph of the relationships between different individuals within a particular environment. Despite the decades of research done on how these procedures can be applied to interpersonal relationships, seemingly no research has been done looking at whether these procedures can be applied on an intrapersonal level, treating individual aspects and the relationships between them in the same way.

Density

Density is a function of the number of ties within a network compared to the total possible number of ties. It is operationalized as a ratio between the meaningful edges present in a particular graph and the total number of possible edges. An edge was determined to be meaningful if the participant ranked it above a 4 on a 7 point scale in response to the question "To what extent does thinking about yourself as [Aspect 1] make you think of yourself as [Aspect 2]". A perfectly dense network would be one in which every node is perfectly connected to every other node. Within the model of the self, that would mean that a participant thinks about every single one of their aspects when prompted with any of their identities. Comparing this measure to previously established work, we expected to see a high correlation between density of the self-network and Self-Concept Clarity. When an individual is likely to think about their entire identity (as would be expected in an individual with a highly dense network), we would expect them to have a clearer sense of who they are.

Clustering

Clustering is a measure of the extent to which networks possess natural divisions of nodes in densely connected subgroups (Newman & Girvan, 2004). It is calculated using a community detection algorithm. The particular algorithm used in this project is based on “betweenness” of edges (Newman & Girvan, 2004). Betweenness is a refers to the extent to which individual nodes are essential to spread of activation within a network. To calculate shortest-path betweenness, the algorithm calculates the shortest paths between all possible nodes. It then assigns scores to each edge based on the number of these shortest paths that passes through that particular edge. Edges high in betweenness are crucial for spread of activation between otherwise unconnected subregions of the network. The community detection algorithm removes the highest betweenness edges, calculates new betweenness scores for the remaining edges, calculates the strength of all possible subgroupings of nodes, and repeats this process until it fails to significantly improve the strength of the subsequent communities. The algorithm removes the edges most important to intercommunity spread of activation until those communities are sufficiently isolated and dense. It then returns the final number of communities found. These resulting communities consist of clusters of aspects that individuals see as highly connected. Unlike previous methods of clustering, these clusters may be based around linguistic categories (as in Semin & Fiedler’s work), particular social roles (as in Linville’s work), a mix of the two, or a previously unknown method of grouping self-aspects. Despite the more holistic approach, we are expecting that clustering should still strongly correlate with complexity. Self-complexity is heavily affected by the number of groupings created by participants during the card-sorting task. We would expect to see similar clusters emerge from the community detection algorithm.

Current Research

In the present studies, we will be attempting to establish discriminant, and predictive validity for this new way of measuring and quantifying the self-concept. Individual participants generate each particular network of the self-concept, based on the twenty statements task (Cousins, 1989). This operationalization avoids any prior assumptions of the ways in which any particular aspect may be related to any other aspect.

Methods

Participants

One hundred and twenty-seven Amazon mechanical Turk workers participated in the study. In total, 29 participants were excluded from the analyses: exclusions occurred based on whether or not the IP addresses of the participants were suspicious, whether or not participants fully completed the task, and whether or not participants provided obviously fake networks. The final sample consisted of 98 participants (70 men and 28 women).

Self-Net Task

The procedure detailed here is a novel version of a social network generation task for the purpose of generating an individual's unique self-concept map. We utilized a modified version of the Twenty Statements Test in order to get each participant's “nodes”. Participants were instructed to write fifteen answers to the prompt ‘Who am I’, then were asked to think about the importance of each identity to them. Following this, their responses were automatically fed into a network generation task. We asked participants to consider the extent to which thinking about themselves in terms of one identity makes them think about themselves in terms of another identity. We asked this question for each possible “edge” in the network. Within this context, we’re defining an edge as a directional relationship between each self-aspect and another self-aspect, such that there can be a different level of activation between node A and node B than there is between node B and node A. We were then able to take this information to calculate a variety of network metrics, including density of the network, and number of communities within the network.

Self-Complexity

The procedure here follows from that of previous work on self-complexity (Campbell, 1990). To assess the complexity of their cognitive representation of the self, participants arranged 33 pre-determined attributes into a maximum of 10 self-relevant groups. A single self-complexity score was calculated through the following equation: $H = \log_2 n - (\sum n_i \log_2 n_i)/n$; in which n is equal to the number of traits supplied (n=33), n_i is equal to the number of traits in the i^{th} group combination, i refers to each specific combination of groups ($i = 1 \ldots 2^k$), and k is the number of self-concept groups created.

Self-Concept Clarity

To assess self-concept clarity, participants completed the Self-Concept Clarity Scale (Campbell et al., 1996). The scale items assess the extent to which participants have a clear sense of who they are (e.g. "My beliefs about myself often conflict with one another") by asking them to self-report the extent to which they agreed to each of 12 statements on a five point scale (*1= Strongly Disagree to 5=Strongly Agree*).

Explicit Self-Esteem

To assess the self-esteem of participants, participants completed the Rosenberg Self-Esteem Scale (RSES; Rosenberg, 1965). This scale assesses an individual's level of self-esteem ("I feel that I have a number of good qualities") on a four point scale *(1=Strongly Agree, 2=Agree, 3=Disagree, 4=Strongly Disagree).*

Big-Five Inventory

To collect a benchmark, commonly used measure of individual differences in personality, participants completed the ten-item version of the Big-Five Inventory scale (BFI; Rammstedt & John, 2007). This instrument assesses an individual's responses along a number of personality-based dimensions (Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism) by having them rate the extent to which they agree with statements on a five point scale *(1=Disagree Strongly, 2=Disagree a Little, 3=Neither Agree nor Disagree, 4=Agree a Little, 5=Agree Strongly).*

Procedure

All participants completed the study online at a time and location of their choosing. We asked participants to complete a series of activities in which they would describe different important parts of their lives. After consenting, participants then completed the Self-Net Task, responding to the prompt “I am_____” up to fifteen times and indicating the extent to which these aspects were related. They then completed the self-complexity task in which they arranged a list of words into groups that represent aspects of their life. After doing so, we asked about their thoughts about themselves more generally (including Self-Clarity, Self-Esteem, and Big-Five Personality Traits), and basic personality, demographic and background information.

Results

The descriptive statistics of all measured variables can be found in Table 1. The extent to which the metrics associated with the self-net task are correlated with previously established attempts to measure the self-concept can be found in Table 2. Density of the network and the number of clusters found within each network are highly negatively related to each other (r=-0.433). Density was negatively correlated with both Self Concept-Clarity (r=-0.239) and Neuroticism (r=-0.202), but was not significantly correlated with Self-Complexity (r=0.004). Clustering was not significantly correlated with any further metrics.

Regarding previously established self-concept metrics, Self-Complexity was correlated with Openness (r=0.225) and Agreeableness (r=0.251) and was negatively correlated with Neuroticism (r=-0.186). Self-Concept Clarity was strongly correlated with Self-Esteem (r=0.499), Openness (r=0.353), Conscientiousness (r=0.497), Extraversion (r=0.312), Agreeableness (r=0.328), and was negatively correlated with Neuroticism (r=-0.381).

Discussion

Summary of results

The research attempted to establish discriminant and convergent validity for a social network analysis-based measurement of the self-concept. As it stands, the present data fail to provide sufficient evidence in support of this new measure of the self-concept. The self-net and related metrics are not correlated with any of the tested established measures to have any reasonable amount of confidence in its validity. Although this new measure is clearly different from previously established measures, we failed to find any evidence that the new metrics truly captured valuable information about the self-concept.

Limitations

There are a number of potential reasons for the lack of supporting evidence for this particular measure and a number of potential limitations. One such limitation is the assumption that individuals would be willing and able to report the extent to which attributes are related with a level of nuance. When asked the extent to which two of their identities were related, the most common responses by participants were either ‘Not at all related’ or ‘Very much’ related (1 or 7 on a 1-7 scale, respectively). This might indicate that participants were either unable to infer the extent to which two aspects were related or that the participants did not want to exert the amount of effort needed to make these judgments. In order to effectively gauge every possible relationship between each of the

15 aspects, participants had to answer 210 questions. This may have proven too mentally taxing for them to be able to adequately think about each possible interaction. In development of this measure, this potential mental strain was taken into consideration. We ultimately decided that the balance between the benefit of additional information and the cost of mental fatigue associated with 15 aspects was optimal, but this was based on instinct rather than experimental work. More work could be done to shorten or lengthen this procedure to find the optimum balance to ultimately improve this measure. Important to consider, however, is the fact that many of the other measures participants responded to correlated in accordance with previous research. Self-Concept Clarity has consistently correlated with self-esteem (Campbell, 1990) and we find that same correlation in this work. This suggests that the failure to find meaningful evidence in support of the novel measure is not entirely due to participants' response to the task.

The failure to find meaningful evidence in support of the novel measure may instead be due to an issue with the application of social network analysis. In testing of this novel measure of the self-concept, we also attempted to apply a typically interpersonal measure to the intrapersonal level. It may in fact be inappropriate to try to apply methods and measurement designed for group-level organizations to individual-level aspects. In order to determine whether or not this is the case, more work needs to be done.

Theoretical Implications

In addition to adjusting the task, it may be worth pursuing other methods than self-report to get at the relationships between aspects of the self. Potential future avenues to evaluate the extent to which each aspect serves to automatically activate each other aspect of the self without the need for accurate introspection include a modified version of 'bona fide pipeline' (Fazio, Jackson, Dunton, & Williams, 1995), for example, we might expect that if two aspects are related, then presentation of one of these aspects would facilitate the response to a "me" or "not me" judgment for a subsequently presented aspect. In other words, when primed with one aspect, participants should be faster to decide that another aspect is self-relevant if the two aspects are closely related. Alternatively, utilizing voxel-to-voxel representational similarity analysis (Kriegeskorte, Mur, & Bandettini, 2008) might show that if two aspects or identities are related, then representation patterns while participants are thinking about those identities will be significantly similar.

Further research might also examine if the proposed procedure could be, not as an overall, stable measure of the self-concept, but a measure of an individual's current, working self-concept. As previously established in other works and earlier in this work, the self-concept can also be situationally and temporally defined (Markus & Kunda, 1986; McConnell, 2011). Rather than trying to capture an individual's self-concept in a single session, it may be worthwhile to measure participants' self-concepts at multiple timepoints to see how the self-concept changes and evolves depending on the particular environment.

Practical Implications

Regardless of the failure of this current measure, the limitations of previous measures still stand, meaning that social psychologists still need an accurate and appropriate measure of the self-concept.

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Appendix A: Figures & Tables

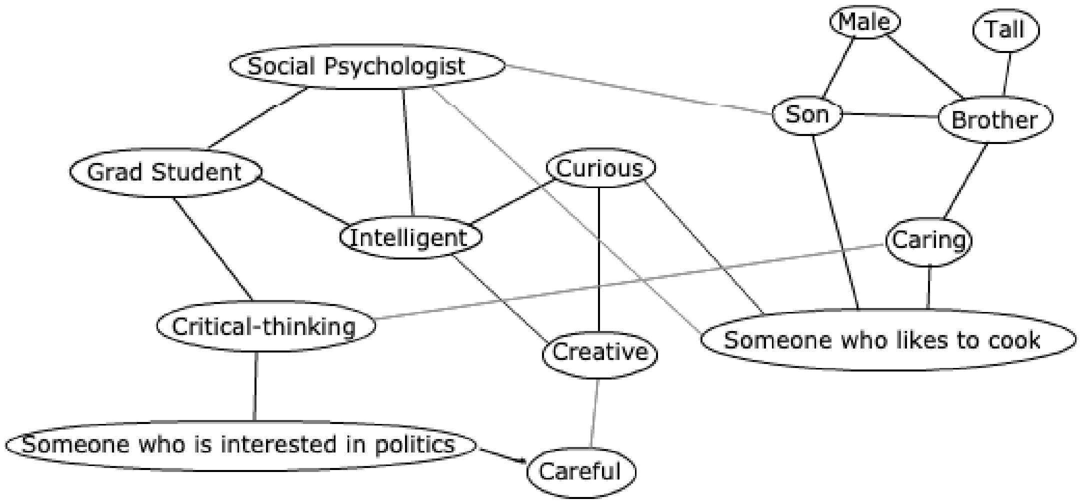

Figure A1. Example model of the self-concept. Black lines indicate meaningful edges. Gray lines indicate nonmeaningful edges between aspects.

Table 1: Descriptive Statistics of Major Variables

	Density	Clustering	Complexity	SCC	Self Esteem
Minimum	0.08	1.00	0.00	18.0	10.0
Maximum	1.00	9.00	4.48	60.0	40.0
Mean	0.46	3.12	2.36	44.6	28.7
Std. Deviation	0.260	1.986	.906		

Table A1. Minimum values, maximum values, means, and standard deviations of the following values: Density = Density of the network; Clustering = Number of communities within the network; Complexity = Self-Complexity; SCC = Self-Concept Clarity; SE = Self-Esteem;

Table 2: Correlations Between Major Variables

	Dens.	Clust.	Comp.	SCC	SE	BFI-O	BFI-C	BFI-E	BFI-A	BFI-N
Dens.	-	-0.433***	0.004	-0.239*	0.014	-0.188	0.040	0.177	0.055	-0.202*
Clust.	-	-	-0.051	0.113	0.052	0.025	-0.119	-0.016	0.025	0.080
Comp.	-	-	-	0.024	0.198	0.225*	0.251*	0.002	0.184	-0.186*
SCC	-	-	-	-	0.499***	0.353***	0.497***	0.312**	0.328**	-0.381***

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

Table A2. Correlational values between the following variables: Dens. = Density of the network; Clust. = Number of communities within the network; Comp. = Self-Complexity; SCC = Self-Concept Clarity; SE = Self-Esteem; BFI-O = Big Five Inventory-Openness; BFI-C = Big Five Inventory-Conscientiousness; BFI-E = Big Five Inventory-Extraversion; BFI-A = Big Five Inventory- Agreeableness; BFI-N = Big Five Inventory-Neuroticism