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From single attitudes to belief systems: Examining the centrality of STEM attitudes using belief network analysis

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A R T I C L E I N F O

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A B S T R A C T

Many achievement and motivation theories claim that a specific set of beliefs, interests or values plays a central role in determining career choice and behavior. In order to investigate how attitudes determine behaviors, researchers generally investigate each attitude in isolation. This article argues that studying belief systems rather than single attitudes has several explanatory advantages. In particular, a system-level approach can provide clear definitions and measures of attitude importance. Using a nationally representative sample of 13,283 9th graders and measures of 136 STEM-related attitudes, I implement a belief network analysis to investigate which attitudes are most influential in determining STEM career choice. The results suggest that identity beliefs, educational expectations and ability-related beliefs play central roles in individuals' belief systems.

1. Introduction

A large body of research has focused on the motivations that influence achievement and career-related behaviors. In particular, an abundance of theories has been proposed regarding which sets of beliefs are most influential in determining career interests, goals and choices. Well-known theories such as expectancy value theory (Wigfield & Eccles, 2000) and social cognitive theory (Bandura, 2012; Lent et al., 2008) posit that beliefs about one's ability to succeed (often referred to as self-concept or self-efficacy beliefs) play a central role in determining achievement and career-related behaviors. Expectancy value theory also focuses on the values attached to a task or occupation (Eccles & Wigfield, 2020), while social cognitive theory also focuses on goals and outcome expectations (Schunk & DiBenedetto, 2020). Other prominent theoretical accounts have highlighted, among other things, the importance of beliefs about the nature of intellectual ability (or "mindset" beliefs; e.g., Yeager & Dweck, 2012), beliefs about the enduring sense of self (or "identity" beliefs; e.g., Cribbs, Hazari, Sonnert, & Sadler, 2015), beliefs about which groups or types of people are better (or "status" beliefs; e.g., Ridgeway & Correll, 2004), and beliefs about the immediate environment (for instance, beliefs about the classroom or teacher; e.g., Maltese & Tai, 2011).

Career or achievement motivation theories intend to explain various phenomena, including how individuals' beliefs and other

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mental states (which I will broadly refer to as "attitudes"[1]) are shaped by the environment, how the core attitudes relate to other attitudes, and how they determine particular behaviors (Eccles & Wigfield, 2020). Yet a key component of these theories involves a claim about which sets of attitudes are at the core of individuals' decision-making processes, i.e., which sets of attitudes are most influential in determining achievement or career-related behaviors. By identifying these core attitudes, we would be able to understand the main reasons why individuals choose to engage or disengage in different activities (Eccles & Wigfield, 2002). In particular, these theories are commonly used to explain engagement and persistence in science, technology, engineering, and mathematics (STEM) occupations and fields (Ridgeway & Correll, 2004; Wang & Degol, 2013).

Despite a vast literature on the topic, the claim that a set of attitudes lies "at the core" or are "most influential" in determining behavior is often vague or ambiguous. Clarifying this claim is essential for understanding and testing achievement and motivation theories. In this paper, I argue that these theories should be interpreted in structural terms. Specifically, these theories claim that a particular set of attitudes lies at the center of individuals' belief systems,[2] while other attitudes lie at the periphery. In other words, these theories make assertions about structural features –related to center-periphery distinctions– of individuals' belief systems.

The goal of this study is to examine the structure and centrality of STEM-related attitudes by conducting a belief network analysis (Boutyline & Vaisey, 2017). This approach consists of modeling individuals' belief systems as networks, and then measure the importance of specific attitudes using network centrality measures (e.g., Boutyline & Vaisey, 2017; Brandt, Sibley, & Osborne, 2019). More specifically, I estimate the structure of 136 STEM-related attitudes using a nationally representative dataset of 9th graders. I include one behavioral measure (enrolling in a STEM major), which allows me to examine which attitudes are more closely related to this behavioral outcome. I also estimate the attitudes' betweenness and closeness centrality, which are measures associated with different definitions of what counts as structural importance. The results suggest that identity beliefs, educational expectations and ability-related beliefs play central roles in individuals' belief systems.

2. Attitudes and career-related behaviors

Achievement and motivation theories are driven by the assumption that some key attitudes –beliefs, desires, interests, etc.– motivate individuals' educational decision-making processes. For example, several theories claim that beliefs about individuals' own abilities, often referred to as "self-efficacy" beliefs, play a determining role in individuals' career choices and behaviors (Correll, 2001; Eccles & Wang, 2016; Ridgeway & Correll, 2004). Differences in self-efficacy beliefs have also been considered a key explanation of the gender gap in STEM (Cheryan, Ziegler, Montoya, & Jiang, 2017; Correll, 2001; Kahn & Ginther, 2017). Research suggests that girls systematically underestimate their own abilities in STEM fields, which ultimately affects their career choices and aspirations (Correll, 2001; Eccles & Wang, 2016; Ridgeway & Correll, 2004).

Differences in self-efficacy beliefs can also contribute to socioeconomic disparities in educational outcomes (Chevalier, Gibbons, Thorpe, Snell, & Hoskins, 2009; Filippin & Paccagnella, 2012). Researchers have found that, compared to individuals from high socioeconomic backgrounds, individuals from low socioeconomic backgrounds tend to underestimate their abilities (Filippin & Paccagnella, 2012). Given that attitudes such as self-efficacy beliefs are likely influenced by family background, the intergenerational transmission of attitudes becomes a key driver of educational inequalities (Holtmann, Menze, & Solga, 2021).

Other theories emphasize a different set of attitudes as key determinants of individuals' educational decision-making processes. For instance, the theory of relative risk aversion argues that educational decision making is primarily motivated by individuals' desire to avoid downward mobility (Breen & Goldthorpe, 1997; Holm & Jæger, 2008). This theory explains the persistence of educational inequalities by arguing that the desire to avoid downward mobility is stronger than the desire to be upwardly mobile.

In sum, much of the theoretical literature on educational decision-making processes focuses on identifying the attitudes that determine career choices and behaviors. In relation to educational outcomes in STEM, researchers have focused on attitudes such as STEM-related self-efficacy beliefs, identity beliefs, aspirations, interest and values (Eccles & Wigfield, 2020; Maltese & Tai, 2011; Quintana & Saatcioglu, 2022; Xie, Fang, & Shauman, 2015). These attitudes are considered key explanatory components of individuals' career choices and behaviors. In addition, these attitudes are often used to explain disparities in STEM-related outcomes such as the gender GAP in STEM fields (Cheryan et al., 2017; Kahn & Ginther, 2017; Morgan, Gelbgiser, & Weeden, 2013; Wang & Degol, 2013).

In order to investigate how attitudes determine educational choices and behaviors, researchers typically investigate each attitude in isolation. For example, a vast literature focuses on the relationship between self-efficacy beliefs and educational outcomes (Chevalier et al., 2009; Marsh & Martin, 2011; Marsh, Trautwein, Lüdtke, Köller, & Baumert, 2005; Wu, Guo, Yang, Zhao, & Guo, 2021). The results of these studies are often used to inform social-psychological interventions, defined as interventions that target specific attitudes (thoughts, feelings, belief, etc.) to improve educational outcomes (Yeager & Walton, 2011). For example, a national experiment showed that modifying students' mindset beliefs (i.e., beliefs about the nature of intelligence) improved academic outcomes (Yeager et al., 2019). These interventions assume that the attitude under consideration affects behavior, and that it can be modified in isolation

[1] By "attitudes" I mean propositional attitudes, which include beliefs, intentions, expectations, desires, fears, wishes, and so on. Propositional attitudes are defined as cognitive relations toward a thought or proposition (Nelson, 2019), e.g., the belief that doing well in school is useful, the desire to be a scientist, or the expectation to graduate from college. Several philosophers have argued that propositional attitudes constitute the fundamental units of thought (Nelson, 2019).

[2] I use the term "belief system" in accordance with the literature on the topic. However, in this study belief systems can involve beliefs as well as other attitudes.

(e.g., that one can "surgically" change individuals' mindset beliefs, and that this will have meaningful behavioral consequences).

This conventional one-attitude-at-a-time approach has important limitations. Social scientists have long recognized that the attitudes that individuals hold are functionally interrelated (Boutyline & Vaisey, 2017; Brandt & Sleegers, 2021). This means that attitudes are mutually constrained, in the sense that it is difficult to change one attitude without changing other attitudes (Martin, 2002). For instance, individuals' educational expectations might depend on their beliefs about the value of school or perceived social and economic barriers. The consistency between attitudes is reflected in concepts such as "worldview" or "ideology". More generally, a configuration of attitudes that are functionally interdependent is often referred to as a "belief system" (Converse, 1964).

Shifting the unit of analysis from single attitudes to belief systems has several explanatory advantages. By taking into account the connections among attitudes, one can explain why attitudes tend to be related (Dalege et al., 2016) and why attitudes can be difficult to change (Martin, 2002). In addition, belief systems can clarify in what sense specific attitudes are more influential than others (Brandt et al., 2019). As explained below, by locating attitudes within larger belief systems one can provide clear definitions and measures of attitude importance.

In this study, I argue that studying belief systems rather than single attitudes can shed light on how individuals' attitudes connect to each other, and ultimately shape individuals' educational choices and behaviors. In the next section, I explain the advantages of conceptualizing belief systems as networks. In the methods section, I review methods that can be used to estimate the structure of belief systems (conceived as networks), as well as different measures of importance based on center-periphery distinctions. I connect these measures to theoretical claims that have been made about the importance of individual attitudes. Finally, I illustrate this method by examining the most influential attitudes in relation to educational outcomes in STEM.

3. Modeling belief systems as networks

In order to investigate the role that our beliefs and other attitudes play in determining our behavior we need to take into account two important principles. The first principle is that the interconnections among attitudes, as well as the relations between attitudes and actions, should be conceived as causal (Brandt & Sleegers, 2021). Researchers refer to this idea by stating that attitudes are "causally relevant" or "causally efficacious" (Woodward, 2008). For instance, expectancy-value theory (Eccles & Wigfield, 2020) hypothesizes that cultural beliefs about gender roles *cause* certain beliefs about one's abilities, which will then *cause* certain career-related actions (e.g., enrolling or not in a STEM major). Interpreting these relationships as causal implies that modifying the gender beliefs will lead to a change in self-efficacy beliefs, which will then lead to a change in career-related behaviors. The idea that beliefs are causally relevant is an assumption underlying social-psychological interventions (e.g., Yeager & Dweck, 2012).

In principle, single attitudes can be causally relevant. For example, the belief "it will rain today" can lead me to take an umbrella. The assumption that single attitudes can be causally efficacious underlies many motivation theories. For instance, there is a vast literature examining the implications of having the belief that intelligence is a fixed characteristic (e.g., Yeager & Dweck, 2012). This theory implies that modifying this belief will lead to significant behavioral changes (Yeager & Dweck, 2012).

Yet despite the fact that single attitudes can be causally relevant researchers have argued that attitudes typically depend or are determined by other attitudes that the individual holds (Boutyline & Vaisey, 2017; Brandt et al., 2019). For instance, religious and political beliefs are interconnected to a wide range of other religious and political beliefs. That is, attitudes should not be conceived as autonomous elements but rather as constituents of larger structures or systems of attitudes (Boutyline & Vaisey, 2017). The second principle states, then, that attitudes are interconnected to other attitudes and are embedded in systems.

Belief network analysis (BNA) is an approach that investigates belief systems as networks (Boutyline & Vaisey, 2017). Following the two principles described above, the basic premises of BNA –as interpreted in this study– is that attitudes are causally relevant, and that we need to examine the interdependencies among attitudes in order to understand how they affect behavior. In BNA the nodes in the network represent attitudes, and the connections (or edges) represent relationships among attitudes. As any psychometric network analysis, BNA has two main phases: network structure estimation and network description (Borsboom et al., 2021). The first stage consists in estimating a network (or graph) based on the observed dependencies between variables in a dataset. The second stage consists in characterizing the structural features of the estimated network using descriptive tools of network science (Borsboom et al., 2021).

Depending on one's theoretical interests and assumptions, one can estimate and describe a belief network in a different way. In this study, I use a structure learning algorithm that identifies the direct and indirect relationships among the variables in the dataset (Spirtes, Glymour, Scheines, & Heckerman, 2000). Structure learning (or causal discovery) methods are based on causal principles, and their ultimate goal is to identify causal relations (Spirtes et al., 2000). Using causal discovery methods to estimate the network structure is consistent with the idea that belief systems should represent causal relationships among attitudes. Once the network has been estimated, I use three measures to estimate the importance of individual attitudes: distance to the behavioral outcome, betweenness centrality and closeness centrality. As explained below, these three measures capture different notions of importance implicit in several achievement and motivation theories.

4. Data

4.1. Dataset

The data comes from the High School Longitudinal Study of 2009 (HSLS:09) conducted by the National Center for Education Statistics (Ingels et al., 2011). The study includes approximately 21,440 students in ninth grade from around 940 schools in the United

States. The sample design had two stages: first, public and private schools were selected using stratified random sampling at the national level; second, around 27 students were randomly sampled from each school. The first round of data collection took place in the fall of 2009–10 school year, and the first follow-up took place in the spring of 2012, when most students were in 11th grade. A second follow-up was taken in 2015, when most respondents were 3 years beyond high school graduation.

The HSLS:09 focuses on the transition between secondary and postsecondary education with an emphasis in STEM. In particular, the HSLS:09 focuses on students' decision-making processes. For this reason, a student questionnaire was administered in order to gather data on a wide range of beliefs, aspirations, expectations, values, interests, perceived opportunities, barriers and costs that might affect students' course taking and career-related choices. This dataset is ideal, then, to study the motivations that explain why individuals decide to pursue STEM courses and careers (Ingels et al., 2011).

In the present study, the analytic sample is defined as 13,283 individuals who have a non-zero value in the analytic weight W4W1W2W3STU. This weight accounts for differential nonresponse (which can generate sampling bias in the analysis) and is appropriate for studies using data from the base-year as well as the first and second follow-ups.

4.2. Measures

4.2.1. Attitudes

Researchers have argued that centrality measures should be computed and interpreted in belief systems with meaningful boundaries, i.e., in networks that include all relevant nodes (Neal & Neal, 2021). Yet these authors also note that the universe of relevant attitudes is likely very large, and the boundaries of belief systems are often ambiguous or unknown. In response to this challenge, I included all attitudes gathered in the first follow-up survey, when most sample members were completing 11th grade.

Table 1
Summary of the 136 attitudes included in the analysis.

Attitude type	Example	Number of items	Number of response categories	Measurement occasion
Academic aspirations	How far in school teenager would like to go	1	4	2
Academic expectations	How far in school teenager thinks he/she will get	3	4	2
Academic trade-offs	Time/effort in math/science means not enough time with friends	4	4	1
Attitudes on school belonging	9th grader is proud to be part of his/her school	5	4	1,2
Beliefs about gender differences	How teen compares males and females in math	3	5	2
Beliefs about effort	Thinks would earn higher grades if spent more time studying	3	2,4	1,2
Beliefs about the value of school	Importance of HS grades for getting into typical 4-year college	6	4	2
Beliefs about the value of work	9th grader thinks working is more important for him/her than college	2	4	1,2
Economic barrier beliefs	Even if accepted to college, family can't afford to send teen	2	4	2
Expectancy beliefs	9th grader thinks he/she has the ability to complete a Bachelor's degree	1	4	1
Mindset beliefs	You have to be born with the ability to be good at math	4	4	2
Life expectations	Expects to start family/take care of children in fall 2013	5	2	2
Math and science identity beliefs	Teenager sees himself/herself as a science person	4	4	2
Math and science interest	Teen thinks (spring 2012) math course is a waste of time	8	2,4	2
Math and science self-efficacy beliefs	Teen certain can understand (spring 2012) math textbook	8	4	2
Math and science utility beliefs	Teenager thinks math is useful for future career	6	4	2
Perceptions of teacher's pedagogical efficacy	Teen's spring 2012 math teacher wants students to think, not memorize	8	4	2
Perceptions of math and science teacher	9th grader's fall 2009 science teacher treats students with respect	14	2	1,2
Reasons for choosing college	Importance of good social life when choosing college/school	12	3	2
Reasons for not studying more	Does not study more because would not be popular	8	2	2
Reasons to take math and science courses in high school	Teen is taking spring 2012 math because he/she likes to be challenged	26	2	2
School usefulness beliefs	Teen thinks studying in high school rarely pays off later with good job	3	4	2

Note. HS = high school. All data was collected through a student survey. All items are categorical, with a minimum of 2 and a maximum of 5 response categories. The first measurement occasion represents the base-year (when students were in 9th grade) and the second measurement occasion represents the first follow-up (when most students were in 11th grade). The attitudes are sorted by attitude type. Table S1 in Supplemental Material presents the entire list of the items included.

I focused on this wave of data collection (rather than when students are in 9th grade), as students are closer to finish high-school in 11th grade, and thus their attitudes at this stage are more likely to influence their postsecondary plans and decisions (Legewie & DiPrete, 2014). However, I included some relevant attitudes from the base-year data collection that were not gathered in the first follow-up survey (see Table S1 in the Supplemental Material for the wave of data collection per item).

Propositional attitudes are composed by an "attitude" (represented by a verb such as believe, desire, expect, fear, value, etc.) and a content of the attitude (represented by an expression such as "math is boring" or "go to college"). The "attitude" component implies a cognitive or subjective aspect that differentiates propositional attitudes from factual or non-subjective items. One way of testing if an item is factual is by asking if it can be verified against objective records (Boutyline & Vaisey, 2017). Using this test, I excluded non-subjective (i.e., non-attitudinal) items such as the number of times the teenager performed an activity; the number of friends that the teenager has; whether the teenager will meet specific academic requirements; the teenager's academic coursework or performance; and teenager's behaviors inside and outside the classroom. Finally, I excluded items with large numbers of missing values (around 90% or more) given that they only applied to specific subsamples, e.g., students enrolled in specific courses. Table S2 in the Supplemental Materials includes examples of items from the 2012 student survey that were not included in the analysis.

In total, 136 attitudes were included in the analysis. Table 1 presents a summary and examples of the items included (see Table S1 in the Supplemental Material for the full list of items). As Table 1 indicates, the items can be grouped in 22 different types. These categories contain attitudes that have been considered central according to several achievement and motivation theories, including expectancy and self-efficacy beliefs (Bandura, 2012; Eccles & Wigfield, 2002, 2020); beliefs and feelings about the importance and usefulness of academic and career-related activities (Hulleman, Kosovich, Barron, & Daniel, 2017); values, interests and enjoyment in relation to a particular task or activity (Eccles & Wigfield, 2020); the sense of belonging in an environment or field (Cheryan, Plaut, Davies, & Steele, 2009); mindset beliefs (Yeager & Dweck, 2012); goals and aspirations (Maltese & Tai, 2011; Schunk & DiBenedetto, 2020); trade-offs and costs of engaging in an activity (Barron & Hulleman, 2015); situational interests and perceptions of the teacher, classroom and school characteristics (Maltese & Tai, 2011; Wang & Degol, 2013); cultural beliefs and norms (Ridgeway & Correll, 2004); identity beliefs (Cribbs et al., 2015); and lifestyle preferences (Wang & Degol, 2013).

It is worth noting that the attitudes included in Table 1 can be categorized and labeled in different ways (for discussions on conceptual and measurement issues related to key motivational construct see, e.g., Hulleman, Schrager, Bodmann, & Harackiewicz, 2010). The groupings and labels presented in Table 1 are based on HSLS:09′s student survey conceptual map (see Ingels et al., 2011). These groupings help summarize the data as well as interpret the results. However, the method implemented does not rely on these categorizations. As explained above, a basic premise of network models is that each node is causally relevant. By ascribing causal properties to observable items, one does not need to assume the existence of underlying latent variables. In other words, in network models the construct is isomorphic to the observed variable (Borsboom et al., 2021).

Several of the attitude types presented in Table 1 include items that are the same, except that some are about science and others are about mathematics. For example, one identity item is about whether the person sees himself/herself as a science person, and another whether the person sees himself/herself as a math person. These items are included as different variables given that researchers have argued that attitudes are discipline-specific as they can align with different behaviors (Bandura, 2012). Thus, it is possible, for instance, that an identity belief about science operates differently than an identity belief about math.

4.2.2. Behavioral outcome

This study focuses on the attitudes that motivate individuals' educational choices and behaviors. In order to investigate how the 136 attitudes summarized in Table 1 relate to career-related choices and behaviors, I included an indicator measuring whether the individual chose STEM or a different field as his or her first major. This behavioral outcome was obtained from the second follow-up survey, approximately three years after the modal high school completion. In the analytic sample, 2224 (24%) individuals chose a STEM major, while 7172 (74%) individuals did not choose a STEM major. Including this node in the network helps determine which attitudes are more closely related to a career decision –particularly in relation to STEM, which has been a key focus of the achievement and motivation literature (e.g., Wang & Degol, 2013)–. The attitudes included in this study have been considered key factors in determining individuals' decision to pursue a STEM career (see, e.g., Eccles & Wigfield, 2020; Maltese & Tai, 2011; Wang & Degol, 2013).

4.2.3. Limitations due to missing nodes

Despite the wide range of attitudes included in the analysis, it is likely that important attitudes are missing. For instance, the HSLS:09 does not include attitudes that have been considered important for career-related choices and behaviors (particularly in relation to STEM) such as perceived racial discrimination (Grossman & Porche, 2014), or specific achievement goals (Hulleman et al., 2010). Even if some measured variables can be considered proxies or indirect measures of these attitudes, missing nodes can generate spurious edges (Spirtes et al., 2000) as well as affect the centrality measures (Neal & Neal, 2021). Given these limitations, the edges among variables should be interpreted as representing either direct causal connections or statistical association due to unobserved confounders. On the other hand, the estimated centrality measures should be interpreted as conditional on the attitudes included in the analysis (Neal & Neal, 2021).

4.2.4. Missing data

The variables included had missing values due to a variety of reasons, such as: the respondent did not answer the question; the respondent indicated "don't know" as a response; the respondent did not answer a prerequisite question; or the question was not applicable due to prior information. The percentage of missing data in the analytic sample ranged from around 1% to 29%, with an average of 9% (Table S1 in the Supplemental Material shows the percentage of missing data per item).

Common structure learning methods require complete data (Spirtes et al., 2000). However, dealing with missing values using complete case analysis (listwise deletion) is problematic, given that the sample size will be reduced considerably (due to the large number of variables included), and will introduce bias unless the data is missing completely at random (Enders, 2010). Multiple imputation has become a common way of dealing with missing values, but current structure learning algorithms do not support multiple imputed datasets. In this scenario, a reasonable option is to impute single values using stochastic imputation (Enders, 2010). Thus, in order to preserve the entire sample size stochastic regression was conducted using chained equations in STATA 17 (White, Royston, & Wood, 2011). Single values in the behavioral outcome were also imputed. In order to improve the imputation models, the following auxiliary variables were included: race, gender, socioeconomic status, ability estimates in mathematics, urbanicity, and final grade in 9th grader's science and mathematics courses.

5. Method

5.1. Network estimation

The network was estimated using the Fast Greedy Equivalence Search (FGES) algorithm implemented in the Tetrad 6.8.0 software (Spirtes et al., 2000). I use this algorithm as it has been found to be more accurate than other commonly used structure learning methods (Nandy, Hauser, & Maathuis, 2018). FGES is a structure learning algorithm that intends to estimate the graph that best describes the dependence structure in the data (e.g., Drton & Maathuis, 2017). In particular, FGES is a Bayesian algorithm that searches for the highest-scoring graph using heuristic optimization techniques (Chickering, 2002). FGES assigns a goodness-of-fit score to each graph. For discrete data –as the one used in this study– the Bayesian Dirichlet equivalent uniform (BDeu) score is typically used (Chickering, 2002). The idea is that a graph encoding the wrong conditional independence relations will have a bad BDeu score, and maximizing this score will yield a graph that encodes the true dependence structure of the data (Spirtes et al., 2000).

Some of the assumptions required to identified causal structures (in particular the absence of hidden confounders) are likely not to be met given the available data. For this reason, the results should be interpreted with caution. A link or edge between two attitudes represents a statistical association that cannot be explained by other attitudes in the dataset. This association might arise due to a causal connection or an unmeasured confounder. Given the possibility of confounders, this study focuses on undirected rather than directed edges. The undirected graph represents conditional independencies without assuming causal directionality. In other words, the method identifies connections among attitudes, but is agnostic about the direction and strength of these connections.

To ensure stability in the results, the search procedure was conducted using 200 bootstrapped samples. An edge was retained if it appeared in 50 percent or more of the bootstrapped samples. That is, if any adjacency (which can include edges with different orientations) was present in 50 percent or more of the bootstrapped samples, then the adjacency was retained.

5.2. Centrality measures

5.2.1. Proximity

The first and probably most intuitive way of defining attitude importance in the context of motivation theories is in terms of how proximal or distal is an attitude or set of attitudes with respect to the behavioral outcome of interest. An attitude is considered proximal if it has a direct effect on the outcome, and it is considered distal if its effect on the outcome is mediated by other attitudes. Well-known theories such as expectancy value theory or social cognitive theory can be characterized by the set of beliefs that are presumed to have a direct (i.e., proximal) effect on key achievement and career-related behaviors (e.g., Eccles & Wigfield, 2020; Schunk & DiBenedetto, 2020). For example, Eccles and Wigfield (2002, p.118) explain that according to expectancy-value theory "expectancies and values are assumed to directly influence performance, persistence, and task choice." Eccles and Wigfield (2020, p.3) also explain that expectancies and values "are the most proximal psychological determinants of task and activity choice, performance and engagement." In other words, expectancy-value theory claims that there can be many beliefs and contextual factors affecting career-related behaviors, but all of these influences are mediated by specific expectancy beliefs and values. This claim is reflected in the graphical representations typically associated with this theory (e.g., Eccles & Wigfield, 2020).

In network analysis, the idea of proximity can be operationalized using the notion of distance. The distance between two nodes refers to the number of edges in the shortest path connecting the nodes (Wasserman & Faust, 1994). A "path" refers to a sequence of edges in which all nodes and all edges are distinct, and the "shortest path" between two nodes is the minimum number of edges connecting these nodes. In other words, the distance between attitudes n_i and n_j, denoted as $d(n_i, n_j)$, represents the length of the shortest path between n_i and n_j.

5.2.2. Betweenness centrality

Another way of defining attitude importance is in terms of betweenness centrality. The idea behind this measure is that a node is important if it lies "between" many paths in the network. More specifically, this measure represents the number of shortest paths passing through a specific node (Borgatti, 2005). Based on this measure, an attitude will be considered important if it "links" or "mediates" the effect of other attitudes in the system. From this perspective, the most central attitudes will be conceptualized as "super-mediators" that constrain or intermediate the effect of other attitudes. In motivation theory, this notion of importance is implied by the idea that "expectations for success, confidence in one's abilities to succeed, and personal efficacy have long been recognized by decision and achievement theorists as important mediators of behavioral choice" (Eccles, 1994, p.592).

The betweenness centrality of a node n_i is defined as

$$C_B(n_i) = \sum_{j<k} \frac{g_{jk}(n_i)}{g_{jk}} \tag{1}$$

where $g_{jk}(n_i)$ is the number of shortest paths between n_j and n_k containing n_i, and g_{jk} is the number of shortest paths connecting n_j and n_k (Wasserman & Faust, 1994). The standardized version of this index is obtained by dividing $C_B(n_i)$ by the number of pairs of nodes not including n_i, $(g-1)(g-2)/2$.

5.2.3. Closeness centrality

The third way of defining attitude importance is in terms of closeness centrality. A node will have high closeness centrality if it is proximally related to many other nodes in the system. More specifically, closeness centrality measures the average shortest distance of a node to all other nodes (Borgatti, 2005). This notion of importance is suggested by Bandura, Barbaranelli, Caprara, and Pastorelli (2001), who explain that "perceived self-efficacy occupies a central role in the causal structure of social cognitive theory because efficacy beliefs affect adaptation and change not only in their own right, but through their impact on other determinants" (Bandura et al., 2001, 187). Given that self-efficacy beliefs affect other beliefs it is "posited as a pivotal factor in career choice and development" (Bandura et al., 2001, 187).

Formally, the closeness centrality of a node n_i is defined as

$$C_C(n_i) = \left[\sum_{j=1}^{g} d(n_i, n_j)\right]^{-1} \tag{2}$$

That is, closeness centrality measures the inverse of the distances from node i to all other nodes in the system (smaller distances imply higher closeness). The maximum value of this measure depends on the size of the network. One can standardize this index by multiplying $C_C(n_i)$ by $g-1$. This standardized measure will range between zero and one, and will equal one if a node is adjacent to all other nodes (Wasserman & Faust, 1994).

5.3. Community detection

The measures of importance discussed above describe the network at the node or micro-level. However, it is often useful to understand the structure of a network at a mesoscopic or intermediate level between the individual nodes and the network as a whole. This level of description can help identify the nodes that typically "hang together." A basic premise of belief network analysis is that attitudes do not operate in isolation, but rather in conjunction with other attitudes. This implies that it might be difficult to change single attitudes, as each individual attitude depends on or is determined by other attitudes.

A common way of describing a network at a mesoscopic level is by using community detection algorithms. The goal of these algorithms is to find groups or clusters of nodes that are densely connected internally and sparsely connected externally (Hoffman, Steinley, Gates, Prinstein, & Brusco, 2018). Several algorithms have been developed, without clear consensus on which algorithms should be preferred under different scenarios. In this study, I implement the Walktrap algorithm (Pons & Latapy, 2005), which has been identified as a top performing algorithm in comparative studies (Hoffman et al., 2018). This algorithm is based on the idea that random walks tend to get "trapped" within communities. The algorithm uses these random walks to calculate the distance between pairs of nodes, and merges nodes into communities by minimizing the average square distance between each node and its community (Hoffman et al., 2018). Finally, the algorithm chooses the number of clusters based on the maximum modularity.

5.4. Using a random forest to predict STEM enrollment

The methods presented above examine the structural features of STEM-related attitudes. A node will be considered important based on closeness and betweenness centrality if the node relates in a particular way to other nodes in the system. It is worth noting that these two measures of importance are unrelated to the predictive power of the variable. On the other hand, the distance with respect to the behavioral outcome does provide predictive information. Attitudes that are proximally related to an outcome represent statistical associations that cannot be explained by other measured variables. More specifically, the nodes that are proximally related to another node carry all the information about that node in that particular dataset (Aliferis, Statnikov, Tsamardinos, Mani, & Koutsoukos, 2010).[3] Thus, if we know the value of the proximal nodes of an outcome we know all the information on the outcome available in the dataset (Aliferis et al., 2010; Quintana, 2020, 2021).

A predictive model (a random forest) was implemented in order to validate the predictive power of the proximal nodes in the estimated network, as well as examine the extent to which the outcome can be predicted using all the attitudes in the dataset. A random

[3] More precisely, the Markov blanket of a variable X is the set of variables that renders X conditionally independent of all the other variables in the system (Aliferis et al., 2010). The Markov blanket is composed by the direct causes of X, the direct effects of X, and other direct causes of the direct effects of X.

forest is a form of nonparametric regression based on recursive partitioning. The basic idea of recursive partitioning is to recursively segment the feature space into regions that containing similar observations (Strobl, Malley, & Tutz, 2009). The building blocks of recursive partitioning are decision trees. A decision tree stratifies the predictor space into non-overlapping regions with similar observations. Specifically, a tree is built using algorithms that identify predictors and cutting points on these predictors that minimize prediction error, e.g., entropy or Gini if the outcome is categorical (James, Witten, Hastie, & Tibshirani, 2021).

Random forests are based on the production of many trees. By combining different models, random forests provide more stable and accurate predictions than single trees. When constructing a random forest, each tree is built from a bootstrapped sample of the data (bagging), which reduces the variance of the prediction and makes it more stable (Strobl et al., 2009). The observations that were not included in the bootstrapped samples are referred to as out-of-bag observations, and the prediction error obtained using these observations is referred to as the out-of-bag error. In addition, only a random sample of the available predictors are available each time a split is considered. The idea of only including a subsample of the predictors is to decorrelate the trees, which leads to a more thorough exploration of the available data (James et al., 2021)

Random forests have several advantages which makes this method well suited to the present application. In particular, random forests can deal with many predictors, do not make functional form assumptions, and are appropriate for modeling ordinally scaled variables (Strobl et al., 2009). It is worth noting that all the variables included in this study are binary or ordinal. In addition, random forests can be used to determine the predictive importance of individual predictors. The predictive importance is measured by the change in classification accuracy after permuting each predictor (James et al., 2021).

When constructing a random forest, one needs to select the number of predictors that can be chosen when making a split. This is considered a tuning parameter (*mtry*). In order to select an optimal value for *mtry* I considered the out-of-bag error of trees with different parameters. After selecting the optimal value of *mtry* the random forest was estimated.

5.5. Transparency and openness

The dataset used in the empirical analysis is publicly available and can be downloaded here: https://nces.ed.gov/surveys/hsls09/hsls09_data.asp. The FGES algorithm was implemented in the Tetrad 6.8.0 software. Pseudo-code of the FGES algorithm can be found in Ramsey, Glymour, Sanchez-Romero, and Glymour (2017). All network description measures were estimated using the *igraph* package in R (Kolaczyk & Csárdi, 2020). The tunning and estimation of the predictive model were implemented using the *randomForest* package in R (RColorBrewer & Liaw, 2018). The study design and analysis were not pre-registered.

6. Results

6.1. Estimated network

The estimated network consists of 137 nodes (136 attitudes and 1 behavioral outcome) and 324 edges. An edge (either directed or undirected) was retained if it appeared in 50 percent or more of the bootstrapped samples. The list of edges as well as the frequency in which the edge was found across the bootstrapped samples is included in Table S3 in the Supplemental Material. A graphical representation of the estimated network is presented in Figure S1 in the Supplemental Materials.

6.2. Proximity

Table 2 presents the attitudes that have the shortest distance (i.e., are proximally related) to the behavioral outcome, namely enrolling in a STEM major right after finishing high school. There are two attitudes that are directly related to the outcome: the belief that he/she is a science person, and the belief that others see himself/herself as a science person. These beliefs have a distance of 1, given that there is only 1 edge connecting these attitudes to the outcome. These beliefs are generally referred to as "identity beliefs" (Cribbs et al., 2015). The other two identity beliefs in the dataset have a distance of 2, implying that identity beliefs are the most proximal among all attitudes considered.

Other attitudes that are closely though not directly related to the behavioral outcome (i.e., have a distance of 2) are 3 mindset beliefs (e.g., "you have to be born with the ability to be good at science"); 3 ability or self-efficacy beliefs (e.g., "teen confident can do an excellent job on math tests"); 2 usefulness beliefs (e.g., "science is useful for everyday life"); 2 enjoyment values (e.g., "9th grader is enjoying science course very much"); and the motive of taking science because it was assigned.

Fig. 1 presents the distribution of the distance between the attitudes in the network and the behavioral outcome. The distribution is bell-shaped with a mean of 4.3 and a standard deviation of 1.8. This means that, on average, there are around 4 edges (or 3 nodes) mediating the attitudes in the system and the behavioral outcome.

The results displayed in Table 2 have two important implications. First, the two identity beliefs directly related to the outcome provide all the information in the dataset regarding who will enroll in a STEM major. That is, once we know the value of these two identity beliefs, then none of the remaining 134 attitudes will provide any additional information (Quintana, 2020). Second, there are several attitudes that are directly related to the two most proximal identity beliefs. In particular, mindset beliefs, ability or self-efficacy-beliefs, usefulness beliefs and extrinsic reasons are directly associated with these beliefs. This suggests that there are different paths (or necessary and/or sufficient conditions) that can make someone identify himself or herself as a science or math person.

The results in Table 2 have two structural components that are illustrated in Fig. 2. First, there are two math and science identity

Table 2
Attitudes that are proximally related to the behavioral outcome (enrolling in a STEM major).

Attitude	Distance	Local evaluation fit χ^2	df	RMSEA	p-value
Teenager sees himself/herself as a science person	1				
Others see teenager as a math person	1				
Others see teenager as a science person	2	65.7	12	0.036	<0.001
Teenager sees himself/herself as a math person	2	116.5	12	0.046	<0.001
You have to be born with the ability to be good at science	2	19.9	12	0.009	0.069
Most people can learn to be good at math	2	30.2	12	0.017	<0.01
Most people can learn to be good at science	2	15.5	12	0.009	0.215
Teen is taking science because does well in science	2	29.9	4	0.038	<0.001
Teen confident can do an excellent job on math tests	2	79.6	12	0.036	<0.001
Teen is taking math because does well in math	2	22.1	4	0.037	<0.01
Teenager thinks science is useful for everyday life	2	33.7	12	0.017	<0.001
Teenager thinks science is useful for future career	2	135.6	12	0.042	<0.001
Teen is taking science because he/she really enjoys science	2	43.1	4	0.036	<0.001
9th grader is enjoying science course very much	2	4.9	12	0.000	0.961
Teen is taking science because it was assigned	2	99.5	4	0.078	<0.001

Note. The local evaluation tests assess whether an attitude is independent of the outcome conditioning on a science or math identity belief (the two attitudes with a distance of one).

beliefs I_n that are directly related to the behavioral outcome Y. Based on theoretical suppositions and given that Y was measured after I_n –and assuming no unobserved confounders–, one can reasonably assume that the causal direction points toward Y (i.e., $I_n \rightarrow Y$). Second, there are 13 attitudes (A_p) that are directly related to the identity beliefs I_n but not directly related to the outcome Y. In this case, causal directionality is harder to establish using background knowledge, so we can have either $A_p \rightarrow I_n$, $A_p \leftarrow I_n$ or $A_p \leftrightarrow I_n$.[4] Regardless of which model is closer to reality, all the three scenarios imply that A_p is independent of Y conditional on I_n (Ankan, Wortel, & Textor, 2021; Spirtes et al., 2000).

The conditional independence relationships implied by this structural model can be tested with the data using local evaluation tests (Thoemmes, Rosseel, & Textor, 2018). For example, following Fig. 2, one can test whether knowing individuals' self-efficacy beliefs do not provide additional information regarding individuals' career choice once we know their identity beliefs. In other words, one can test whether *Self-efficacy beliefs* are independent of *STEM major* conditional on *Identity beliefs.* Local evaluations test can provide, then, empirical support for each conditional independence implied by the graph in Fig. 2.

Given that all variables are categorical, one can use a chi-square test to test each conditional independence. An implied independence is contradicted by a low p-value and a high RMSEA and χ^2 (Ankan et al., 2021). In other words, contrary to traditional hypothesis tests, we expect to have large p-values and small effect sizes. However, the p-values will typically be small in large datasets, so it is recommended to focus instead on whether the associated effect size (RMSEA) is close to zero (Ankan et al., 2021). The test statistic χ^2, RMSEA and p-value associated with each conditional independence assumption is presented in Table 2.[5] The conditioning variable was the math or science identity belief, depending on whether the attitude involved science or math (this is consistent with theoretical expectations as well as the estimated graph). For instance, I tested whether the belief "Most people can learn to be good at math" is independent of enrolling in a STEM major conditional on the identity belief that "Others see teenager as a math person." One can see in Table 2 that the RMSEA values are generally low, supporting the conditional independence assertions (RMSEA values below 0.05 are generally considered acceptable, Ankan et al., 2021). In particular, there is strong evidence regarding the conditional independence relationship of mindset beliefs and enjoyment attitudes.

The local evaluation tests support, then, the results presented in Table 2. As Fig. 2 illustrates, these results suggest that identity beliefs are proximally related to choosing a STEM major. Thus, one would expect that a change in individuals' identity beliefs will have a direct effect on individuals' career choices. In addition, Fig. 2 shows different kinds of attitudes (self-efficacy, mindset and usefulness beliefs; enjoyment values and the motive of being assigned to science courses) that are directly related to individuals' identity beliefs.

6.3. Betweenness centrality

Fig. 3 presents the attitudes in the estimated network with the highest betweenness centrality score. The values are normalized so that the values lie between 0 and 1. Based on this measure, the most central attitude is the expectation of how far in school the teenager thinks he/she will get (high school, Bachelor's degree, Master's degree or higher). Specifically, more than 25% (around 2373) of shortest paths go through this particular attitude. This suggests that this attitude plays a pivotal role, as it connects different parts of the system (see Figure S2 for a graphical representation). This attitude is followed by the teenager's belief that he/she has the ability to complete a bachelor's degree.

[4] The first scenario indicates that the effect of A_p on Y is mediated by I_n; the second scenario indicates that A_p is not a cause of Y; and the third scenario indicates a reciprocal relationship between A_p and I_n.

[5] The conditional independence tests were computed using the R package dagitty (Ankan et al., 2021).

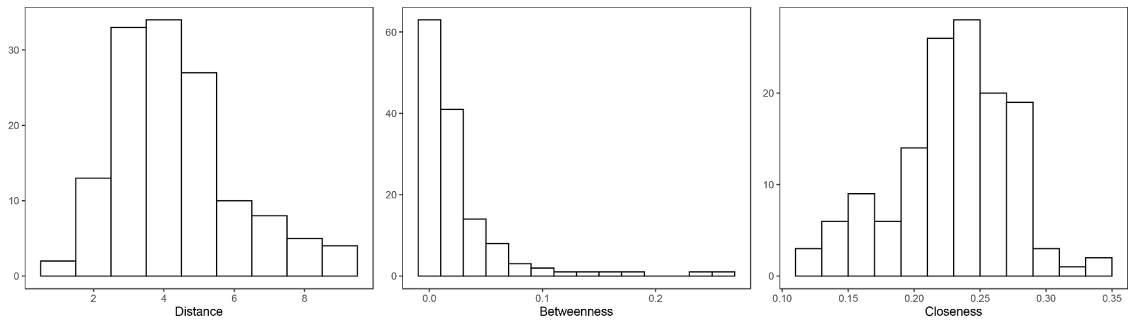

Fig. 1. Distributions of the estimated distance, betweenness centrality and closeness centrality scores.

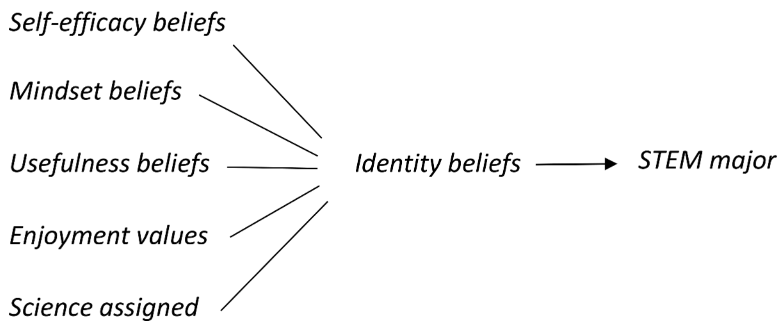

Fig. 2. Attitudes that are proximally related to the behavioral outcome.

The third highest centrality (0.19) is associated with another ability-related belief, and the fourth (0.16) with the perceived importance or value of academic achievement. Other three attitudes with a betweenness centrality higher than 0.10 include the expectation that he/she will pursue bachelor's degree (0.15), the perception that he/she has an adult to talk to about problems (0.11) and the belief that he/she is as a science person (0.11). By looking at the distribution of this centrality measure (Fig. 1), one can see that few attitudes (those above 0.10) have noticeably higher centrality scores compared to the rest. The mean betweenness score across all attitudes is around 0.03, and the betweenness centralization is around 0.23.[6] This suggests that some attitudes in the graph have a meaningfully higher betweenness centrality score. Figure S2 in the Supplemental Material shows the estimated network with color and size of attitudes based on their betweenness centrality.

The high betweenness centrality of educational expectations and self-efficacy beliefs is consistent with several theories, in particular social cognitive career theory (Lent et al., 2008) and expectancy-value theory (Eccles & Wigfield, 2020), which highlight the importance of these attitudes in career choice. This study clarifies in which sense these attitudes can be considered important. These attitudes play a central role in individuals' belief systems because they "bridge" or "connect" different parts of the network. For instance, Figure S2 shows that the belief that the student has the ability to complete a bachelor's degree connects academic tradeoffs (e.g., the belief that time/effort in math/science means not enough time with friends) and other attitudes with the rest of the network.

6.4. Closeness centrality

Fig. 4 presents the normalized value of the highest closeness centrality scores. Interestingly, 9 of the 15 attitudes were also among the nodes with the highest betweenness centrality scores. In particular, the belief that the teenager is taking math because he/she does well in math (0.33), and the expectation of how far in school the teenager thinks he/she will get (0.33) are the most central beliefs according to this measure. These results highlight again the structural importance of ability-related attitudes and expectations. Yet as Fig. 1 indicates, the distribution of the closeness centrality scores resembles a normal curve, without noticeably high values. This is reflected in a slightly lower closeness centralization score (0.21). Figure S3 in the Supplemental Materials shows the estimated network with the color and size of nodes based on their closeness centrality.

[6] Whereas centrality indices are measured at the node level, centralization scores are measured at the graph level. A graph will have a high centralization if it is structured around a highly central node. In particular, the centralization score will be equal to zero if all nodes have the same centrality, and will equal to one if one node dominates the centrality of the network (Wasserman & Faust, 1994)

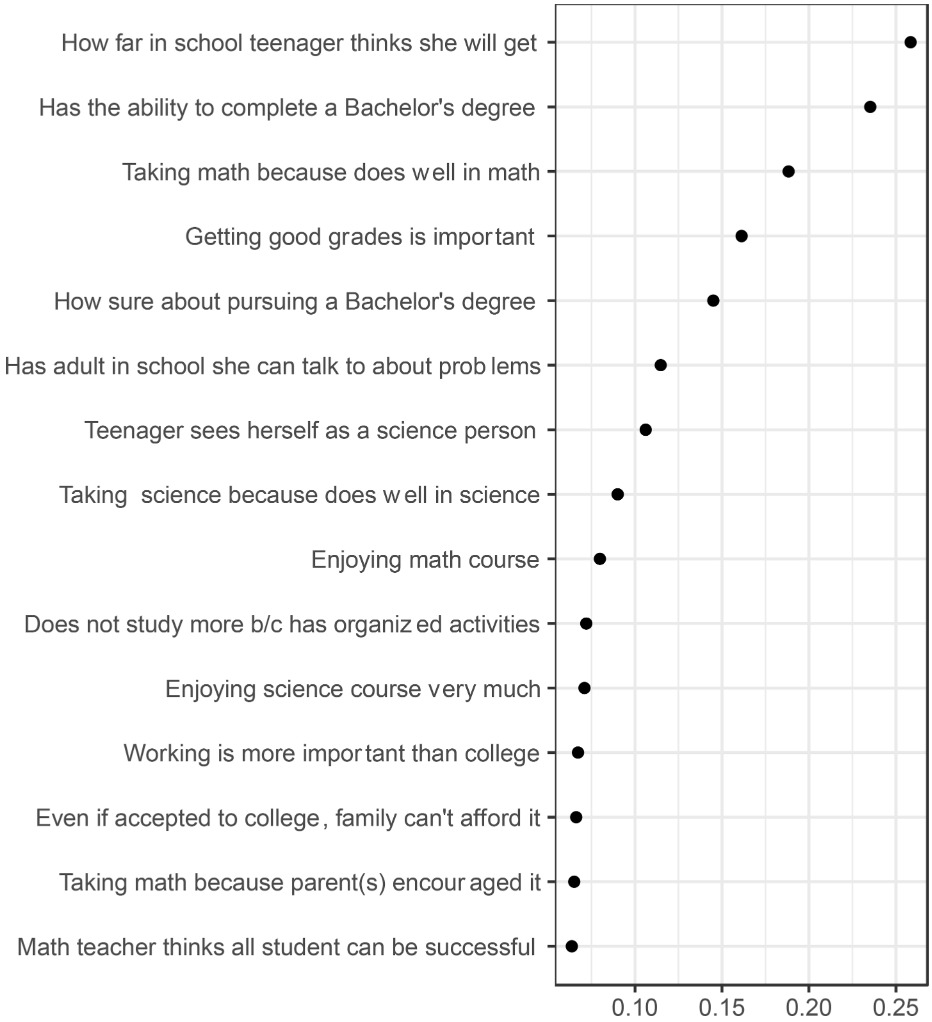

Fig. 3. Attitudes with the highest betweenness centrality.

6.5. Community detection

The centrality measures considered so far make inferences about the importance of individual attitudes within the estimated network (e.g., single identify beliefs). However, we know that there are some attitudes that typically "hang together" because of underlying causal processes. For example, one would expect close associations among students' perceptions of STEM teachers. In this section, I explore the meso-level properties of the estimated network, i.e., the intermediate level between the network as a whole and the individual attitudes.

In order to investigate the mesoscopic organization of the estimated network, a community detection algorithm (Walktrap) was implemented. The algorithm found 15 clusters. The clusters were labeled based on the typologies presented in Table 1.[7] Fig. 5 presents a graphical representation of the network with colors assigned to each cluster, and Table S4 in the Supplemental Materials presents the cluster assignment by node. It is worth noting that these clusters are based on structural features of the nodes (their position in the network) and are not meant to represent latent constructs. Table 3 presents the cluster labels, number of items in each cluster, and average importance of the cluster according to the three measures. Fig. 6 presents the cluster importance information in graphical form.

Table 3 and Fig. 6 show that the mindset beliefs are the set of attitudes that are most closely related to the behavioral outcome (2.25), followed by the utility, interest and identity cluster (2.75), and the math (2.75) and science (3.00) self-efficacy clusters. The distance of these clusters to the behavioral outcome is similar and not statistically significant, $F(3,\ 34) = 0.70,\ p = 0.556$. Once we

[7] The categorization was based on the majority –not necessarily the totality– of items. Thus, in some clusters there can be items that might be categorized using different labels.

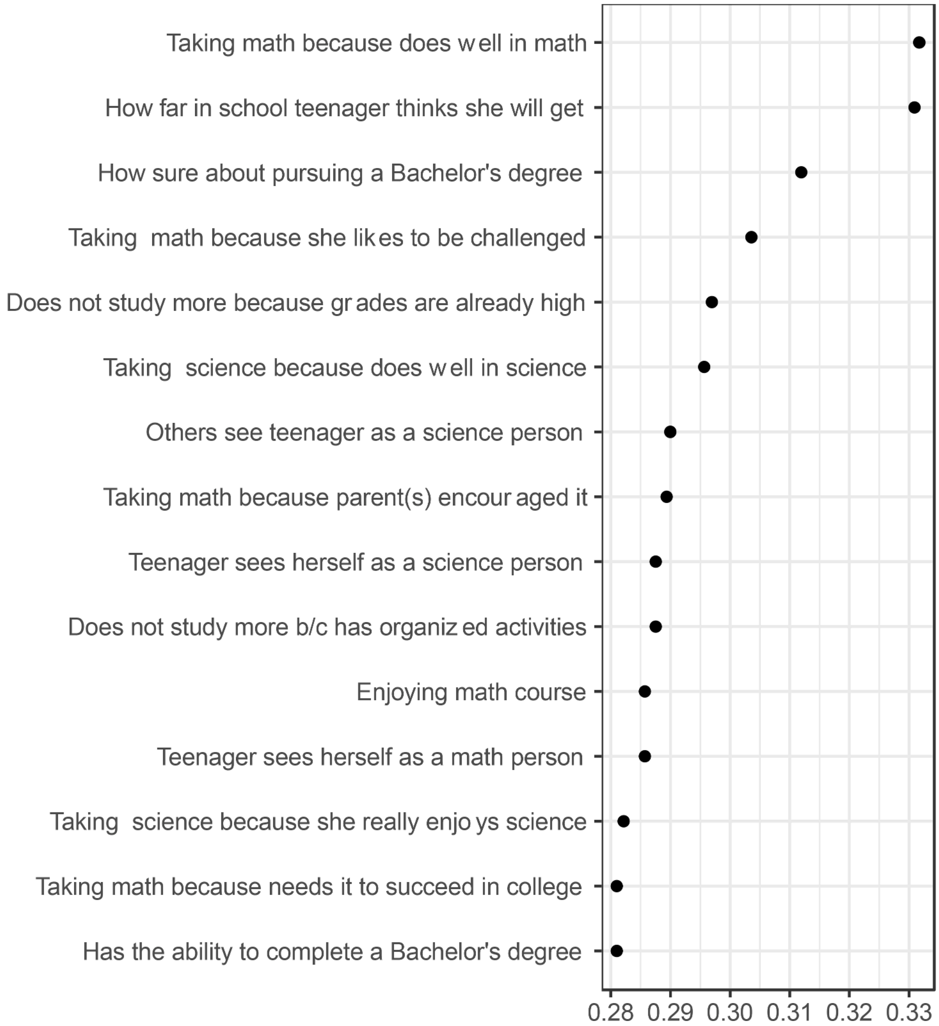

Fig. 4. Attitudes with the highest closeness centrality.

include the following cluster (which includes attitudes related to math and science courses) we approximate statistical significance, $F(4,\ 51) = 2.54,\ p = 0.051$, and these differences become stronger once we consider other clusters. This suggests that among all clusters, mindset beliefs, self-efficacy beliefs, and utility, interest and identity attitudes are more proximally related to choosing a STEM major.

Table 3 also shows that differences in betweenness centrality among these 4 clusters is similar and not statistically significant, $F(3,\ 34) = 0.71,\ p = 0.550$. However, differences between the closeness centrality scores are statistically significant, $F(3,\ 34) = 4.92,\ p = 0.006$. The reason for this is that the utility, interest and identity cluster is closer to other attitudes in the graph. In Fig. 5, one can see that this cluster (colored in light yellow) is at the center of the graph, whereas the mindset cluster (colored in turquoise blue), the science-self efficacy cluster (colored in bright blue), and the math-self-efficacy cluster (colored in red), are more peripheric.

Another distinguishing feature of the utility, interest and identity cluster is that the nodes in this cluster tend to have more connections than the nodes in other clusters. The number of connections that a node has is referred to as degree centrality. The average degree centrality in the graph is 4.75 which means that, on average, each attitude is connected to 4.75 other attitudes. The average degree centrality of the utility, interest and identity cluster is 6.3 (Figure S4 in the Supplemental Materials presents the network with the color and size of nodes based on their degree centrality). On the other hand, the average degree centrality of the mindset cluster is 3.3. This means that the nodes in the utility, interest and identity cluster are highly interconnected, while the connectivity of the mindset cluster are relatively sparse.[8]

[8] It is worth noting that the degree centrality of the cluster might depend on the data available, and that in reality the mindset cluster might be composed of many interrelated attitudes. How closed or open are these clusters is an empirical question that we cannot answer with the available data.

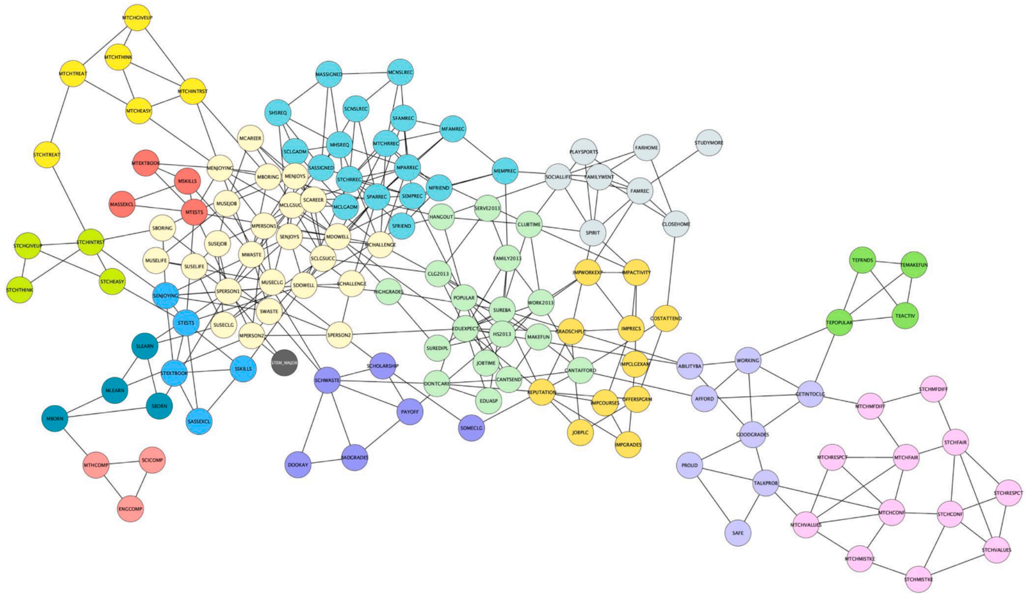

Fig. 5. Estimated network with 15 clusters identified by the Walktrap algorithm. The behavioral outcome is colored in dark gray.

Table 3
Cluster label, number of items, and average importance based on the distance to the behavioral outcome, betweenness centrality and closeness centrality.

Cluster	Number of items	Importance measures Distance	Betweenness	Closeness
Mindset beliefs	4	2.25	0.03	0.22
		(0.250)	(0.008)	(0.009)
Utility, interest and identity	25	2.72	0.04	0.26
		(0.169)	(0.008)	(0.006)
Math self-efficacy	4	2.75	0.01	0.24
		(0.250)	(0.010)	(0.012)
Science self-efficacy	5	3.00	0.02	0.23
		(0.316)	(0.013)	(0.011)
Math and science courses	18	3.28	0.01	0.25
		(0.135)	(0.004)	(0.005)
Perceptions of science teacher	4	3.75	0.01	0.19
		(0.250)	(0.010)	(0.009)
Expectations	18	4.17	0.04	0.27
		(0.146)	(0.015)	(0.006)
Perceptions of math teacher	6	4.50	0.01	0.20
		(0.224)	(0.004)	(0.009)
Usefulness beliefs	6	4.67	0.01	0.23
		(0.211)	(0.007)	(0.008)
Gender differences beliefs	3	4.67	0.01	0.15
		(0.333)	(0.010)	(0.007)
Values	11	5.00	0.01	0.23
		(0.191)	(0.005)	(0.007)
Belonging	8	5.63	0.09	0.22
		(0.324)	(0.029)	(0.012)
Reasons for college	8	5.63	0.01	0.22
		(0.263)	(0.003)	(0.007)
Tradeoffs	4	6.75	0.01	0.17
		(0.250)	(0.011)	(0.008)
Perceptions of teacher	12	8.08	0.02	0.15
		(0.229)	(0.006)	(0.005)

Note. Cluster labels are based on the majority of items included. The order of clusters is based on the estimated distance to the behavioral outcome. The clusters labeled as "perceptions of science teacher" and "perception of math teacher" are associated with teacher's pedagogical practices (e.g., whether teachers make the subject matter easy to understand). On the other hand, the cluster labeled as "perceptions of teacher" involves teachers' social characteristics (e.g., whether the teacher treats every student fairly). Standard errors are in parentheses.

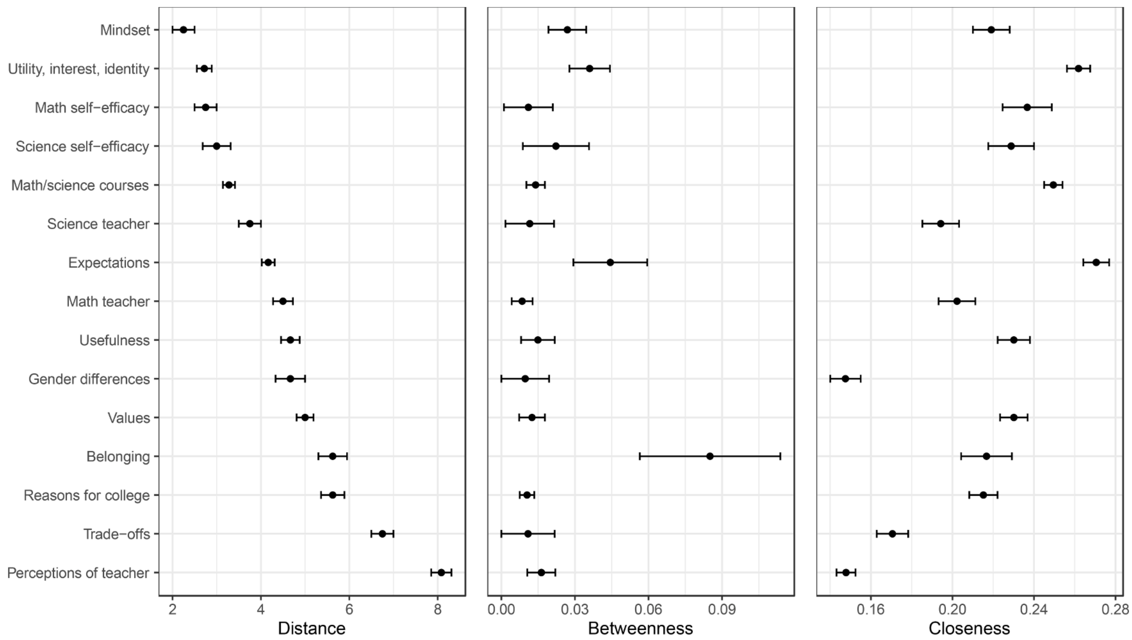

Fig. 6. Importance measures by cluster (the clusters are ordered by the estimated distance to the behavioral outcome).

In sum, the implementation of a community detection algorithm provides several insights into the mesoscopic organization of the estimated network. First, the results suggest that there are four clusters of attitudes that are proximally related to the behavioral outcome. These clusters are composed of utility, interest, identify, self-efficacy and mindset beliefs. This suggests that enrolling in a STEM major is a complex process involving several attitudes, and as a consequence it requires a multicausal explanation (Quintana, 2022). Second, the cluster conformed by utility, interest, and identity beliefs, as well as the cluster conformed by educational expectations (colored in light green in Fig. 5) lie at the center of the network. Third, the attitudes in these two clusters are tightly interconnected, as on average each attitude is directly connected to approximately 6 other attitudes. This suggests that these attitudes are mutually constrained, and that it might be difficult to change one of these attitudes without changing others. The extent to which one attitude can be changed without changing others is, however, an empirical question that needs to be directly tested.

6.6. Random forest

A random forest was implemented to predict enrollment in a STEM major using the 136 STEM-related attitudes included. Based on the out-of-bag error, the number of splitting variables (*mtry*) was set to 11, and the number of trees generated was set to 3000. The out-of-bag estimated error rate was 19.07%. The classification error of individuals not enrolling in a STEM major is very low (0.02%), but the classification error of individuals enrolling in STEM is high (0.83%).

Based on the random forest implemented, one can obtain a summary of the predictive importance of each of the predictors. Fig. 7 presents the estimated importance of the 15 most predictive variables based on the mean decrease in accuracy. Consistent with prior results, this plot indicates that the four identity beliefs are by far the most predictive attitudes. Specifically, the beliefs “teenager sees himself/herself as a science person” and “others see teenager as a math person” appear to be particularly important. This is consistent with the estimated distance reported in Table 2. In addition, enjoyment attitudes and usefulness beliefs also appear to be predictive. The other attitudes included have less than half of the predictive power of the top identity beliefs.

Two robustness checks were performed. First, a random forest was built only with students who went to college. In the analytic sample, 79% (10,469) individuals attended college at some point, whereas 21% (2804) individuals did not attend college. Consistent with prior results, within the sample of students who attended college identity beliefs are the most predictive attitudes of enrolling in a STEM major (see Figure S5 in the Supplemental Materials). Second, a random forest was implemented with school fixed effects (the model contained 1080 predictors). The results remained consistent with prior specifications (see Figure S6 in the Supplemental Materials).

7. Discussion

This study uses a belief network analysis approach to investigate which attitudes are most central in the context of STEM career choices. The empirical analysis was divided in two phases. First, I estimated the network representing the statistical dependence relationships between 136 achievement and career-related attitudes and one behavioral outcome using a structure learning algorithm. Second, I assessed the importance of the attitudes in the network based on three structural features: proximity to the behavioral

Fig. 7. Most important variables based on mean decrease accuracy in a random forest.

outcome (enrolling in a STEM major); betweenness centrality, which measures the extent to which an attitude connects or mediates the effect of other attitudes in the system; and closeness centrality, which measures the extent to which an attitude is closely related to other attitudes in the system. I argued that these structural characteristics provide a clear way of interpreting and assessing the claim –found in many achievement and motivation theories– according to which a specific set of beliefs plays a "central" role in determining behavior.

The results suggest that different attitudes will be considered more influential or important depending on the structural attribute one focuses on. The attitudes that are proximally related to enrolling in a STEM major are identity beliefs. In other words, identity beliefs mediate the effect of all the other attitudes considered. This means that choosing a STEM major is directly related to the enduring sense of self, and that other attitudes need to modify these core identity beliefs to become effective. The attitudes with a direct connection to these core identity beliefs include mindset beliefs, ability or self-efficacy-beliefs, and usefulness beliefs. The results according to which identity beliefs are the most proximal attitudes –and as a consequence are most predictive of the outcome– were validated using a random forest and local evaluation tests.

While proximal measures highlight the role of identify beliefs, both betweenness and closeness centrality highlight the role of educational expectations and ability-related beliefs. These results are consistent with several theories (e.g., expectancy-value theory and social cognitive theory) according to which ability-related beliefs (in particular self-efficacy beliefs) and expectations are influential in determining behavior. The results of this study suggest that the importance of these attitudes is not based on their proximal relationship to the outcome nor a high predictive power, but rather on their capacity to mediate or influence many other attitudes in the system.

In addition to estimating the importance of single attitudes, I used a community detection algorithm to examine how attitudes are connected to each other. The results suggest that there are 15 clusters of attitudes. These clusters might represent "mechanistic property clusters", i.e., variables that typically "hang together" due to underlying causal processes (Kendler, Zachar, & Craver, 2011). Among other things, the results of this analysis indicates that while mindset beliefs are sparsely connected to other attitudes, identity beliefs are connected to a range of other attitudes (in particular related to interest and utility values and beliefs). This suggests that these attitudes are mutually constrained, and that it might be difficult to change one of these attitudes without changing others.

It is important to note that even if the present study includes a wide range of attitudes, it is likely that many relevant attitudes are not included. Consequently, the connections among attitudes do not necessarily represent causal relationships, and the importance measures are conditional on the variables considered in the analysis. Finally, the results of the random forest indicate a low prediction accuracy for individuals enrolling in a STEM major. This suggests that other unmeasured factors play an important role in getting students to enroll in STEM majors. Future research should be conducted to identify important attitudes that are not included in this study, as well as investigating how contextual factors influence career choice either directly or by modifying some attitudes in individuals' belief systems.

In conclusion, I have argued that researchers investigating the connection between attitudes and behaviors can benefit by studying belief systems rather than single attitudes. Prior researcher generally follows the one-attitude-at-a-time approach, and social-psychological interventions typically assume that one can "surgically" modify individuals' attitudes (e.g., self-efficacy or mindset beliefs). The claim that a specific attitude is constrained by other attitudes (and thus cannot be changed in isolation) needs to be empirically tested. More generally, in the present study I argued that by adopting a system-level perspective, one can examine how attitudes are functionally interrelated as well as the role that attitudes play in the system. In this study, I focused on different ways to define and measure the influence of attitudes. However, this approach can be extended in several ways, for example by comparing belief systems across groups, implementing other centrality-based measures, or estimating the strength of the connections among the elements in the network.

Declaration of Competing Interest

None.

References

Aliferis, C. F., Statnikov, A., Tsamardinos, I., Mani, S., & Koutsoukos, X. D. (2010). Local causal and markov blanket induction for causal discovery and feature selection for classification part i: Algorithms and empirical evaluation. *Journal of Machine Learning Research, 11*(1), 171–234.

Ankan, A., Wortel, I. M. N., & Textor, J. (2021). Testing Graphical Causal Models Using the R Package "dagitty. *Current Protocols, 1*(2). https://doi.org/10.1002/cpz1.45

Bandura, A. (2012). On the Functional Properties of Perceived Self-Efficacy Revisited. *Journal of Management, 38*(1), 9–44. https://doi.org/10.1177/0149206311410606

Bandura, A., Barbaranelli, C., Caprara, G. V., & Pastorelli, C. (2001). Self-Efficacy Beliefs as Shapers of Children's Aspirations and Career Trajectories. *Child Development, 72*(1), 187–206. https://doi.org/10.1111/1467-8624.00273

Barron, K. E., & Hulleman, C. S. (2015). Expectancy-Value-Cost Model of Motivation. *International encyclopedia of the social & behavioral sciences* (pp. 503–509). Elsevier. https://doi.org/10.1016/B978-0-08-097086-8.26099-6

Borgatti, S. P. (2005). Centrality and network flow. *Social Networks, 27*(1), 55–71. https://doi.org/10.1016/j.socnet.2004.11.008

Borsboom, D., Deserno, M. K., Rhemtulla, M., Epskamp, S., Fried, E. I., McNally, R. J., et al. (2021). Network analysis of multivariate data in psychological science. *Nature Reviews Methods Primers, 1*(1), 58. https://doi.org/10.1038/s43586-021-00055-w

Boutyline, A., & Vaisey, S. (2017). Belief Network Analysis: A Relational Approach to Understanding the Structure of Attitudes. *American Journal of Sociology, 122*(5), 1371–1447. https://doi.org/10.1086/691274

Brandt, M. J., Sibley, C. G., & Osborne, D. (2019). What Is Central to Political Belief System Networks? *Personality and Social Psychology Bulletin, 45*(9), 1352–1364. https://doi.org/10.1177/0146167218824354

Brandt, M. J., & Sleegers, W. W. A. (2021). Evaluating Belief System Networks as a Theory of Political Belief System Dynamics. *Personality and Social Psychology Review, 25*(2), 159–185. https://doi.org/10.1177/1088868321993751

Breen, R., & Goldthorpe, J. H. (1997). EXPLAINING EDUCATIONAL DIFFERENTIALS: TOWARDS A FORMAL RATIONAL ACTION THEORY. *Rationality and Society, 9*(3), 275–305. https://doi.org/10.1177/104346397009003002

Cheryan, S., Plaut, V. C., Davies, P. G., & Steele, C. M. (2009). Ambient belonging: How stereotypical cues impact gender participation in computer science. *Journal of Personality and Social Psychology, 97*(6), 1045–1060. https://doi.org/10.1037/a0016239

Cheryan, S., Ziegler, S. A., Montoya, A. K., & Jiang, L. (2017). Why are some STEM fields more gender balanced than others? *Psychological Bulletin, 143*(1), 1–35. https://doi.org/10.1037/bul0000052

Chevalier, A., Gibbons, S., Thorpe, A., Snell, M., & Hoskins, S. (2009). Students' academic self-perception. *Economics of Education Review, 28*(6), 716–727. https://doi.org/10.1016/j.econedurev.2009.06.007

Chickering, D. M. (2002). Optimal structure identification with greedy search. *Journal of Machine Learning Research, 3*(Nov), 507–554. https://doi.org/10.1162/153244303321897717

Converse, P. E. (1964). The Nature of Belief Systems in Mass Publics. *Ideology and discontent,ed. david apter.* New York: Free Press.

Correll, S. J. (2001). Gender and the Career Choice Process: The Role of Biased Self-Assessments. *American Journal of Sociology, 106*(6), 1691–1730. https://doi.org/10.1086/321299

Cribbs, J. D., Hazari, Z., Sonnert, G., & Sadler, P. M. (2015). Establishing an Explanatory Model for Mathematics Identity. *Child Development, 86*(4), 1048–1062. https://doi.org/10.1111/cdev.12363

Dalege, J., Borsboom, D., van Harreveld, F., van den Berg, H., Conner, M., & van der Maas, H. L. J. (2016). Toward a formalized account of attitudes: The Causal Attitude Network (CAN) model. *Psychological Review, 123*(1), 2–22. https://doi.org/10.1037/a0039802

Drton, M., & Maathuis, M. H. (2017). Structure Learning in Graphical Modeling. *Annual Review of Statistics and Its Application, 4*(1), 365–393. https://doi.org/10.1146/annurev-statistics-060116-053803

Eccles, J. S. (1994). Understanding Women's Educational And Occupational Choices: *Applying the Eccles* et al. *Model of Achievement-Related Choices*. *Psychology of Women Quarterly, 18*(4), 585–609. https://doi.org/10.1111/j.1471-6402.1994.tb01049.x

Eccles, J. S., & Wang, M.-T. (2016). What motivates females and males to pursue careers in mathematics and science? *International Journal of Behavioral Development, 40*(2), 100–106. https://doi.org/10.1177/0165025415616201

Eccles, J. S., & Wigfield, A. (2002). Motivational Beliefs, Values, and Goals. *Annual Review of Psychology, 53*(1), 109–132. https://doi.org/10.1146/annurev.psych.53.100901.135153

Eccles, J. S., & Wigfield, A. (2020). From expectancy-value theory to situated expectancy-value theory: A developmental, social cognitive, and sociocultural perspective on motivation. *Contemporary Educational Psychology, 61*, Article 101859. https://doi.org/10.1016/j.cedpsych.2020.101859

Enders, C. K. (2010). *Applied missing data analysis*. Guilford press.

Filippin, A., & Paccagnella, M. (2012). Family background, self-confidence and economic outcomes. *Economics of Education Review, 31*(5), 824–834. https://doi.org/10.1016/j.econedurev.2012.06.002

Grossman, J. M., & Porche, M. V. (2014). Perceived Gender and Racial/Ethnic Barriers to STEM Success. *Urban Education, 49*(6), 698–727. https://doi.org/10.1177/0042085913481364

Hoffman, M., Steinley, D., Gates, K. M., Prinstein, M. J., & Brusco, M. J. (2018). Detecting Clusters/Communities in Social Networks. *Multivariate Behavioral Research, 53*(1), 57–73. https://doi.org/10.1080/00273171.2017.1391682

Holm, A., & Jæger, M. M. (2008). Does Relative Risk Aversion explain educational inequality? A dynamic choice approach. *Research in Social Stratification and Mobility, 26*(3), 199–219. https://doi.org/10.1016/j.rssm.2008.05.004

Holtmann, A. C., Menze, L., & Solga, H. (2021). Intergenerational Transmission of Educational Attainment: How Important Are Children's Personality Characteristics? *American Behavioral Scientist, 65*(11), 1531–1554. https://doi.org/10.1177/0002764221996779

Hulleman, C. S., Kosovich, J. J., Barron, K. E., & Daniel, D. B. (2017). Making connections: Replicating and extending the utility value intervention in the classroom. *Journal of Educational Psychology, 109*(3), 387–404. https://doi.org/10.1037/edu0000146

Hulleman, C. S., Schrager, S. M., Bodmann, S. M., & Harackiewicz, J. M. (2010). A meta-analytic review of achievement goal measures: Different labels for the same constructs or different constructs with similar labels? *Psychological Bulletin, 136*(3), 422–449. https://doi.org/10.1037/a0018947

Ingels, S. J., Pratt, D. J., Herget, D. R., Burns, L. J., Dever, J. A., Ottem, R., et al. (2011). *High school longitudinal study of 2009 (HSLS: 09): Base-year data file documentation. nces 2011-328*. National Center for Education Statistics.

James, G., Witten, D., Hastie, T., & Tibshirani, R. (2021). An introduction to statistical learning. *With applications in r* (Second edition). Springer.

Kahn, S., & Ginther, D. (2017). *Women and stem (No. w23525; p. w23525)*. National Bureau of Economic Research. https://doi.org/10.3386/w23525

Kendler, K. S., Zachar, P., & Craver, C. (2011). What kinds of things are psychiatric disorders? *Psychological medicine, 41*(6), 1143–1150.

Kolaczyk, E. D., & Csárdi, G. (2020). *Statistical analysis of network data with r* (Second edition). Springer.

Legewie, J., & DiPrete, T. (2014). Pathways to Science and Engineering Bachelor's Degrees for Men and Women. *Sociological Science*, 41–48. https://doi.org/10.15195/v1.a4

Lent, R. W., Sheu, H.-B., Singley, D., Schmidt, J. A., Schmidt, L. C., & Gloster, C. S. (2008). Longitudinal relations of self-efficacy to outcome expectations, interests, and major choice goals in engineering students. *Journal of Vocational Behavior, 73*(2), 328–335. https://doi.org/10.1016/j.jvb.2008.07.005

Maltese, A. V., & Tai, R. H. (2011). Pipeline persistence: Examining the association of educational experiences with earned degrees in STEM among U.S. students. *Science Education, 95*(5), 877–907. https://doi.org/10.1002/sce.20441

Marsh, H. W., & Martin, A. J. (2011). Academic self-concept and academic achievement: Relations and causal ordering: Academic self-concept. *British Journal of Educational Psychology, 81*(1), 59–77. https://doi.org/10.1348/000709910X503501

Marsh, H. W., Trautwein, U., Lüdtke, O., Köller, O., & Baumert, J. (2005). Academic Self-Concept, Interest, Grades, and Standardized Test Scores: Reciprocal Effects Models of Causal Ordering. *Child Development, 76*(2), 397–416. https://doi.org/10.1111/j.1467-8624.2005.00853.x

Martin, J. L. (2002). Power, Authority, and the Constraint of Belief Systems. *American Journal of Sociology, 107*(4), 861–904. https://doi.org/10.1086/343192

Morgan, S. L., Gelbgiser, D., & Weeden, K. A. (2013). Feeding the pipeline: Gender, occupational plans, and college major selection. *Social Science Research, 42*(4), 989–1005. https://doi.org/10.1016/j.ssresearch.2013.03.008

Nandy, P., Hauser, A., & Maathuis, M. H. (2018). High-dimensional consistency in score-based and hybrid structure learning. *The Annals of Statistics, 46*(6A). https://doi.org/10.1214/17-AOS1654

Neal, Z. P., & Neal, J. W. (2021). Out of bounds? The boundary specification problem for centrality in psychological networks. *Psychological Methods*. https://doi.org/10.1037/met0000426

Nelson, M. (2019). Propositional Attitude Reports. In Edward (Ed.), *The stanford encyclopedia of philosophy*. https://plato.stanford.edu/archives/spr2019/entries/prop-attitude-reports.

Pons, P., & Latapy, M. (2005). Computing communities in large networks using random walks. In *International Symposium on Computer and Information Sciences* (pp. 284–293). https://doi.org/10.1007/11569596_31

Quintana, R. (2020). The Structure of Academic Achievement: Searching for Proximal Mechanisms Using Causal Discovery Algorithms. *Sociological Methods & Research*. https://doi.org/10.1177/0049124120926208, 004912412092620.

Quintana, R. (2021). What race and gender stand for: Using Markov blankets to identify constitutive and mediating relationships. *Journal of Computational Social Science*. https://doi.org/10.1007/s42001-021-00152-6

Quintana, R. (2022). The ecology of human behavior: A network perspective. *Methodological Innovations, 15*(1), 42–61. https://doi.org/10.1177/20597991221077911

Quintana, R., & Saatcioglu, A. (2022). The Long-Lasting Effects of Schooling: Estimating the Effects of Science and Math Identity in High School on College and Career Outcomes in STEM. *Socius: Sociological Research for a Dynamic World, 8*. https://doi.org/10.1177/23780231221115405, 237802312211154.

Ramsey, J., Glymour, M., Sanchez-Romero, R., & Glymour, C. (2017). A million variables and more: The Fast Greedy Equivalence Search algorithm for learning high-dimensional graphical causal models, with an application to functional magnetic resonance images. *International Journal of Data Science and Analytics, 3*(2), 121–129.

RColorBrewer, S., & Liaw, M. A. (2018). *Package 'randomForest*. Berkeley, CA, USA: University of California, Berkeley.

Ridgeway, C. L., & Correll, S. J. (2004). Unpacking the Gender System: A Theoretical Perspective on Gender Beliefs and Social Relations. *Gender & Society, 18*(4), 510–531. https://doi.org/10.1177/0891243204265269

Schunk, D. H., & DiBenedetto, M. K. (2020). Motivation and social cognitive theory. *Contemporary Educational Psychology, 60*, Article 101832. https://doi.org/10.1016/j.cedpsych.2019.101832

Spirtes, P., Glymour, C. N., Scheines, R., & Heckerman, D. (2000). *Causation, prediction, and search*. MIT press.

Strobl, C., Malley, J., & Tutz, G. (2009). An introduction to recursive partitioning: Rationale, application, and characteristics of classification and regression trees, bagging, and random forests. *Psychological Methods, 14*(4), 323–348. https://doi.org/10.1037/a0016973

Thoemmes, F., Rosseel, Y., & Textor, J. (2018). Local fit evaluation of structural equation models using graphical criteria. *Psychological Methods, 23*(1), 27–41. https://doi.org/10.1037/met0000147

Wang, M.-T., & Degol, J. (2013). Motivational pathways to STEM career choices: Using expectancy–value perspective to understand individual and gender differences in STEM fields. *Developmental Review, 33*(4), 304–340. https://doi.org/10.1016/j.dr.2013.08.001

Wasserman, S., & Faust, K. (1994). *Social network analysis: Methods and applications, 8*. Cambridge university press.

White, I. R., Royston, P., & Wood, A. M. (2011). Multiple imputation using chained equations: Issues and guidance for practice. *Statistics in Medicine, 30*(4), 377–399. https://doi.org/10.1002/sim.4067

Wigfield, A., & Eccles, J. S. (2000). Expectancy–Value Theory of Achievement Motivation. *Contemporary Educational Psychology, 25*(1), 68–81. https://doi.org/10.1006/ceps.1999.1015

Woodward, J. (2008). Mental Causation and Neural Mechanisms. In J. Howhy, & J. Kallestrup (Eds.), *Being reduced: New essays on reduction, explanation, and causation* (pp. 218–262). Oxford University Press.

Wu, H., Guo, Y., Yang, Y., Zhao, L., & Guo, C. (2021). A Meta-analysis of the Longitudinal Relationship Between Academic Self-Concept and Academic Achievement. *Educational Psychology Review, 33*(4), 1749–1778. https://doi.org/10.1007/s10648-021-09600-1

Xie, Y., Fang, M., & Shauman, K. (2015). STEM Education. *Annual Review of Sociology, 41*(1), 331–357. https://doi.org/10.1146/annurev-soc-071312-145659

Yeager, D. S., & Dweck, C. S. (2012). Mindsets That Promote Resilience: When Students Believe That Personal Characteristics Can Be Developed. *Educational Psychologist, 47*(4), 302–314. https://doi.org/10.1080/00461520.2012.722805

Yeager, D. S., Hanselman, P., Walton, G. M., Murray, J. S., Crosnoe, R., Muller, C., et al. (2019). A national experiment reveals where a growth mindset improves achievement. *Nature, 573*(7774), 364–369. https://doi.org/10.1038/s41586-019-1466-y

Yeager, D. S., & Walton, G. M. (2011). Social-Psychological Interventions in Education: They're Not Magic. *Review of Educational Research, 81*(2), 267–301. https://doi.org/10.3102/0034654311405999