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Exploring the dynamics of situated expectancy-value theory: A panel network analysis

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ABSTRACT

Students' competence beliefs and task values are proximal psychological predictors of their achievement-related choices and academic achievement. Situated expectancy-value theory (SEVT) suggests that these beliefs are situationally sensitive and interact over short periods of time. In the present study, we explored the dynamic nature of students' situation-specific expectancy-value beliefs in five sections of an introductory calculus course across one semester (11 weeks, $N = 429$). Using psychometric network analysis, we examined how facets of the SEVT framework are related between persons (i.e., between-person network), within situations (i.e., within-person contemporaneous network), and from one time point to the next across one semester (i.e., within-person temporal network). Results suggested that differences existed among motivational constructs across the three networks in that costs and positively-valenced facets of motivation (i.e., competence and values) were relatively independent of each other within a given situation, but showed some significant cross-lagged effects over time. Our results suggest that interventions to support students in STEM should target positively and negatively valenced constructs (i.e., values and costs).

1. Introduction

Expectancy-value theory (EVT, Eccles et al., 1983) is one of the most prominent theories focusing on student motivation, achievement, and achievement-related choices. According to EVT, students' academic achievement and choices are driven by their expectancies and task values, where expectancies refer to how well a student believes they will do on an upcoming task and subjective task values refer to the extent to which a student wants to complete the task. Subjective task values are further decomposed into specific facets reflecting different reasons for engaging in a particular task (Eccles et al., 1983). That is, students may engage in a given task because it is interesting (interest value), important for their identity (attainment value), useful for current or future goals (utility value), and/or does not require them to give up too much in order to complete the task (relative cost).

Substantial evidence has supported the key role of students' expectancies and task values for important educational and occupational choices such as the pursuit of career paths and major selection in the domains of science, technology, engineering, and mathematics (STEM; e.g., Guo, Parker, Marsh, & Morin, 2015; Lauermann, Tsai, & Eccles, 2017; Robinson et al., 2019). Recently, research grounded in EVT has begun to examine more situated components of the model at a smaller grain size (e.g., using situation-specific measures of expectancies and subjective task values across days or weeks; Benden & Lauermann, 2022; Dietrich, Viljaranta, Moeller, & Kracke, 2017; Dietrich, Moeller, Guo, Viljaranta, & Kracke, 2019; Parrisius, Gaspard, Zitzmann, Trautwein, & Nagengast, 2022). Indeed, Eccles and Wigfield (2020) recently renamed EVT to *situated* expectancy-value theory (SEVT) in order to highlight that students' expectancy-value beliefs are situation-specific (i.e., they vary across situations and are influenced by situational characteristics). Yet, little is known about how students' situation-specific expectancies and subjective task values influence each other within learning situations and from one learning situation to the next over short time periods (e.g., one semester in college). Furthermore, prior research on the interrelations of students' expectancies and task values has rarely separated within-person and between-person associations (for an exception, see Moeller et al., 2022). Examining the relations among students' situation-specific expectancies and task values within-person and across situations at the intraindividual level can allow researchers to understand how the associations of these motivational beliefs differ from

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between-person associations, which have been traditionally studied. In doing so, researchers can conduct targeted interventions on student motivation during specific situations. Further, understanding how these situative processes function over time is particularly needed at critical time periods in students' college careers, such as required introductory courses that can be a barrier to further engagement and success in STEM majors (Chen, 2013; Seymour & Hewitt, 1997).

In order to examine students' situation-specific motivation, an analytic framework allowing for the investigation of these dynamic processes is needed. The relatively novel psychometric network approach (Epskamp, 2020) is particularly well-suited for analyzing the associations of students' expectancy beliefs, values, and costs as a dynamic system, which is in line with the conceptualization of students' motivational beliefs in SEVT (Eccles & Wigfield, 2020; Murayama & Elliot, 2012; Moeller, Viljaranta, Tolvanen, Kracke, & Dietrich, 2022; Tamura et al., 2022). Specifically, psychometric network modeling can provide insights not only into how students' expectancy beliefs, values, and costs are related to each other between students, but also within students (i.e., within-person contemporaneous relations) and across learning situations (i.e., within-person temporal relations). Accordingly, the aim of the present study was to explore the dynamics of students' expectancy beliefs, values, and costs unfolding from one week to another over the course of a semester in introductory calculus courses. We focus on introductory calculus, as it is often a course that acts as a gateway course in STEM majors (Chen, 2013; Seymour & Hewitt, 1997) and declines in students' motivation in introductory math courses have been identified as precursors of low academic achievement and dropout tendencies in STEM majors (Benden & Lauermann, 2022).

1.1. *Situated expectancy-value theory: concurrent and temporal relations of students' motivational beliefs*

As mentioned above, research based in SEVT suggests that students' academic outcomes are influenced by their expectancies and task values for a given task or domain. Expectancy beliefs are conceptually related to other competence beliefs such as students' self-concept of ability and self-efficacy (Bong & Skaalvik, 2003; Eccles & Wigfield, 2020; Marsh et al., 2019). Whereas expectancies of success are quite time- and task-specific and future-oriented, students' self-concept of ability in a given domain typically reflects rather stable and retrospective judgments about their competence in that domain (Eccles & Wigfield, 2020; Marsh et al., 2019). In the present study, we focus on students' situation-specific competence beliefs (i.e., their retrospective assessment about whether they were learning or getting better at something they did in class on a particular day), because we wanted to capture students' competence beliefs about the specific content covered in class each week.

As previously stated, task values are further decomposed into four components (Eccles (Parsons) et al., 1983; Eccles & Wigfield, 2020). The three positively-valenced task values consist of utility value, attainment value, and interest value. In the current study, we focus on attainment and utility values together and asked students how important a particular day's class was to them (i.e., importance value; see Watt et al., 2012). We also asked students how interesting a particular day's class was for them (i.e., interest value). The negatively-valenced task value refers to relative cost (i.e., the perception of what a student must give up in order to complete a task; Eccles et al., 1983; Eccles & Wigfield, 2020), where the task is the object focus (i.e., course, activity, field). Although research on students' cost perceptions has increased recently (e.g., Flake, Barron, Hulleman, McCoach, & Welsh, 2015; Jiang, Rosenzweig, & Gaspard, 2018; Perez, Cromley, & Kaplan, 2014), there is no consensus regarding how many dimensions of cost there are (Wigfield & Eccles, 2020; Wigfield, Rosenzweig, & Eccles, 2017). In the present study, we use the operationalization by Flake, Barron, Hulleman, McCoach, and Welsh (2015), in which cost is further broken down into four components. Task effort cost refers to the negative appraisals of effort or time needed to complete a task, whereas outside effort cost refers to the negative appraisals of effort or time put forth on other activities that take away from completing the focus task. Loss of valued alternatives cost refers to the negative appraisal of what must be given up in order to complete a task. Finally, emotional cost refers to the negative appraisals of a psychological state resulting from completing a task.

Most studies grounded in SEVT have studied global assessments of competence and subjective task value beliefs and their consequences for students' academic achievement and decision-making over several years (e.g., "How much do you like doing math?"; Eccles & Wigfield, 1995). Only recently have researchers begun to adopt a more situated perspective on students' competence and task value beliefs by using situation-specific measures (e.g., "I like these contents"; Dietrich, Viljaranta, Moeller, & Kracke, 2017). These studies underscore the importance of studying students' situated expectancy-value beliefs over comparatively shorter time frames (e.g., one semester in college; Benden & Lauermann, 2022; Dietrich, Viljaranta, Moeller, & Kracke, 2017; Dietrich, Moeller, Guo, Viljaranta, & Kracke, 2019; Kosovich, Flake, & Hulleman, 2017). For instance, researchers have found that students' situation-specific expectancy-value beliefs show substantial variability across lessons and topics (Dietrich, Viljaranta, Moeller, & Kracke, 2017) and decline across one semester in postsecondary settings, which has been linked to lower academic achievement and retention intentions (Benden & Lauermann, 2022; Kosovich, Flake, & Hulleman, 2017). Indeed, Eccles and Wigfield (2020) discuss the need for more experience sampling and diary studies to understand the dynamics and short-term development of SEVT constructs. In order to do so, researchers must assess situationally sensitive competence beliefs and task values because class content may differ from week-to-week or day-to-day.

According to SEVT, competence beliefs and subjective task values are significantly related to each other, with positive correlations between competence beliefs and interest value and importance value and negative associations between perceived cost and competence beliefs as well as interest and importance values (Wigfield & Eccles, 2020). This has been further corroborated by substantial evidence across different domains and educational settings such as high school and college (e.g., Gaspard et al., 2015; Perez, Cromley, & Kaplan, 2014; Robinson et al., 2019; Trautwein et al., 2012). Furthermore, SEVT posits that students' expectancies and task values influence each other over time (Eccles & Wigfield, 1995, 2020). Most of the available evidence examining such links has focused on students' domain-specific expectancy-value beliefs over many years or a few time points across one semester (Arens, Schmidt, & Preckel, 2019; Marsh, Trautwein, Lüdtke, Köller, & Baumert, 2005; Perez et al., 2019). These studies found quite substantial autoregressive (i.e., self-reinforcing) effects for students' math-related competence-related beliefs and subjective task values over time (Arens, Schmidt, & Preckel, 2019; Marsh, Trautwein, Lüdtke, Köller, & Baumert, 2005; Perez et al., 2019; Viljaranta, Tolvanen, Aunola, & Nurmi, 2014). In addition, although exceptions exist (e.g., Marsh, Trautwein, Lüdtke, Köller, & Baumert, 2005), when significant cross-lagged effects between students' math-related competence-related beliefs and task values emerged, they were mostly limited to effects from competence-related beliefs on subjective task values rather than vice-versa (Arens, Schmidt, & Preckel, 2019; Perez et al., 2019; Viljaranta, Tolvanen, Aunola, & Nurmi, 2014).

Still, it is unclear if these findings would be similar across shorter time periods using situation-specific measures of students' expectancies and task values (e.g., one semester in college). Reciprocal effects may depend on the chosen time lag, and time lags of typically one year may overestimate the autoregressive and cross-lagged effects of the studied constructs (Voelkle, Oud, Davidov, & Schmidt, 2012). Examining reciprocal effects of students' expectancies and task values across shorter periods of time is important to better understand whether declines in some motivational beliefs (e.g., expectancies) are linked to declines in others (e.g., interest value), thus contributing to motivational declines that have been identified in prior research (e.g., Benden & Lauermann, 2022). Moeller et al. (2022) is one of the few examples examining short-term relations of students' situation-specific expectancies and task values. The authors used a multilevel structural equation modeling approach to examine autoregressive and cross-lagged effects among expectancy beliefs and the different task values within a 90-min psychology lecture across 11 time points during the semester. The authors found relatively few significant autoregressive effects of students' expectancy-value beliefs across the 90-min lectures and found no evidence of significant cross-lagged effects between expectancies and task values. However, in this study, only two constructs were modeled together at a time as a constraint of the analysis approach used. Multiple expectancy and task value facets likely work as a complex system, however, and concurrent correlations and temporal associations between two constructs may depend on the other expectancy-value constructs included in the model (Eccles & Wigfield, 2020; Wigfield & Eccles, 2020). Accordingly, in the present study, we explore how different facets of SEVT (i.e., competence beliefs, interest value, and importance value, and different cost components) are related to each other between-person, within-person, and temporally from one week to the next across a semester in college. One way to explore these relations is through the use of psychometric network modeling (Epskamp, 2020; Epskamp, Waldorp, Mõttus, & Borsboom, 2018).

1.2. Benefits of psychological network modeling in the context of SEVT

Psychometric network models were first introduced as an alternative to the common cause model, which is the basis of latent variable models (Schmittmann et al., 2013; van der Maas et al., 2006). In common cause models, it is assumed that observed variables caused by (i.e., loading on) the same latent factor are not causally related, an assumption which is unlikely to hold for many psychological constructs (e.g., Borsboom, 2008; Dalege et al., 2016). Instead, by modeling potential dynamic causal relationships of variables included in the network, psychometric network models can give insights into the relation between a (large) set of variables, whereas other statistical frameworks are unable to handle large sets of variables due to multicollinearity issues. This provides a strong exploratory method that can aid in generating hypotheses of possible causal links between variables (Tamura et al., 2022). More specifically, in a psychometric network model, the associations between a set of *nodes* (e.g., indicators of competence beliefs and task values) are shown by *edges* (i.e., partial correlations between the indicators) connecting the nodes (e.g., Schmittmann et al., 2013). Network models can then show how the included nodes are related and how they interact over time, giving insight into temporal dynamics (Epskamp, 2020) and potential efficient targets for interventions (Borsboom & Cramer, 2013; McNally, 2016).

Recently, researchers have begun using network analysis to examine relations of motivational constructs. Using cross-sectional data, in which the focus is on individual differences, Sachisthal et al. (2019) found that science interest can be described as a network model of mutually interacting motivation constructs, such as self-beliefs (i.e., self-efficacy), values (i.e., interest, instrumental value), and enjoyment, that represents the science interest network model (SINM). Moreover, Tang, Lee, Wan, Gaspard, and Salmela-Aro (2022) compared networks including expectancies, task values and achievement across contexts (i.e., grade levels, subject domains and countries). Tang et al. (2022) found context-specific differences as well as commonalities, such as the close relation between expectancies and achievement across all networks. Tang et al. (2022), on the other hand, studied the within-person contemporaneous network of motivational engagement based on intensive longitudinal data of four individuals collected over the course of a year. The resulting network showed the close relations between affective experiences and core motivational components (i.e., expectancy beliefs, goal) within individuals, with intrinsic reason (having fun doing the job) having a central role within the network. Relatedly to the approach taken in this study, Moeller and colleagues (2022), have argued that applying dynamic systems theory – for instance by using network approaches – is a fruitful avenue to study the dynamic nature of expectancies, values, and costs grounded in SEVT.

Using the network approach on panel data, as done in the current study, is in line with some of the objectives of SEVT highlighted by Eccles and Wigfield (2020). First, it enables the investigation of SEVT-constructs as a complex system of interacting expectancies and task values by disentangling how these different constructs are related to each other on a between-subject level (i.e., *between-persons* network), as well as on a situational-level (i.e., *within-subjects contemporaneous* network) and from one time point to the next (i.e., *within-subjects temporal* network; Epskamp, 2020; Epskamp, Waldorp, Mõttus, & Borsboom, 2018). In a between-subjects network, the associations between the means (over time and subjects) of the included measures are estimated, which addresses differences between individuals. For example, we can ask: Is someone who finds the task more important than the average student over time also more interested in the task? Next, in a within-subjects contemporaneous network, the relations between measures at the same time point are estimated. Here we can ask questions such as: Is someone who finds the task more important than usual on a specific day also more interested in the task on the same day? Lastly, in a within-subjects temporal network, the relations of each SEVT construct with itself, as well as the other included constructs at the next time point (i.e., one week later) are estimated. These so-called lagged associations can give insights into questions such as: Is someone who finds the task more important than usual on a specific day more interested in the task one week later?

Second, the relative importance of the different task values can be studied, which are theorized to differ not only at the between-person level but also across time at the within-person level (Eccles & Wigfield, 2020). In the current study, this is done by investigating the centrality of the different nodes within each network, which reflects each node's importance within the model. Given that change is thought to travel throughout the network (Schmittmann et al., 2013), nodes that are more closely connected to other nodes (i.e., central nodes) have been assumed to be promising targets for effective interventions (Borsboom & Cramer, 2013; McNally, 2016). Investigating centrality has allowed researchers to examine central nodes as predictors of later outcomes (Sachisthal, Jansen, Dalege, & Raijmakers, 2020) and interventions targeting central nodes have been shown to lead to changes in behavior (Zwicker, Nohlen, Dalege, Gruter, & van Harreveld, 2020).

Techniques to analyze time-series networks have only been recently developed (Epskamp, 2020; Epskamp, Waldorp, Mõttus, & Borsboom, 2018). Thus, the empirical applications of such models are still scarce (cf. Bar-Kalifa & Sened, 2020; Faelens et al., 2021). Time series networks generally require many time points (i.e., >20) per participant; however, the recently developed panel network model requires only three time points at minimum (Epskamp, 2020). These models thus allow researchers to examine between-person as well as concurrent and temporal associations of multiple constructs in educational settings, a context that can be limited by constraints such as the number of weeks in a semester.

1.3. The present study

In the present study, we explored panel networks of students' competence beliefs and task values in introductory calculus from week-to-week in order to better understand, first, how the facets are related across individuals (i.e., between person), second, how different facets of the SEVT framework are related within a given situation (i.e., within-person contemporaneous), and third, how these facets are related to each other over time (i.e., within-person temporal). Although these networks were exploratory, we used theory and empirical evidence to guide hypotheses when possible.

1.3.1. Between-person network

SEVT (Eccles et al., 1983) has proposed that competence beliefs, interest value, and importance value are all positively-valenced constructs, whereas costs are negatively-valenced. Further, empirical research has shown that cost facets tend to be negatively correlated with competence beliefs and task values (Benden & Lauermann, 2022; Beymer, Ferland, & Flake, 2021; Flake, Barron, Hulleman, McCoach, & Welsh, 2015; Perez et al., 2019; Perez, Cromley, & Kaplan, 2014; Robinson et al., 2019). Previous research has also found tight clusters of closely related motivational variables to form when using network analysis on cross-sectional data (Sachisthal et al., 2019). Because of this, we expected that nodes representing constructs of similar valence would form tight clusters of positively-related nodes. That is, we expected that two clusters would emerge: one cluster of competence beliefs, interest value, and importance value and one cluster of perceived costs. We did not make specific hypotheses regarding the links between constructs of different valence given that the strength of associations between costs and positively-valenced constructs are often dependent on the specific facets and because we computed partial correlations as compared to bivariate correlations.

1.3.2. Within-person contemporaneous network

Although there is less empirical research examining within-person relations of SEVT- constructs, Moeller et al. (2022) found that costs had a negative concurrent correlation with other task values and competence beliefs, but the degree of those relations depended on the specific cost facets. Further, the authors found positive concurrent correlations between intrinsic value (or interest value), utility/attainment values (or importance value), and competence beliefs. Research examining within-person correlations between cost facets has found moderate positive correlations (Beymer, Ferland, & Flake, 2021). Thus, regarding the within-person contemporaneous network, we expected relatively similar patterns as in the between-person network. That is, we expected to see two positively related clusters of constructs of similar valence (e.g., the four cost components will be positively related).

1.3.3. Within-person temporal network

Although research has been conducted examining auto-regressive and cross-lagged associations between EVT constructs (Moeller et al., 2022; Perez et al., 2019; Perez, Cromley, & Kaplan, 2014), the time lag we use in the current study (i.e., week-to-week) is fairly unique. Whereas some researchers have focused on moment-to-moment dynamics of SEVT constructs across lessons (Moeller et al., 2022), others have focused on longer timeframes across years or a few time points across a semester (Perez, Cromley, & Kaplan, 2014; Perez et al., 2019). Eccles and Wigfield (2020) posit that the microprocesses of competence beliefs and task values likely interact across short-term situations; however, because we focus on week-to-week relations, we did not make any specific hypotheses regarding autoregressive or cross-lagged relations. Still, we expected to see some autoregressive and cross-lagged relations.

1.3.4. Strength centrality

We also examined which construct is most influential within each of the three networks. This was done by computing the strength centrality of the constructs per network (Freeman, 1978; Opsahl, Agneessens, & Skvoretz, 2010). Although exploratory in nature, strength centrality may indicate efficient routes for possible interventions (e.g., Borsboom & Cramer, 2013; McNally, 2016; Zwicker, Nohlen, Dalege, Gruter, & van Harreveld, 2020) and may reveal interesting differences between the three networks.

2. Method

2.1. Course description and sample

Five sections of introductory calculus courses at a midwestern university in the United States participated in this study. Two of the sections were generally taken by students who intend to pursue a major in business or were in a program for premedical studies. The remaining three sections were meant for students who intend to major in a STEM discipline. Both courses were designed to teach students foundational calculus knowledge (i.e., limits and derivatives) so that they can apply these skills in the future. All sections met in-person Monday, Wednesday, and Friday, during the fall 2018 semester. Large lectures occurred on Mondays and Wednesdays and were taught by the faculty of record. Students met on Fridays in smaller sections that were taught by a teaching assistant. Four instructors taught these sections (three instructors for the three sections for STEM majors; one instructor for the two sections for business and pre-med students). Across the five sections, 1098 students were enrolled. Of those, 596 students provided consent and were then invited to the diary portion of the study. Out of the 596 students, 429 completed at least one diary survey and comprise the sample for the current study. Of the 429 students who participated, 37 % were women, 62 % were white, 5 % were Black, 5 % were Hispanic/Latinx, 6 % were Asian, 2 % were two or more races, and 20 % were international students. Most of the students who participated in the study were either first-year students (78 %) or second-year students (15 %), with only 7 % being in their third year or later.

2.2. Procedure

Prior to the study, procedures were approved by the human subjects review board at the university where the research was conducted. Ethical safeguards were respected in the treatment of research participants as described in the American Psychological Associations' Ethical Principles of Psychologists and Code of Conduct (APA, 2017). Data were collected using a diary approach throughout the semester. This type of intensive longitudinal methodology (Bolger & Laurenceau, 2013) is used to collect individuals' subjective experiences regarding a specific event, or in the case of this study, a single day's class. Similar to other studies using intensive longitudinal methodologies (Durik, Schwartz, Schmidt, & Shumow, 2018; Schmidt et al., 2017), students completed a survey once a week for 11 consecutive weeks after one of their large lectures. An online platform, *Remind*, was used to distribute weekly surveys. Email reminders were sent during the last 10 min of class and included a *Qualtrics* survey link. Students then had the remainder of the day to respond to the survey before it closed at midnight. The surveys rotated between Monday and Wednesday each week in order to avoid day-of-the-week effects. Students enrolled in the calculus sections for STEM majors who completed 80 % of the surveys were entered into one of two drawings for a $75 Amazon gift card in their course section. In total, gift cards were given to six students. Students who were enrolled in the calculus section for business and pre-med students received course credit if they completed 80 % of the surveys. The difference in incentives was due to instructor preference. Overall, 2435 responses were collected. Students responded to an average of 5.68 surveys ($SD = 3.56$), with a range of responses between 1 and 11. The response rate for the surveys was 52 %, as is expected in intensive longitudinal studies with college students (Feldman Barrett, 2004; Hektner, Schmidt, & Csikszentmihalyi, 2007).

2.3. Measures

As is typical with studies using intensive longitudinal methodologies (Goetz, Bieg, & Hall, 2016; Zirkel, Garcia, & Murphy, 2015), single items were used to assess each construct. Single items have been shown to be psychometrically sound alternatives to longer questionnaires for assessing motivational variables in educational research (Gogol et al., 2014). Further, researchers have shown that single item measures perform just as well as multiple-item measures and are suitable for use with intensive longitudinal designs (Song, Howe, Oltmanns, & Fisher, 2022). Here, we used retrospective assessments of students' competence beliefs and task values in order to assess their motivational beliefs referencing the specific content taught in class in a given week. These assessments are situationally sensitive because students need to reflect on the specific content that was covered in class that day. In contrast, prospective items (e.g., "How well do you think you will do in your math course this year?; Eccles & Wigfield, 1995) are likely less situation-specific because students do not have any information yet about the content of a class and would likely rely on their previous experiences in class.

Competence beliefs and task values were assessed using items from prior studies that have shown validity properties similar to other scales (Schmidt et al., 2018; Beymer, Rosenberg, & Schmidt, 2020). Four dimensions of cost were assessed using a shortened cost scale with strong validity evidence (Beymer, Ferland, & Flake, 2021). The items were as follows: *Competence beliefs*: "Thinking about the work you did in class today, were you learning anything or getting better at something?"; *Importance value*: "Thinking about the work you did in class today, was it important to you?"; *Interest value*: "Thinking about the work you did in class today, was it interesting?"; *Task Effort Cost*: "After today's class I feel like this class requires too much effort."; *Outside Effort Cost*: "After today's class I feel like because of other things that I do, I don't have time to put into this class."; *Loss of Valued Alternatives*: "After today's class I feel like this class requires me to give up too many other activities that I value."; *Emotional Cost*: "After today's class I feel like this class is emotionally draining.". All items were assessed using a 7-point Likert scale (1 = *strongly disagree*, 7 = *strongly agree*). Competence-beliefs and positively-valenced value items were asked on a separate page than cost items in *Qualtrics*.

2.4. Data analytic strategy

The 2435 responses collected from 429 students were used in estimating all three of the networks in an effort to separate within- and between-person processes. Before estimating the three networks, we checked to ensure that the assumption of stationarity held in order to proceed with the panel network estimation. Given the relatively short time lags and that the focus of the current analysis was the correlational structure of the included variables, assuming stationarity of the mean and variance across time points is appropriate in the current context (Rovine & Walls, 2006; Speyer et al., 2021). If stationarity cannot be assumed, which is often the case in studies with longer time-lags, the network approach can still be used by de-trending the data (e.g., de Vos et al., 2017). For each variable of each student, we checked for stationarity (i.e., the mean and variance of each variable do not change as a function of time) using the Kwiatkowski-Phillips-Schmidt-Shin unit root test (Kwiatkowski, Phillips, Schmidt, & Shin, 1992) as is common when examining repeated-measures networks (Aalbers, McNally, Heeren, de Wit, & Fried, 2019; Bringmann, 2016). Additionally, we tested each variable for normal distribution using the Kolmogorov-Smirnov test. Bonferroni corrections were applied for both assumption checks to control for multiple testing. Finally, we checked whether response rates of the diary survey differed among gender, race/ethnicity, and course grades.

To estimate the networks, we used the *psychonetrics* package (Epskamp, 2021) in R Core Team (2021) (see supplemental materials for code). Missing data were handled using full information maximum likelihood estimation. The dynamic associations between variables were analyzed using a panel design (Epskamp, 2020). Three network structures were estimated within the panel model. First, a between-person network, which is a Gaussian graphic model (GGM) depicting the partial correlations between any set of two variables after taking into account all other variables included in the model. In other words, the between-person network shows the relations between stable means (Epskamp, 2020). Second, a within-person contemporaneous network, which is a GGM depicting the relations between variables at the same time point after controlling for temporal associations. Third, a within-person temporal network, which is a directed network showing the lagged associations of one variable on another variable from one measurement moment to the next, after controlling for all variables at the previous measurement moment. The within-temporal network is estimated by regressing each node on all other nodes of the previous time point (Bringmann et al., 2013; Epskamp, Waldorp, Mõttus, & Borsboom, 2018).

The three networks provide complementary insights into the covariation and possible dynamics of the included motivational variables. First, the between-person network provides insights into associations between means (across measurement moments and persons) of the included variables, and results based on this network can be compared with results from cross-sectional studies (Epskamp, Waldorp, Mõttus, & Borsboom, 2018). Second, the within-subjects contemporaneous network provides insights into the relations between students' expectancy-value beliefs at the same measurement moment. That is, this model focuses on whether the differences from a person's mean on a variable at a certain measurement moment are related to their mean on a different variable at the same measurement moment. Finally, the within-person temporal network provides insights into the relations between students' expectancy-value beliefs across any two time points. That is, this network focuses on the differences from a person's mean on a variable at a certain measurement moment related to their mean on a different variable one week later.

For each model, three steps were performed to choose the best fitting network model. First, we estimated the saturated model, in which all edges were included. We then estimated a pruned model to include only edges that were significant at $p < .05$. Finally, we used the *stepup* function to estimate a model. This function uses a model search strategy in which the edge with the strongest modification index is added stepwise until the Bayesian information criterion (BIC) of the model no longer improves (Epskamp, 2020). The best-fitting network model was chosen based on the BIC, Akaike information criterion (AIC), and chi-square difference tests (Epskamp, 2020).

We then plotted the final networks using the *qgraph* package (Epskamp, Cramer, Waldorp, Schmittmann, & Borsboom, 2012). In the network plots, blue lines represent positive relations between variables, whereas red lines represent negative relations. The thickness of the lines represents the strength of the association, with thicker lines representing stronger relations and thinner lines representing weaker relations. The temporal effects in the within-person temporal network are represented by arrows. As an indication for the stability of the edges, we calculated the 95 % confidence intervals per edge and network. The results of this analysis are displayed in Fig. S1 in the online supplemental materials.

We further calculated strength centrality for all networks (Freeman, 1978; Opsahl, Agneessens, & Skvoretz, 2010). In the contemporaneous and between-subjects networks, strength centrality is the sum of all significant absolute edges connecting one node to another node, thus showing which node is the most influential (i.e., strongest) within a situation and across individuals. In the temporal network, strength centrality is broken down into in-strength and out-strength, where in-strength centrality is the sum of edge weights of significant incoming connections and out-strength centrality is the sum of edge weights of significant outgoing connections. Here, a node with a high in-strength is strongly predicted by the other nodes, whereas a node with a high out-strength strongly predicts other nodes. The centrality indices are standardized.

3. Results

3.1. Preliminary analyses

Within-person means and standard deviations for all variables are included in Table 1 and were as expected. Results from the Kwiatkowski-Phillips-Schmidt-Shin Unit Root tests suggested that the assumption for stationarity was met for each variable in the network (Bonferroni

Table 1
Contemporaneous correlations (below diagonal; white shading), between-person correlations (above diagonal; grey shading), and within-person means and standard deviations.

	Comp. Beliefs	Importance Val.	Interest Val.	TECost	OECost	LVCost	EMCost
Comp. Beliefs		.41***	.49***	.17	.14	−.27*	−.02
Importance Val.	.27***		.41***	.09	−.04	−.02	.11
Interest Val.	.31***	.26***		−.17	−.19	.33***	−.24**
TECost	−.02	−.02	.01		.02	.58***	.39***
OECost	−.07**	−.03	.04	.16***		.66***	.06
LVCost	.01	.05	−.05*	.26***	.31***		.08
EMCost	−.00	.04	−.06*	.28***	.14***	.19***	
M (*SD*)	4.57 (1.22)	4.64 (1.38)	3.79 (1.46)	3.18 (1.40)	2.85 (1.32)	2.87 (1.36)	3.25 (1.53)
SD (*SD*)	1.05 (0.58)	1.02 (0.60)	0.98 (0.54)	0.81 (0.53)	0.82 (0.55)	0.79 (0.56)	0.85 (0.59)
Node Name	Comp	Imp	Int	Tecost	Oecost	Lvcost	Emcost

Note. Comp. = competence; val. = value; TECost = take effort cost; OECost = outside effort cost; LVCost = loss of valued alternatives cost; EMCost = emotional cost.
**p* < .05.
***p* < .01.
****p* < .001.

corrected *ps* > .05). Thus, we did not de-trend the data. The Kolmogorov-Smirnov tests suggested that normality could not be assumed for the variables (Bonferroni corrected *ps* < .05). Distributions of competence beliefs and importance value were slightly negatively skewed, whereas interest value and cost variables were slightly positively skewed. It may be that the scales were slightly skewed given students' self-selection into calculus. Further, it is common to see slight skews in these variables. Because the variables were only slightly skewed, we proceeded to treat variables as continuous, as is common in much of the network literature (Robinaugh, Hoekstra, Toner, & Borsboom, 2020).

Missing data analysis was conducted to ensure that data were missing at random, a requirement for using Full Information Maximum Likelihood (FIML) estimation (Cham, Reshetnyak, Rosenfeld, & Breitbart, 2017). First, we examined whether there were significant differences in diary response rates by gender and underrepresented minority (URM) status (defined as Black, Hispanic/Latinx, and people of color. Individual response rates were calculated by dividing the number of diary responses for each student by the total number of possible diary responses (i.e., 11) to check for survey completion rates between students. A *t*-test indicated that there were no significant differences in diary response rates for URM status, $t\,(62.58) = 1.14$, $p = .26$; however, there was a significant difference in diary response rates among gender, $t\,(339.63) = 3.07$, $p = .002$, suggesting that women had somewhat higher response rates (57 %) than men (48 %). Second, we examined if there was attrition from the course. Little attrition occurred among the students that participated in the study (only 16 students did not complete the course), and there were no significant differences in attrition as a function of students' gender or URM status. In sum, these analyses suggest that there were no systematic differences in response rates and attrition across the semester between students, and we used FIML for handling missing data.

3.2. Network estimation

The fit indices of the models estimated were as follows: Saturated: BIC = 47,361.30, AIC = 46,909.33; Pruned: BIC = 47,129.79, AIC = 46,891.69; Stepup: BIC = 47,129.79, AIC = 46,891.69. There was no change from the pruned model to the stepup model and despite the decreased BIC and AIC in the pruned model from the saturated model, the chi-square difference test suggested that the model fit significantly worse (change in $\chi^2\,(53) = 88.37$, $p = .002$). Thus, we chose the saturated model as our final model (i.e., a lag-1 process explained the data adequately and relations between variables were stationary over time; Deserno, Sachisthal, Epskamp, & Raijmakers, 2021). See Fig. 1 for the final networks and Tables 1 and 2 for parameter estimates.

3.2.1. Between-person network

In the between-person network, competence beliefs, importance value, and interest value were all positively related suggesting that a student with higher competence beliefs over time compared to the average student also reported comparatively higher importance and interest value (see Fig. 1, Panel A). Students' cost perceptions were not consistently linked to each other (i.e., only three out of six relations were significant): Students with higher levels of loss of valued alternatives cost compared to others also reported higher levels of outside effort and task effort cost. Additionally, emotional cost was positively related to task effort cost. Three relations were found between the positively-valenced and negatively-valenced constructs: loss of valued alternatives cost was negatively related to competence beliefs and positively linked to interest value and emotional cost was negatively related to interest value.

The strength centrality of the between-person network is depicted in Panel A of Fig. 1. Loss of valued alternatives cost had the highest strength centrality, being strongly positively connected with two other cost components and interest value and negatively linked to competence beliefs. Interest value had the second-highest strength centrality, being positively linked with both importance value and competence beliefs and having a negative relation with emotional cost along with the positive link with loss of valued alternatives cost.

3.2.2. Contemporaneous network

Two tightly related clusters of variables emerged in the contemporaneous network (see Fig. 1, Panel B): one cluster of competence beliefs, importance value, and interest value and one with all four cost components. That is, when an individual found the task interesting at a

Network Plots of the Three Network Models (Left) and Their Centrality (Right).

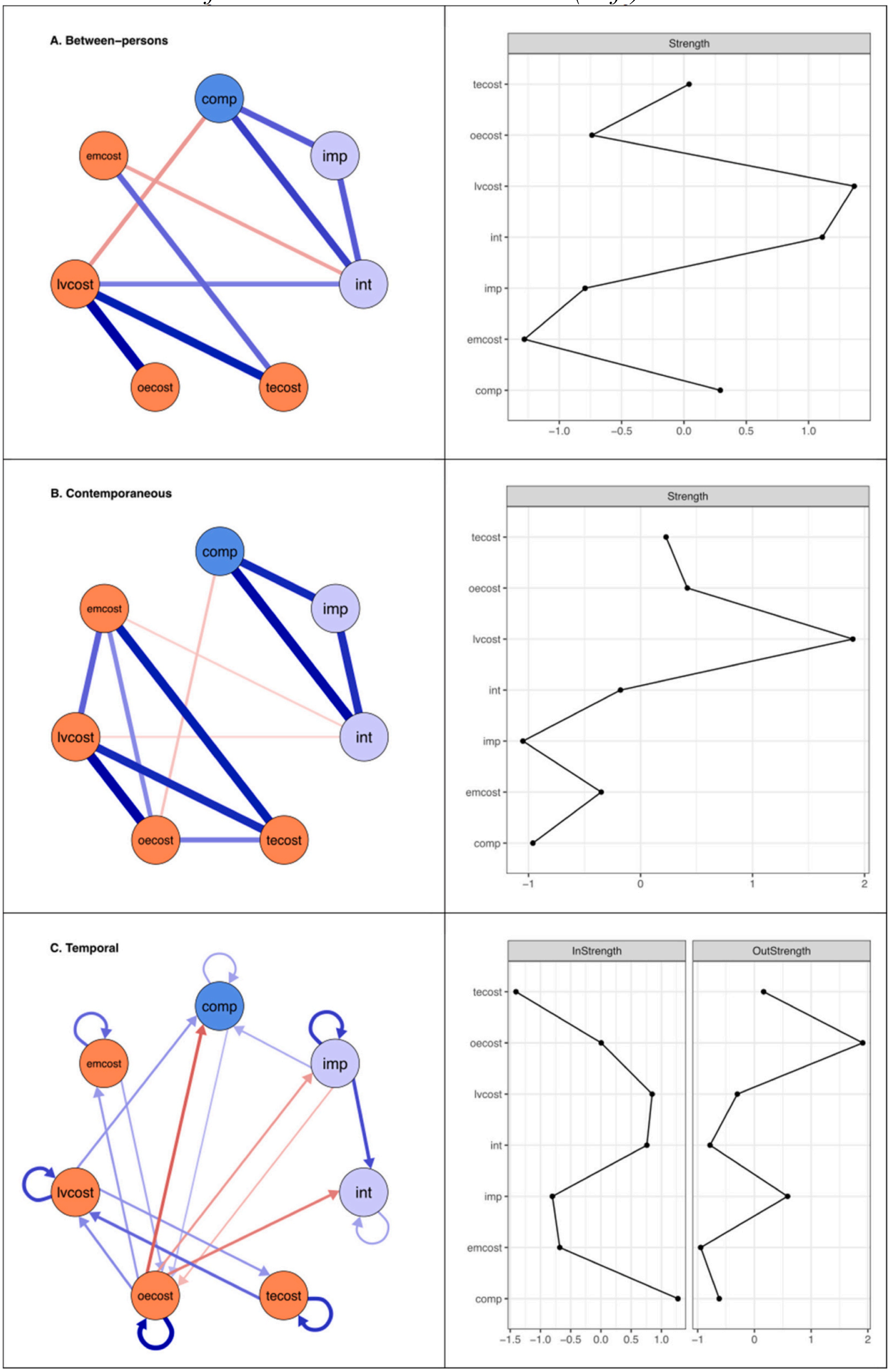

Fig. 1. *Note.* Panel A represents the between-person network, panel B represents the within-person contemporaneous network, and panel C represents the within-person temporal network. On the left side, partial correlations between nodes are displayed with edges or arrows for the temporal network. Arrows represent temporal predictions from one time point to the next. The thickness of edges/arrows represents the strength of the relation/prediction between nodes. Blue edges/arrows represent positive relations and red edges/arrows represent negative relations. comp = competence; imp = importance value; int = interest value; tecost = take effort cost; oecost = outside effort cost; lvcost = loss of valued alternatives cost; emcost = emotional cost. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 2
Temporal network estimates and standard errors.

Outcomes	Predictors (t − 1)						
	Comp. beliefs	Importance val.	Interest val.	TECost	OECost	LVCost	EMCost
Comp. beliefs	0.08* (0.03)	0.07* (0.03)	0.02 (0.03)	−0.04 (0.04)	−0.14*** (0.04)	0.09* (0.04)	0.02 (0.04)
Importance val.	0.06 (0.03)	0.17*** (0.03)	0.06 (0.03)	−0.03 (0.04)	−0.09* (0.04)	0.00 (0.04)	−0.01 (0.04)
Interest val.	−0.01 (0.03)	0.15*** (0.03)	0.08* (0.03)	−0.02 (0.04)	−0.11** (0.04)	−0.02 (0.04)	0.02 (0.04)
TECost	0.00 (0.03)	−0.04 (0.03)	0.01 (0.03)	0.17*** (0.04)	0.06 (0.03)	0.09** (0.04)	0.00 (0.03)
OECost	0.06* (0.03)	−0.06* (0.03)	−0.03 (0.03)	0.06 (0.03)	0.22*** (0.03)	−0.00 (0.04)	0.07* (0.03)
LVCost	0.03 (0.03)	−0.03 (0.03)	−0.03 (0.03)	0.13*** (0.03)	0.10** (0.03)	0.16*** (0.03)	−0.03 (0.03)
EMCost	−0.03 (0.03)	−0.02 (0.03)	0.02 (0.03)	0.04 (0.04)	0.09** (0.03)	0.04 (0.04)	0.13*** (0.04)

Note. Comp. = competence; Val. = value; TECost = take effort cost; OECost = outside effort cost; LVCost = loss of valued alternatives cost; EMCost = emotional cost. * $p < .05$. ** $p < .01$. *** $p < .001$.

certain time point, they were also likely to feel competent and found the task important. Further, if a student was experiencing one type of cost, such as loss of valued alternatives, they were also likely experiencing the other types of cost, such as task effort, outside effort, and emotional cost at the same time point. Three negative edges between the two clusters emerged. Interest value was negatively linked with emotional cost and loss of valued alternatives cost and competence beliefs were negatively linked with outside effort cost. Thus, when a student felt interested, they were less likely to experience emotional cost and loss of valued alternatives cost at the same time and vice versa. Similarly, when a student felt competent at a particular time point, they were less likely to experience outside effort cost at the same time, and vice versa.

The strength centrality for the within-person contemporaneous network is displayed in Fig. 1, Panel B. Similar to the between-person network, loss of valued alternatives cost was the node with the highest strength centrality within the contemporaneous network, followed by task effort cost and outside effort cost. Compared to competence beliefs and interest value, importance value had the lowest strength centrality, whereas of those three constructs, interest value had the highest strength centrality.

3.2.3. Temporal network

In the temporal network, all variables showed a positive autoregression, meaning students who reported higher competence beliefs, importance value, interest value, or cost compared to their baseline also reported higher motivational beliefs the following week (see Fig. 1, Panel C). After controlling for all constructs at the previous time point, competence beliefs only had a significant positive forward influence on outside effort cost, but none of the other variables. That is, those with high competence beliefs during the week, had higher outside effort costs the following week. Furthermore, importance value had a positive forward influence on competence beliefs and interest value, and a negative forward influence on outside effort cost. Thus, when reports of importance were high during a week, reports of interest value and competence beliefs were higher the following week, and outside effort cost was lower. There were no forward influences from interest value to any variables.

Regarding students' cost perceptions, results showed positive reciprocal links between task effort and loss of valued alternatives cost as well as between emotional cost and outside effort cost; lastly, outside effort cost also predicted loss of valued alternatives. Interestingly, significant predictive effects of the different cost facets on students' competence beliefs, importance value, or interest value were limited to outside effort cost: outside effort cost emerged as a significant negative predictor of students' competence beliefs, importance value, and interest value, controlling for students' other cost beliefs. This suggests that students who experienced a higher amount of outside effort cost compared to their personal baseline in one week reported lower levels of competence beliefs, importance value, and interest value the next week. The only exception was a positive forward influence of loss of valued alternatives on students' competence beliefs.

Consequently, outside effort cost had the highest out-strength (see Fig. 1, Panel C), followed by importance value, task effort cost, and loss of valued alternatives cost suggesting that these variables are important predictors of the other expectancy-value beliefs in the model. In-strength, on the other hand, represents the extent to which a variable is predicted by the other variables in the model. Competence beliefs were found to have the highest in-strength, followed by loss of valued alternative cost, and interest value, whereas task effort cost, importance value, and emotional cost were not well-predicted by the other variables in the model a week earlier.

4. Discussion

The purpose of this study was to explore the relations among students' competence beliefs and task values across one semester in introductory college calculus, highlighting the importance of understanding the dynamic and situated nature of students' motivational beliefs. We employed a novel psychometric network approach to examine the complex interplay of students' situated expectancies, values, and costs grounded in SEVT. Doing so allowed us to not only examine relations of these motivational beliefs between students, but also within-person relations of expectancy-value beliefs, both at the same moment and from one week to the next. Our findings highlight the importance of examining the complex interrelations of motivational beliefs on different levels as well as the value of taking into account the different constructs within the same analysis (Eccles & Wigfield, 2020). Differences across the relations of beliefs within- and between-person emerged and relevant temporal relations from one week to the next were revealed, having both theoretical as well as practical implications.

4.1. Between- and within-person associations of students' motivational beliefs in SEVT

In examining the between-person and within-person contemporaneous networks, we observed a few key differences. In the within-person contemporaneous network, we found two tight clusters of nodes (i.e., a cluster of competence beliefs, interest value, and importance value and a cluster of all cost components); however, in the between-person network, not all cost components clustered together. Thus, though it appears that all costs tend to fluctuate together during a specific week (within-person contemporaneous), on the between-person level, students who generally experienced more emotional cost than others may not experience higher levels of the other costs.

The emergence of the two clusters at the within-person level, which were largely unrelated, suggested that students' experiences of competence and positively-valenced task values and their cost perceptions in a given week are likely differentially shaped by situational characteristics (e.g., situation-specific demands, performance feedback), highlighting the importance of examining the role of such situational factors (Eccles & Wigfield, 2020). This finding suggests the potential benefit of intervening on multiple forms of motivation at a time - as change within one cluster may not travel to the other clusters. Indeed, our analysis of strength centrality identified loss of valued alternatives cost and interest value as the most influential variables. By targeting both value and cost simultaneously, and not only one specific facet of motivation (e.g., utility value interventions; Harackiewicz & Priniski, 2018; cost reduction interventions; Rosenzweig, Wigfield, & Hulleman, 2020), students may see increased benefits of interventions. Future research should thus consider examining the effects of intervening on multiple SEVT-facets (Rosenzweig, Wigfield, & Eccles, 2022).

Of note is the wording of items used in the diary surveys. That is, when students were asked to report on positive facets of motivation, the stem "Thinking about the work you did in [class] today, …" was used; however, the stem "After today's class, I feel like…" was used when students were asked to report on their cost beliefs. These stems were kept due to researchers using them in prior research (Beymer, Rosenberg, & Schmidt, 2020; Beymer, Ferland, & Flake, 2021; Schmidt et al., 2018). Thus, the object of focus is slightly different between positive and negative facets of motivation. That is, positive facets asked students to reflect on "the work" from class, whereas negative facets asked students to reflect on the class more broadly. This may be another factor contributing to the two largely unrelated clusters of positive and negative motivational beliefs that we found in the between-person and contemporaneous networks.

Interestingly, the relation between loss of valued alternatives cost and interest value was negative within-person, but positive between-person. Perhaps between-person, a student who is more interested than the average student may generally be more interested in other classes as well and thus feel like they have to give up more for their calculus course because of the time that is not available for other classes; however, within-person, a student who is more interested than usual in a given week, may also believe that giving up other things is worth it and thus perceives lower loss of valued alternatives cost than usual. This finding suggests the importance of disentangling between- and within-person motivational processes, which is especially important for informing interventions.

4.2. Within-person temporal associations of students' motivational beliefs in SEVT

On the temporal level, we found that all variables had positive autoregressive loops, meaning that from one week to the next, variables positively reinforced themselves, a finding in line with earlier research across two time points during a semester (Perez et al., 2019; Perez, Cromley, & Kaplan, 2014). Expectancy-value constructs thus seem to consistently positively reinforce themselves across longer time scales, such as weeks and even years (e.g., Arens, Schmidt, & Preckel, 2019; Perez et al., 2019; Perez, Cromley, & Kaplan, 2014; Weidinger, Spinath, & Steinmayr, 2020), whereas the same was not found for students' task values on a shorter time scale from situation to situation within the same lesson (Moeller et al., 2022). Indeed, Eccles (2005) has emphasized the importance of using the "right" time frame for measuring developmental processes, which is critical when examining dynamic systems that are dependent on context (McNeish & Hamaker, 2019; Vu et al., 2021). In the present study, the "right" time frame for us to examine lagged relations was week-to-week. The introductory calculus course that we examined was lecture-based, covering different topics each week, as many introductory college courses are. Therefore, we did not expect that there would be much change among motivation within the same day's lesson, but rather as a function of topic on a week-to-week basis.

Interestingly, outside effort cost emerged as the strongest predictor of students' competence beliefs, positively-valenced task values, and other types of costs in the within-personal temporal network. This type of cost likely reflects students' placement of the math course and its contents within their personal hierarchies of expectancies and task values (Eccles & Wigfield, 2020), that is, whether the math course is their top priority or whether other courses or personal obligations are valued higher. Our results suggest that intra-individual comparisons across different tasks and obligations play a role in shaping students' situation-specific expectancies and subjective task values. Thus, outside effort cost may be another potential candidate for intervention — especially when the aim is to increase motivation one week later (vs. within the same lesson); however, outside effort costs may be difficult to intervene on. Outside effort cost may be the least understood dimension of cost as researchers often do not assess this type of cost (Perez, Cromley, & Kaplan, 2014). Further, we assessed *how much* a student feels that they don't have time to put into the class because of other things that they do, but it is unclear what those other things are. More qualitative work is needed to understand the types of things students do that take away from putting time into the focal class. If outside effort costs are largely driven by the workload of other classes, intervention efforts may focus on intersections between courses and how the content of one course could be beneficial for another (thus targeting both cost and utility value perceptions depending on which course is seen as the focal course; see Wigfield & Eccles, 2020).

In contrast to prior studies, we found no significant effects from students' competence beliefs on interest value or importance value in the temporal network (e.g., Arens, Schmidt, & Preckel, 2019; Perez et al., 2019). If significant cross-lagged effects emerged in prior studies, these effects were mostly limited to students' expectancy or competence-related beliefs predicting later subjective task values. Instead, in the present study, students' competence beliefs were significantly predicted by their prior importance value, outside effort cost, and loss of valued alternatives cost. This discrepancy to prior research may be due to the retrospective assessment of competence beliefs in our study compared to (future-oriented) expectancy beliefs or domain-specific self-concepts of ability typically assessed in prior studies. Students who reported higher valuing (e.g., perceived importance) of their calculus course in a given week may have been more engaged in class a week later, which in turn may have affected their perceptions that they have learned something that day. In contrast, students' competence beliefs in one week may not have affected their subjective task values a week later because the perception that they learned something in class on a given day may be limited to the specific material covered on that day and may not reflect their more global beliefs about how well they can do in their calculus course. More research using different types of assessments (e.g., situation-specific vs. course-specific), as well as different time lags between measurement points is needed to better understand the dynamic relations of students' expectancies and task values across short time periods and whether these relations differ from long-term associations of students' expectancies and task values.

4.3. Contributing to theory and practice through a network approach

As researchers continue to embrace complex dynamic systems in motivation research (Eccles & Wigfield, 2020; Kaplan & Garner, 2020), statistical approaches that allow for modeling of situationally sensitive constructs are necessary. Whereas research has focused primarily on between-person cross-sectional analysis, network approaches allow for the within-person examination of many variables at a time (Tamura et al., 2022). Here, we provided new theoretical insights into SEVT by examining differences in between-person, within-person contemporaneous, and within-person temporal networks through a situative lens.

Practically, network analysis provides an exploratory model to aid researchers in exploring causal links between variables (Tamura et al., 2022). In the current study, we found two relatively separate clusters of variables (i.e., competence beliefs/values and costs), suggesting a possible need to intervene on multiple variables at once. Intervening on multiple motivational beliefs at the same time may increase the likelihood of affecting multiple student outcomes (Rosenzweig, Wigfield, & Eccles, 2022). For instance, students' competence beliefs are often the strongest motivational predictor of their academic achievement, whereas students' values and costs more strongly predict their course-taking and retention in STEM (e.g., Perez, Cromley, & Kaplan, 2014; Robinson et al., 2019). However, multiconstruct interventions require more instructional time and effort to be successfully implemented in class (Rosenzweig, Wigfield, & Eccles, 2022); thus, it is important to consider which motivational constructs to target. Our analyses suggest that interventions focusing on students' values and costs may have the largest impact on multiple motivational beliefs and may also be more likely to impact multiple student outcomes (e.g., achievement and retention in STEM). Future research should compare the effectiveness of a combined utility value and cost reduction intervention to interventions that target only one motivational construct.

Additionally, through the examination of centrality, we found that loss of valued alternatives cost and interest may be the most efficient intervention targets for between- and within-person change; however, outside effort cost may be a promising target for intervention when seeking to impact student beliefs week-to-week. Researchers should consider developing and testing interventions to increase interest and decrease cost (i.e., loss of valued alternatives and outside effort cost) simultaneously given their links to achievement and persistence in STEM (Benden & Lauermann, 2022; Perez, Cromley, & Kaplan, 2014; Robinson et al., 2019).

4.4. Limitations and future directions

Using network analysis with panel methods is still in its infancy. To the best of our knowledge, no stability measures have been developed yet to examine centrality stability. As this analytic approach continues to develop, future researchers will need to replicate findings. Still, we employed the best current practices for network analysis using panel methods (Epskamp, 2020). Moreover, the analytical methods used in the current study assume (local) stationarity (Epskamp, 2020; Epskamp et al., 2018; Epskamp, Waldorp, Mõttus, & Borsboom, 2018), an assumption which may be problematic, especially when measuring the same variable across longer periods of time (Rovine & Walls, 2006); however, considering that we examined the correlational structure of variables across a relatively short time period (11 weeks), the stationarity assumption is feasible. Other estimation methods exist when stationarity cannot be assumed (see Jordan, Winer, & Salem, 2020, for an overview).

In the networks that were examined, we included more variables measuring costs than positively-valenced variables. As strength centrality is the sum of the absolute values of all directly connected edges, it represents the direct influence a node has on other edges (Barrat, Barthélemy, Pastor-Satorras, & Vespignani, 2004; Freeman, 1978; Opsahl, Agneessens, & Skvoretz, 2010). Thus, given the strong clusters of positively- and negatively-valenced variables, having one more item measuring cost likely influenced strength centrality. Future research could counteract this imbalance by including a balanced number of task values and costs, for instance by including utility value and attainment value, along with interest value and competence beliefs. Moreover, while we only included one item per measure due to constraints imposed by the longitudinal nature of this study (e.g., survey fatigue; Martin et al., 2015), future research should replicate our findings using more items per measure. It should be noted though, that from a network perspective, inclusion of items should be theory-driven in contrast to the empirically driven approach needed in latent variable models (see Borsboom, Mellenbergh, & van Heerden, 2003; Dalege et al., 2016). Although we focused on how task values and competence beliefs relate with one another across individuals, within situations, and across time points, the analytical methods applied in this study could be used to answer other research questions in the context of SEVT as well. Eccles and Wigfield (2020) discuss the close relation between different motivational variables (e.g., interest and intrinsic motivation; competence beliefs and self-concept). The network approach can be used to map the relation between highly related motivation (and achievement) constructs to empirically test what differentiates constructs. This has been done for interest and curiosity (Tang et al., 2020) and has been discussed by Vu et al. (2021). Moreover, other variables such as task engagement and performance could be included in the networks. This would allow for the studying of pathways from motivation to achievement and even reciprocal effects of motivational variables and achievement.

It is also likely that situational characteristics and students' background characteristics affect their expectancy and task value beliefs. For example, a student's prior achievement in math or the performance feedback they receive from a test may influence motivational beliefs week-to-week or day-to-day. Future research is needed to explore the role of situational characteristics and students' background characteristics in shaping their situated expectancies and task values.

Finally, we focused on a particular introductory calculus course. More research is needed to examine whether these networks are generalizable both across settings (i.e., university and K-12), as well as across domains (i.e., course subjects). For example, contextual differences across college and K-12 courses may play a role in relations between SEVT components, with high school students typically not following a semester schedule that is often used in college settings. Further, students' SEVT beliefs in a college English course may differ from a calculus course, mirroring differences of longitudinal relations between SEVT components and achievement (Clem et al., 2021) as well as different SEVT components across high school subjects (Arens, Schmidt, & Preckel, 2019). Thus, a next step for future research would be to examine whether the identified networks and associations of students' expectancies, values, and costs across short time periods (i.e., one semester) can be replicated in similar math-intensive contexts in college settings, where motivational declines are particularly likely and consequential (e.g., Benden & Lauermann, 2022).

4.5. Conclusion

As proposed in Eccles and colleagues' SEVT, we examined students' situation-specific competence beliefs, values, and costs as a complex and dynamic system of motivational beliefs. Using a novel psychometric network approach, we examined the associations of students' competence beliefs and task values between-persons, within-situations, and temporally. Our results suggest that SEVT constructs may function differently across these three levels, having theoretical as well as practical implications. For example, students' competence beliefs and values were relatively independent from their perceived costs within a given situation, suggesting that motivational interventions are needed to target both positively and negatively-valenced task values. Though more research is needed to replicate results across contexts, we believe that network analysis provides a fruitful avenue to identify potential intervention targets and to shed light on the dynamic relations of SEVT constructs over short periods of time.

Declaration of competing interest

None.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.lindif.2022.102233.

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