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A B S T R A C T

Existing theoretical frameworks on motivation have identified a number of critical components in our motivational engagement process in learning. However, little empirical research has examined how these different components interact with each other to support our overall motivational engagement. This study explores such dynamics in a bottom-up manner by examining the within-person contemporaneous network structure of key components in the motivational engagement process (i.e., reasons/values, expectancy belief, goals, social relations, affective experiences, and perceived autonomy). We tracked four participants working on psychological research projects over the course of a year on a daily basis, and found that their motivational engagement mainly consisted of a large network of nodes that support autonomous forms of self-regulation. Scrutiny of the network also suggests the critical roles of curiosity and intrinsic reason in bridging affective and core motivational aspects of engagement.

1. Introduction

In classrooms, students are engaged in learning activities driven by various types of motivation. In some cases, students study because learning is intrinsically rewarding whereas in others they do so out of a sense of obligation. Students' motivational engagement is also supported by a feeling of competence and the social support they experience while learning. To explain a variety of motivation-relevant phenomena in learning, since the 1970s, researchers in achievement motivation have proposed a number of contemporary theories of motivation, conducted a vast amount of empirical work, and greatly advanced our understanding of different aspects of motivational engagement. However, while each of the contemporary theories of achievement motivation has gained much empirical support in the literature, there has been surprisingly little empirical research that examines how various motivational components derived from different theoretical perspectives are related. This paper reports our preliminary and exploratory attempt to draw a picture of these relationships with a relatively novel bottom-up method—the application of a psychological network approach to year-long intensive longitudinal data from four participants.

1.1. Key motivational components in the learning process

We conceptualize motivational engagement as a mental category that people subjectively construe from a broad range of underlying components such as values, goals, and affective experiences (e.g., enjoyment and anxiety). In other words, we do not see motivational engagement as a unitary construct that can be precisely defined and assessed but as emerging properties resulting from the interaction of

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these components. This perspective is consistent with Murayama and Elliot's (2012) psychological construction view of motivation (see also Dalege et al., 2016; Russell, 2003 for similar views on other constructs). Theories on motivation have identified a number of different and distinct components that underlie the motivational engagement process. Here we summarize several of these key components.

1.1.1. Reasons and values

Some theories of motivation indicate that students are motivated to study based on various reasons and values that determine the quality of their motivated behavior. One of the prominent distinctions made in the literature is motivational engagement for intrinsic reasons (often called "intrinsic motivation") and extrinsic reasons (often called "extrinsic motivation") proposed in the self-determination theory (Deci & Ryan, 1985). An intrinsic reason reflects the situation where students are engaged in a task because of the pleasant experiences coming from the engagement itself. In contrast, an extrinsic reason centers on engagement driven by either tangible rewards (e.g., money) or a fear of social punishment (e.g., punishment by teachers).

While the distinction between intrinsic and extrinsic reasons is intuitive and easy to understand, not all types of people's engagement can be captured by this dichotomy (see also Dyer & Parker, 1975). To cover more diverse types of reasons for motivational engagement, the self-determination theory further proposes that other reasons that are positioned between intrinsic and extrinsic reasons (Ryan & Deci, 2000, 2017). An introjected reason (or introjection) refers to the state when people are motivated by contingent self-esteem (e.g., "I study because it makes me feel proud of myself"). This state of motivation is not purely extrinsic because people internalize the value of the task to some extent, but it is quite different from intrinsic reasons since the focus is on self-esteem, not enjoyment of the task itself. An identified reason (or identification) refers to the state when we are motivated because we acknowledge the value of the task for our personal growth and future. This state of motivation is similar to intrinsic reasoning but the source of motivation comes from recognizing instrumental value rather than intrinsic enjoyment of the task itself (Ryan & Deci, 2000). The state in which it is difficult for people to find a reason to engage in learning is referred to as "amotivation" (Vallerand & Bissonnette, 1992). Empirical studies have demonstrated the separability and different predictive utility of these different reasons for motivational engagement (Howard et al., 2017; Ryan & Connell, 1989).

The importance of reasons or values for learning has also been emphasized in other theories. For example, the four-phase model of interest development (Hidi & Renninger, 2006) distinguishes the task engagement when students are temporarily motivated in response to environmental triggers (situational interest) and when students internalize the task value and engage in learning without needing explicit external support (individual interest). Learners also estimate the "negative" value of the task to decide whether to engage in it. One critical factor that represents learners' negative value is the *perceived cost* of learning (Wigfield & Eccles, 2000). Cost is the subjective perception of the demand the task imposes on students. Previous studies showed that cost perception is one of the bottleneck factors that hinder learner motivation (Jiang et al., 2018).

1.1.2. Goals

Students learn with various types of goals in mind, but one category that has attracted considerable attention in the literature is achievement goals (Murayama & Elliot, 2019). Traditionally, research focused on the two distinct types of achievement goals, namely mastery goals and performance goals (Ames, 1992; Dweck, 1986). More recent studies have added an approach-avoidance dimension to the dichotomy, forming a 2×2 taxonomy of achievement goals (Elliot & McGregor, 2001; Elliot & Murayama, 2008), which includes mastery-approach goals (goals to achieve task mastery), mastery-avoidance goals (goals to avoid failing to master a task), performance-approach goals (goals to do better than other people), and performance-avoidance goals (goals to avoid being worse than other people). Previous studies have shown that these different types of achievement goals have different predictive utility of learning outcomes (Elliot & McGregor, 2001; Elliot & Moller, 2003; Hulleman, Schrager, et al., 2010).

1.1.3. Expectancy belief

One of the critical drivers for student engagement in learning is expectancy belief—their subjective perception about their ability to competently perform the learning activity. We define expectancy belief broadly, including both action-outcome contingency and efficacy belief (Skinner, 1996). For example, even if a student has good reasons to study mathematics, the student may not be willing to engage in the subject if they do not feel competent to understand the subject content. The importance of expectancy belief has been repeatedly underscored by a number of theories of achievement motivation (Skinner, 1996), such as locus of control (Rotter, 1966), self-efficacy (Bandura, 1977), academic self-concept (Arens et al., 2017; Marsh & Craven, 2006), self-determination theory (Ryan & Deci, 2000), and expectancy-value theory (Wigfield & Eccles, 2000). In fact, research has found that expectancy belief is one of the most reliable predictors of academic achievement (e.g., Arens et al., 2017).

1.1.4. Social relations

Recent studies have also shown that students' motivation is supported by social relations and interactions (Burgess et al., 2018; Wentzel, 1998). Thus, the perception that students are recognized and accepted by others predicts academic attainment (Wentzel & Caldwell, 1997). Juvonen et al. (2000) also showed that schoolchildren's perceived loneliness (i.e., the perception that they do not have good social relations) was associated with negative outcomes (i.e., their depressive symptomatology).

1.1.5. Affective experiences

Affective experiences during class have been shown to be proximal predictors of many achievement relevant outcomes (Pekrun et al., 2017). While traditional research on achievement emotions tended to focus on negative and stress-related affective experiences such as anxiety (Zeidner, 1998), more recent studies have paid attention to discrete types of both positive (e.g., enjoyment, pride) and negative emotions (e.g., anxiety, boredom) that occur when one anticipates and engages in a task and receives task feedback (Pekrun, 2006). In addition to these achievement related emotions, recent studies have also highlighted the critical role played by epistemic emotions, such as feelings of curiosity (e.g., Vogl et al., 2020), as well as more general affective states such as depression and well-being (e.g., Kaplan & Maehr, 1999; Weidman et al., 2015), in prompting motivated behavior and task achievement.

1.1.6. Perceived autonomy

One critical motivational factor that does not fall within any of the aforementioned categories is perceived autonomy. People perceive that their need for autonomy is satisfied when they have a feeling that they are making their own decision and acting according to their own values (Ryan & Deci, 2017). This concept is an integral part of the self-determination theory and has been shown to predict a number of adaptive outcomes in a learning context (e.g., Jang et al., 2012).

1.2. Psychological network approach to understand motivational engagement

As can be seen in the previous section, there are a multitude of components that constitute the motivational engagement process, which raises the question: how are they interrelated to each other? Unfortunately, most of the previous literature has focused at most on a subset of these components in individual empirical investigations and fails to provide a broader picture of the motivational engagement process. One primary reason could be that most of the motivation theories have their own specific foci (e.g., expectancy belief), and such theoretical perspectives constrain the scope of variables researchers select for data collection and analysis. While this is a necessary and important step to validate a theory, it implicitly dismisses some other important underlying motivational components occurring in a learning process.

Another practical, perhaps more critical, reason is that until recently there have been few statistical frameworks that can simultaneously handle such a large number of motivation components. In fact, regression analysis and its extension (e.g., structural equation modelling, multilevel modelling) do not work well with many variables due to the potential multicollinearity and singular fit issues. Factor analysis is useful to handle a number of variables, but its main purpose is to "classify" a number of variables by assuming general latent variables that explain observed variables; it is not concerned with whether and how individual components in motivation can be directly related to each other. For example, Marsh et al. (2003) conducted a second-order factor analysis on eight factors of motivational orientations (e.g., intrinsic motivation) and found that there are "big-two" higher-order factors that can explain eight motivational factors: learning and performance, which closely related to mastery goals and performance goals in achievement goals. Similarly, Heggestad and Kanfer (2000) conducted a factor analysis on the Motivation Trait Questionnaire, which aims to provide a comprehensive set of items that assess trait-level motivation, and found that three factors (personal mastery, anxiety, and competitive excellence) sufficiently explain the data. These results provide a parsimonious picture on how various components in a motivational engagement process share common variances. However, standard factor analysis assumes no causal relationship between the observed variables after accounting for the common factors. This poses a conceptual challenge when qualitatively different components are subjected to analysis. For example, when goals and positive affects form a single factor, this implicitly means that goals do not causally influence positive affects because the relationship between them is regarded as a pseudo-correlation produced by a common factor.

Psychological network approach (Borsboom & Cramer, 2013) has been put forward as an alternative to the traditional factor analytic model in psychology. The approach is based on network science (Barabasi, 2002) in physics and applied mathematics and has been applied to various subfields in psychology such as psychiatry (e.g., Robinaugh et al., 2019), health psychology (e.g., Hevey, 2018), and personality psychology (e.g., Clifton & Webster, 2017). Unlike the factor analytic approach, the psychological network approach does not posit latent factors causing observed variables. In contrast, it analyzes the potential dynamic causal relationship of the variables in the system as a whole by describing how the qualitatively different psychological components or phenotypes (referred to as "nodes") are directly related to each other. The relationship between the nodes (referred to as "edges") are typically represented by partial correlations (or some other related metric). To have an intuitive grasp of the approach, readers may want to see Fig. 2 of the current article (our main findings) in advance, which presents the components of the engagement (e.g., "expectancy") as nodes and their relationships as edges (we provide a detailed explanation in the Method section on how edges' strengths are statistically estimated). In this way, we can simultaneously analyze and grasp the relationships of a large number of motivational components. In addition, the approach fits well with the theoretical idea we put forward earlier. Specifically, motivational engagement is an emerging property that we construe from the dynamic causal interaction of motivational components (Murayama, 2022; see also; Sachisthal et al., 2019).

As the edges are essentially represented in correlations, this partial correlation approach does not immediately reveal the causal structure of the variables. However, the approach provides an effective exploratory method to generate a hypothesis regarding the potential causal structure between the variables (i.e., the method can recover the true causal structure when underlying causal assumptions are met; see Epskamp & Fried, 2018).

1.3. Within-person data as a useful tool derive network structure

Only a limited number of studies have applied the psychological network approach to education data in general, let alone to data on motivational engagement. Sachisthal et al. (2019) conducted a network analysis using variables that reflect science interest using 2015 data from Programme for International Student Assessment (PISA; interest appraisal, enjoyment, value, achievement scores, self-efficacy, and engagement behavior with science) and found that enjoyment was central within the network structure. Govorova et al. (2020) also used PISA data from 2018 assessments and examined students' well-being networks, which included variables related to cognitive, psychological, and social well-being as well as teaching style. Abacioglu et al. (2019) compared the networks of students' motivation, ethnic identity, and teachers' cultural education for minority and majority groups in classrooms. Critically, however, all of these studies analyzed cross-sectional data. This means that the network edges derived from these analyses may suffer from a number of potential confounders.

Using within-person data is useful to examine the network structure that suffers from less confounding variables (Rohrer & Murayama, 2021). In a typical cross-sectional data analysis, researchers normally examine the relationship between the variables focusing on individual differences. This type of analysis is often called between-person analysis. On the contrary, within-person data reflects multiple assessments of participants. This type of data allows researchers to examine variable associations within persons (Molenaar, 2004; Schmiz & Skinner, 1993). This "within-person analysis" makes it possible to control for a large amount of potential confounders at the individual level (i.e., time-invariant confounders; Usami, Murayama, & Hamaker, 2019). When there are time-invariant confounders in the focal relations, within-person analysis can provide a more precise estimate for causal effects that could differ considerably from what would have been obtained with between-person analysis (Hoffman & Stawski, 2009; Molenaar & Campbell, 2009; Murayama et al., 2017). Accordingly, although within-person analysis still suffers from potential time-variant confounders, it provides a better basis for causal inference in psychological processes (Rohrer & Murayama, 2021). Thus, psychological network analysis of motivational engagement, which is ultimately interested in causal dynamics of the variables, benefits more from within-person data.

Despite the advantage of within-person data in this regard and its increased use in educational psychology (e.g., Tanaka & Murayama, 2013; Patall et al., 2018), few studies have adopted the within-person approach to conduct network analysis in the context of motivational engagement. In fact, to our knowledge, Moeller (2018) (Study 2) and Tang et al. (2022; Studies 2 and 3) are the only two instances. However, these studies focused specifically on emotions in educational settings; thus, the resultant networks consisted only of affective experiences.

1.4. The current study

This study aims to present the first preliminary exploration of the interrelationship between different components that represent the constituent part of a motivational engagement process. We find network analysis to be most suitable for this purpose and thus used this methodology to derive a broad network structure of motivational engagement (i.e., reasons/values, expectancy belief, goals, social relations, affective experiences, and perceived autonomy). The component variables in motivational engagement in the current study were discussed above and are summarized in Table 1. Note that while our list of components is relatively long (hence, psychological network analysis is well suited), it is not meant to be comprehensive. The selection of the components is partially guided by a recent framework on interest-based engagement (Murayama, 2022). In that respect, they are selective sets of components, although we also tried to include components that are

Table 1
Variables of motivational engagement included in the current study.

Categories	Variables	Item example
Reasons/Values	Amotivation	"I do little because I don't think this work is worth putting efforts into."
	Extrinsic social reason	"To get others' approval (e.g., supervisor, colleagues, family, clients, etc.)."
	Extrinsic material reason	"Because this is my obligation in return for my salary."
	Introjected reason	"Because it makes me feel proud of myself."
	Identified reason	"Because putting efforts in this job aligns with my personal values."
	Intrinsic reason	"Because I have fun doing my job."
	Interest-catch	"I think the project is interesting."
	Interest-hold	"I think what I am learning in this project is important."
Cost values	Cognitive (mental) cost	"How much did you feel that today's work was mentally demanding?"
	Physical cost	"How much did you feel that today's work was physically demanding?"
Expectancy belief	Expectancy	"I feel competent about my current job."
Goals	Mastery-approach	"My goal is to learn as much as possible from the project."
	Mastery-avoidance	"My goal is to avoid learning less than it is possible to learn in the project."
	Performance-approach	"My goal is to perform better than other researchers in the project."
	Performance-avoidance	"My goal is to avoid performing poorly compared to other researchers in the project."
Need satisfaction	Autonomy	"I feel free to do my job the way I think it could best be done."
	Competence	"I am good at the things I do in my job."
	Relatedness	"At work, I feel part of a group."
Discrete affective experiences	Happiness	"How did you generally feel today?–Happiness."
	Pride	"How did you generally feel today?–Pride."
	Sadness	"How did you generally feel today?–Sadness."
	Anxiety	"How did you generally feel today?–Anxiety."
	Frustration	"How did you generally feel today?–Frustration."
	Boredom	"How did you generally feel today?–Boredom."
	Calmness	"How did you generally feel today?–Calmness."
	Curiosity	"How did you generally feel today?–Curiosity."
Global affective experiences	General affective valence	"Generally speaking, how did you feel today."
	Perceived stress level	"Please rate your stress level today."
	Depression	"Please rate your level of depression today."
	Subjective well-being	"How do you feel about your life as a whole?"
Social Relations	Loneliness	"Do you feel that you lack companionship today?"

not directly discussed in the framework (e.g., social relations) to increase the coverage. Admittedly, there are other important theoretical components, such as goal content (Kasser & Ryan, 1993), mindset (Dweck, 1999), goal hierarchy (Kruglanski et al., 2018), emotion regulation (Schlesier et al., 2019), etc., and our list of components could also be more fine-grained (e.g., we can consider different aspects of social relations assessed, different types of expectancy belief, etc.). Nevertheless, we believe that the current initial attempt can serve as a useful stepping stone for future exploration of the more comprehensive network structure of students' engagement in learning.

Importantly, to examine the network structure in a bottom-up manner at a within-person level, we adopted rather a non-standard approach—we tracked four participants engaged in psychological research projects daily for a period of one year. This "large T and small N" data (as opposed to "small T and large N" data, which is common in research on education) provide us with rich information about the within-person network structure of the assessed components. In addition, although not common in the literature, working on psychological research projects entails various forms of learning (e.g., learning new analysis skills, acquiring domain specific knowledge in the literature); thus, the data have great potential to shed light on our understanding of learning and motivational processes in general. With this unique design and research context, in addition to a large set of components we assessed (we included a total of 31 components), we hope to derive an exploratory (i.e., non hypothesis-driven) but relatively broad picture of the network structure of motivational engagement, which may help researchers build an integrative motivation theory in future work.

2. Method

2.1. Participants

Four post-graduate level researchers in two different universities (male = 2, female = 2, ages 27, 28, 31, and 37 at the start of the data collection) participated in the study (There were no dropouts.). This was a convenient sample—given the long duration of the study, we recruited participants from among our acquaintances who were deemed unlikely to drop out. All of the participants started working on separate academic projects in psychology as a new learning experience at the beginning of the assessment. These participants are among the authors of this article but were not involved in the analysis of the data. The first author conducted all analyses independently on anonymized data. We have not published any other papers using this dataset.

2.2. Measures

We assessed a total of 31 components of participants' motivational engagement on a daily basis. As is common with experience-sampling methodology (Hektner et al., 2007), components of motivational engagement were assessed with a shorter form. More specifically, many of the components were assessed with a two-item scale; for some cases where the concepts are relatively simple (e.g., affective experience of enjoyment) or narrowly defined (e.g., achievement goals, as defined by Elliot & Murayama, 2008), we used a single-item scale. We decided to use shortened scales because (1) it is not practical to implement original scales that consist of a number of items given the extensive repeated assessments in the current study and (2) using shortened scales is still informative, although not ideal, in light of our goal of generating hypotheses (rather than testing a specific theory about a specific construct). Longer scales may also not be ideal to assess the "state" of motivation as the process of answering a set of questions is likely to induce trait-like response bias and pre-existing beliefs (see also Drolet & Morrison, 2001). The reliability and validity of single-item or short measures in motivation has been examined and supported by previous research (Gogol et al., 2014; Wanous et al., 1997), and produced sensible results in empirical applications (e.g., Goetz et al., 2016; Martin et al., 2015). For two-item measures, as recommended by Eisinga et al. (2013), we report reliability estimates based on the within-person correlation between the items across time points corrected by a Spearman-Brown formula. Unless otherwise noted, all of the items were assessed on a 10-point scale where 1 = "Not at all true" and 10 = "Extremely true."

2.2.1. Reasons/values

We used the Multidimensional Work Motivation Scale (Gagné et al., 2015) to assess different reasons (from extrinsic to intrinsic) to work on the project. The original scale has three items for each subscale (except for introjection, which has four items) but we selected two items based on the representativeness of the item contents. The scale assessed amotivation, extrinsic social reason, extrinsic materialistic reason, introjected reason, identified reason, and intrinsic reason. We also assessed “catch” and “hold” types of interest (Harackiewicz et al., 2004), which may map well onto the distinction between situational and individual interest (Hidi & Renninger, 2006). We selected two items each from the original scale (Harackiewicz et al., 2008): interest-catch and interest-hold. In terms of subjective cost value for the work, we distinguished two types of costs according to the recent literature (Kool et al., 2010): cognitive (mental) and physical cost. All of these were likewise measured on a 10-point Likert scale where 1 = “Not at all” and 10 = “Extremely.”

2.2.2. Goals

We assessed participants’ four types of achievement goals using a single item measure selected items from Achievement Goal Questionnaire–Revised (AGQ-R) (Elliot & Murayama, 2008). The measurements include four types of goals: mastery-approach, mastery-avoidance, performance-approach, and performance-avoidance. The items were assessed on a 10-point Likert scale where 1 = “Strongly disagree” and 10 = “Strongly agree.” AGQ-R assesses achievement goals with a homogeneous set of items (Murayama et al., 2011); thus, we decided to use single-item measurements.

2.2.3. Expectancy belief

The scale used to measure expectancy belief was adopted from the existing two-item measure of expectancy perception (Law et al., 2012) to assess participants’ perceived confidence in their capacity to perform the project work. This aspect of motivational engagement was also assessed by a need for competence subscale from a need satisfaction scale (see below).

2.2.4. Social relations

Participants’ subjective feelings of belongingness was assessed by a two-item measure, taken from a three-item loneliness scale (Hughes et al., 2004). The items were assessed on a 5-point scale where 1 = “Not at all true” and 5 = “Very true.” This aspect of motivational engagement was also covered by a need for relatedness subscale derived from a need satisfaction scale (Van den Broeck et al., 2010; see below).

2.2.5. Discrete affective experiences

Discrete affective experiences were assessed using a set of single-item measures typically used in emotion research in the context of education (Goetz et al., 2016; Moeller et al., 2018). The types of emotion include happiness, pride, sadness, anxiety, frustration, boredom, calmness, and curiosity.

2.2.6. Global affective experiences

Global affective experiences were assessed using several single-item measures. These included *subjective well-being* (Andrews & Withey, 1976), measured on an 11-point scale where 1 = “Terrible,” 6 = “Mixed, ” and 11 = “Delighted”); *depression* (Barlow & Cerny, 1988), measured on a 9-point scale where 0 = “None” and 8 = “As much as you can imagine”); *general emotional valence*, measured on an 11-point scale where 1 = “Very negative,” 6 = “Neutral,” and 11 = “Very positive”; and *perceived stress level*, measured on a 9-point scale where 0 = “None” and 8 = “As much as you can imagine.”

2.2.7. Perceived autonomy

Participants’ perceived autonomy was assessed by a work-related basic need satisfaction scale (Van den Broeck et al., 2010). We selected one positively worded item (need satisfaction) and one negatively worded item (need frustration; reverse coded) for our assessment of the need satisfaction for autonomy. For completeness, we also included two items assessing need satisfaction for 1) competence and 2) relatedness. Although these measurements focus on the satisfaction of needs, they complement the scales we included to assess expectancy belief and social relations.

2.3. Procedure

Participants were asked to respond to all measurements every evening using an iDialog pad installed on an iPod touch (Kubiak & Krog, 2012). Data collection commenced in April 2017 and lasted until the end of March 2018. Participants were encouraged to respond to the daily questionnaire as frequently as possible. However, they did not respond to the questionnaire for every working day for various reasons (e.g., they were busy, simply forgot, etc.). Participants were assured that their responses were confidential and would be analyzed by an independent researcher. Participants also responded to other health-related questions (e.g., physical activities, general health), which were not analyzed for the current research. After cleaning the data that eliminated unusable responses (e.g., technical errors), the resultant data include 595 data points in total (mean response = 149 data points), of which 468 data points were collected on consecutive days, which we then subjected to the autoregressive analysis.

2.4. Analysis

There are various analytic options to conduct psychological network analysis with longitudinal data. In light of the study purpose and design, we took the following steps. For interested readers, there are excellent accessible tutorials on psychological network analysis written by Costantini et al. (2019) and Epskamp and Fried (2018).

1. First, we selected an analytic model (a graphic vector autoregressive model (GVAR)) and analyzed the data with lag = 1. The model is based on a fixed-effects model, which assumes that there are basically no individual differences in the true parameter values (i.e., observed differences only reflect sampling errors). This is a rather strong assumption; indeed, there are other estimation methods and models that allow us to model individual differences such as multi-level modelling (e.g., Epskamp et al., 2018) and group iterative multiple model estimation (e.g., Bouwmans et al., 2018). However, these estimation methods and models tend to be unstable unless the number of variables is relatively small and the number of time points is large. A recent simulation study suggested that we should reduce the number of variables down to approximately six when the number of time points for a single participant is between 75 and 100 (Mansueto et al., 2022). Considering this issue, we decided to use a fixed-effects model. This allows us to analyze the data as if the data were collected from nearly 595 time points in a single participant, thus ensuring sufficient statistical power. To test whether there is no strong violation of the homogeneity assumption, we also computed the correlations between the final network and individual networks (i.e., networks obtained from each participant).

The model takes a standard multivariate vector autoregression in which variables assessed on day t were jointly predicted by those assessed on day $t-1$ (Epskamp et al., 2018). More specifically,

$$\boldsymbol{y}_t = \boldsymbol{B}\boldsymbol{y}_{t-1} + \boldsymbol{\varepsilon}_t$$

$$\boldsymbol{\varepsilon}_t \sim N(0,\ \boldsymbol{\Theta})$$

where $\mathbf{y}_t$ denotes the vector of variables on day t and the matrix $\mathbf{B}$ encodes temporal predictive effects that represent a type of carry-over effect from day t - 1 to t (e.g., can expectancy belief predict the next day’s enjoyment after controlling for all of the baseline measures?).

Simply put, this is a lag-1 cross-lagged panel model (commonly used in education research) with many variables and time-invariant effects over time. Using the terminologies of the cross-lagged panel model, $\mathbf{B}$ includes autoregressive effects in the diagonal (e.g., effects of expectancy on day $t-1$ on expectancy on day t) and cross-lagged effects in the non-diagonal (e.g., effects of happiness on day t – 1 on the mastery-approach goal on day t). In our data, such carry-over effects across days are generally weak and we identified only a limited number of effects, most of which were a simple autoregressive effect of the same variable. This was not surprising when considering the design of the study. We assessed participants' motivational engagement once a day (unlike some other studies where participants were assessed a few times a day during a certain activity) and participants worked on various tasks (of projects) every day. At times participants continued to work on the same task for two days in a row while at others they worked on a completely different task the next day. In such a situation, it is natural to suppose that major causal dynamics of the elements of motivational engagement should occur within the same day. For example, the intrinsic reason present on a particular day' are likely to affect the affective states on the same day. On the other hand, it is possible, but less likely that the effect of the intrinsic reason on positive affective states manifests only after a delay of one day. As such, we do not discuss the temporal predictive effects in the current manuscript (for completeness, the results of the temporal predictive effects are reported in Fig. S1).

$\boldsymbol{\epsilon}_t$ represents the residuals on day t that cannot be explained by the effects from any of the assessments on day $t-1$. Thus, the variance-covariance matrix of the residuals $\boldsymbol{\Theta}$ reflect the relationship of the variables within the same day after controlling for temporal predictive effects. Using the terminology of the cross-lagged panel model, it is basically the matrix of correlated residuals. In the current research, this variance-covariance matrix was used to construct a so-called *contemporaneous network* (Epskamp et al., 2018), which reflects the within-person relationship of the variables (based on partial correlation) on the same day.

Of course, this contemporaneous network analysis based on observational data does not immediately tell the causal effects (in fact, the method does not specify the direction of the effects). However, it does control for several important sources of confounders (see also Imai & Kim, 2019). First, by analyzing the within-person data, the analysis effectively controls for time-invariant confounders that have constant effects over time (Rohrer & Murayama, 2021). In other words, demographic variables and some fixed traits (cognitive abilities, personality/motivational traits) are unlikely to bias causal estimates even if they are not directly measured and controlled for. Second, because carry-over effects are already modelled, potential confounding effects caused by the effects from the previous time points (e.g., positive emotion at $t-1$ is a common cause of the relationship of variables at t) are also controlled.

At the same time, however, parameter estimates are biased (in terms of causal effects) when there are unmeasured time-varying confounding variables (i.e., the variables that (a) were not measured, (b) change over time, and (c) have effects of the measured variables over time). In addition, while the use of partial correlation allows us to control for the confounding of other variables assessed at the same time point (e.g., expectancy belief at t is the common cause of perceived autonomy and interest at t), this can produce a collider bias, that is, when a variable is the common consequence of other variables assessed at the same time (Pearl et al., 2016). In the following descriptions of the results, we did not avoid using causal language, but we should keep in mind that this statement is reasonable only when these assumptions were met.

2. Because the analytic model we adopted assumes stationarity in the time series data, we decided to remove potential systematic effects from the data before applying the GVAR model. More specifically, to remove potential long-term or periodic systematic change of the variables from the raw data, we conducted a simple regression analysis for each variable for each participant predicting the motivation variable from days that have lapsed from the start of the project and six dummy variables representing the days of the week (i.e., Monday, Tuesday, Wednesday, …). The residuals from the regression analysis are now free from linear trend and days-of-the week effects. The residuals were standardized (thus centered) for each participant and then concatenated. In the following main analysis, the concatenated data (total time points = 468) were analyzed as if the data were from a single participant (this is a common way to apply a fixed-effects model).

3. The concatenated data were entered into the GVAR model to estimate parameter values. In the first step, the model estimates the variance-covariance matrix $\boldsymbol{\Theta}$ as well as $\mathbf{B}$. As we decided to focus on the contemporaneous network, we focus on $\boldsymbol{\Theta}$. Although the estimated $\boldsymbol{\Theta}$ provides a basis to construct contemporaneous network structure (which is generally based on a partial correlation matrix of the variables constructed from $\boldsymbol{\Theta}$), one problem is that there are numerous relationships between the variables in the matrix, thus making it likely that the network includes a number of spurious relationships of the variables due to sampling variation. To obtain a more parsimonious and reliable network structure, it is generally recommended to apply a regularization procedure to obtain a sparser network matrix (but see Williams et al., 2019). In the current analysis, we used the LASSO regularization method (see McNeish, 2015 for an accessible introduction) to address the large number of variables included in the model. This regularization method allows us to suppress small regression coefficients, thus reducing the model complexity and increasing the generalizability of the resultant network (James et al., 2013).

The method requires researchers to set a tuning parameter lambda. This parameter determines the extent to which small regression coefficients are suppressed. Specifically, a smaller lambda value means that the model prefers a complicated picture of the network (when lambda is zero, the original partial correlation network is used), and a larger lambda means that the model prefers a network with smaller number of edges. To find the best lambda that balances both model parsimony and informativeness, we optimized the tuning parameter using a brute force parameter search by comparing models based on an extended Bayesian information criterion (EBIC) (Chen & Chen, 2008). Specifically, we applied the same model to the data repeatedly by slightly changing the tunning parameter lambda and picked up the tunning parameter that returned the best EBIC value. EBIC requires us to set a hyperparameter, γ. This was set to 0.5 (default option of *graphicalVAR* package).

The output of this step determines the network structure that we report in the Results section (i.e., Fig. 2). The nodes represent measured variables, and edges represent the strengths of the partial correlation after regularization. The different colors of the network represent communities, which will be explained in 5.

4. To interpret the results, we first visually inspected the obtained network graph. Then we computed several indices of network centrality for each node to evaluate the potential influence of the individual elements within the network of motivational engagement. When centrality is high, we can infer that the node is likely to play an important role in the engagement process.

Strength centrality is simply the sum of all the associations (i.e., edge weights) that a node has and reflects the extent to which the node is connected with other nodes. The index is simple and intuitive to evaluate the potential influence of the node. *Betweenness centrality* represents the importance of the node in terms of connecting any other two nodes in the network. Simply put, betweenness centrality of node X represents the proportion that the shortest path connecting an arbitrary pair of nodes goes through node X. In other words, nodes with high betweenness centrality are like railway stations through which many trains travel to get from their initial location to their final destination (McWilliams & Fried, 2019). Nodes that bridge different clusters of nodes tend to have high betweenness centrality. Note that the current study computed the index using edge weights (rather than binary edges) to make full use of the information in the network. This index nicely complements the strength centrality in that the metric can detect influential nodes that may not have many associations with other nodes but still bridge different groups of nodes.

One limitation of these centrality indices is that they cannot deal with negative edge weights. In the partial correlation network that we used, edge weights can take negative values (i.e., negative partial regression coefficients). We computed these two indices based on the absolute value of the edge weights, as is commonly done in previous research (e.g., Sachisthal et al., 2019). Although there are some new centrality indices that sum up signed edges weights (e.g., expected influence; D. J. Robinaugh et al., 2016), these indices are not particularly useful in this particular study because the network includes both "adaptive" (e.g., expectancy belief) and "maladaptive" (e.g., loneliness) components in the motivational engagement process. In such a network, positive edges for nodes of adaptive components and negative edges for nodes of maladaptive components are equally important. For example, if a motivational component is positively related to enjoyment and negatively related to sadness, the component is certainly important to sustain the overall motivational engagement process. If we use a signed index, however, positive weights and negative weights cancel each other out, thus failing to reflect the importance of that component in the network. As such, the current study focused only on strength and betweenness centrality (after reversing the negative edge weights) to evaluate nodes' influence.

5. To further facilitate the interpretation of the findings, we also conducted a community detection analysis of the obtained network structure. Community detection analysis allows us to find clusters of the network: Nodes included in a community have dense connections among them but sparse connections with the nodes in other communities. We used the Walktrap algorithm (Pons & Latapy, 2005) to detect communities in the network. The method has been suggested to have a tendency to correctly recover the true community structure (Yang et al., 2016). As discussed above, the sign of the edge weight is arbitrary in our case; thus, we applied the analysis to the absolute edge weights. Following the suggestion of Golino and Epskamp (2017), we also examined the robustness of the results by using a different algorithm, i.e., the Spinglass algorithm (Reichardt & Bornholdt, 2006). Because it provides different results every time when we run it, we ran the algorithm 300 times, identifying the community that the each node belongs to with the highest frequency. The results are reported in Fig. S3 in the Supplementary Online Materials.

All analyses were conducted with R version 3.6.1 (2019-07-05). The graphical vector autoregressive model was performed using the package *bootnet* (https://cran.r-project.org/web/packages/bootnet/index.html), which provides a wrapper function that utilizes the package *graphicalVAR* for modeling time-series data (https://cran.r-project.org/web/packages/graphicalVAR/index.html). Plotting network and calculating centrality indices were conducted using the package *qgraph* (https://cran.r-project.org/web/packages/qgraph/index.html) and community detection analysis was conducted using the package *igraph* (https://cran.r-project.org/web/packages/igraph/index.html). The analysis code and RMarkdown output were uploaded to https://osf.io/svm7p/?view_only=f4fdaa35ce24408db336f092c3066aa3.

3. Results

Means and within-person standard deviations (before mean-centering the data) are reported in Table 2. No variables showed a sign of insufficient within-person variability. We also examined whether there were any redundant sets of variables that are likely to assess the same construct using the goldbricker function in the package *networktools* (https://cran.r-project.org/web/packages/networktools/index.html). This function investigates every possible pair of variables in the data and tests whether the pair is redundant (akin to the issue of multicollinearity) by testing how the pair of variables is correlated with other variables. Specifically, for each pair of variables, it computes the correlations between those two variables and all other variables. If the correlations with the other variables are significantly different in 25% cases or less, the pair of the variables is deemed redundant. With our data, the test did not indicate any redundancy of the variables included in the data, suggesting the validity of using the whole set of the variables in the network analysis.

To provide an overview of the relationship between the variables, Fig. 1 displays a heat map of the within-person correlation of the variables before applying the graphical autoregressive model (i.e., a simple correlation of the variables after controlling for the trend and day effects below the diagonal) and after applying the model (partial contemporaneous correlation after regularization above the diagonal). Note that we do not report the between-person correlation of the variables because there are only four data points to compute it. As can be seen, the raw simple correlations are highly correlated with each other, but after processing the data (which essentially includes the exclusion of temporal predictive effects, computation of partial correlations, and application of regularization), the matrix is considerably sparser, providing a parsimonious (and perhaps generalizable) picture about how the components are related to each other within time points.

Fig. 2 presents the estimated contemporaneous network of motivational engagement, which corresponds to the upper triangle of Fig. 1 (for comparison, Fig. S2 presents contemporaneous network before regularization, which corresponds to the lower triangle of Fig. 1). The nodes are colored based on the community detection analysis via the Walktrap algorithm. The graph consists of a large group of nodes and several isolated nodes. Community detection analysis indicates that a large group of nodes further consists of two subgroups: one with a group of affective experiences (both positive and negative) and one with a mixture of values, expectancy beliefs, and goals that support motivational engagement without explicit external incentives (e.g., intrinsic reason, mastery goals, interest). The former group was further subdivided into positive and negative affective experiences. The latter group seems to be grouped into clusters of components that partially incorporate extrinsic factors (extrinsic, introjected, and identified reasons). However, this community borderline was unreliable when we used a different community detection method (i.e., Spinglass; see Fig. S3 in Supplementary Online Materials). On the other hand, isolated nodes are comprised of the components that are related to more instrumental aspects of motivational engagement (performance-approach goals,

Table 2
Means and within-person standard deviations (Reliability is after mean-centering the data).

Variables	*M*	*SD*	Reliability
Cognitive cost	1.85	2.05	*NA*
Physical cost	1.30	1.70	*NA*
Amotivation	0.66	1.13	.86
Extrinsic social reason	3.45	1.59	.67
Extrinsic material reason	4.79	2.35	.81
Introjected reason	4.78	2.13	.62
Identified reason	5.65	1.44	.86
Intrinsic reason	5.61	1.54	.89
Expectancy	5.29	1.58	.87
Mastery-approach goals	6.34	1.44	*NA*
Mastery-avoidance goals	5.36	2.49	*NA*
Performance-approach goals	2.83	2.16	*NA*
Performance-avoidance goals	3.02	2.01	*NA*
Interest-catch	5.93	1.17	.74
Interest-hold	6.15	1.18	.80
Need satisfaction for relatedness	5.19	1.59	.60
Need satisfaction for competence	5.21	1.53	.63
Need satisfaction for autonomy	5.42	1.74	.58
Happiness	4.93	1.50	*NA*
Pride	3.67	1.76	*NA*
Sadness	1.78	1.77	*NA*
Anxiety	2.54	2.12	*NA*
Frustration	3.17	2.38	*NA*
Boredom	2.02	1.84	*NA*
Calmness	3.22	1.72	*NA*
Curiosity	4.14	1.65	*NA*
Perceived stress level	2.63	1.44	*NA*
Depression	1.85	1.60	*NA*
Subjective well-being	4.84	1.26	*NA*
General affective valence	4.27	1.16	*NA*
Loneliness	1.03	1.06	.84

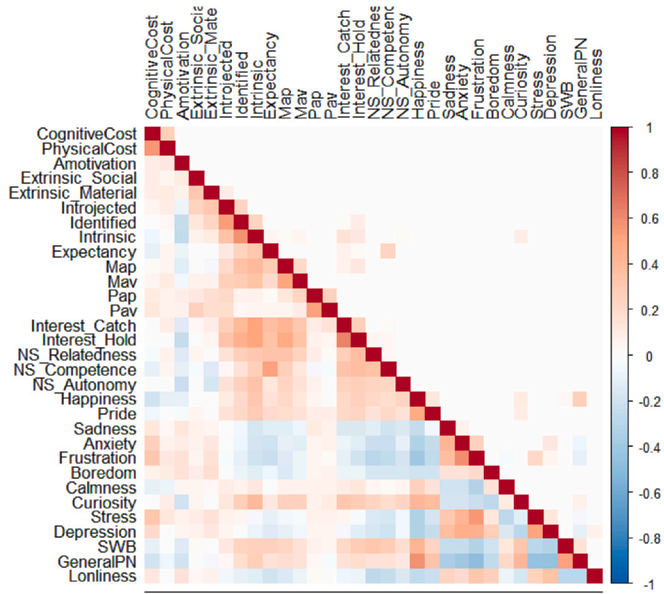

Fig. 1. Heatmap of the within-person relationship of the variables and contemporaneous correlation matrix
Note. Lower triangle shows simple within-person correlations between the variables (after controlling for the effects of trend and date). Upper triangle displays the final partial correlation matrix of contemporaneous relations between the variables (after regularization).

performance-avoidance goals, costs) and the absence of motivational engagement (amotivation, boredom).

Fig. 3 reports the centrality indices of each component. The results indicate that, among the nodes that comprise the main body of the network, intrinsic reasons and curiosity play a central role. This is particularly evident in the high betweenness centrality of these two nodes: from the network figure we can see that both curiosity and intrinsic reasons play a bridging role between the two large groups of nodes discussed above. In terms of strength centrality, in addition to intrinsic reason, interest-hold and general affective valence had the highest values (above 1.5 in the standardized metric). These results indicate that these components are likely to be causally connected to many other components of motivational engagement.

To examine whether the estimated network structure can be deemed representative of the networks derived from individual participants (i.e., whether there is large heterogeneity in individual networks), we estimated the network structure of each participant using the same procedure and computed the similarity of the network from the pooled data (Fig. 2) and individual networks. The average correlation of edge weights between the network from the pooled data and individual network was 0.65 (range: 0.53–0.89), indicating that our main findings hold for all participants to a large extent, notwithstanding certain individual differences.

4. Discussion

The current study is the first attempt to explore the relationships between and dynamics of a relatively large set of components in a motivational engagement process (e.g., reasons, expectancy belief, goals, affective experiences, etc.). For that purpose, we applied a novel network analysis approach to a longitudinal intensive dataset obtained from four participants assessed for a prolonged period of time (over a year). The resultant within-person contemporaneous network from 31 components showed that there was a large cluster supporting relatively autonomous forms of self-regulation. On the other hand, some motivational components representing instrumental aspects (e.g., performance goals, costs) and the absence of motivation (e.g., amotivation) formed small, isolated clusters. These bottom-up observations provide researchers some generative ideas on the relationships between different motivational components, which may serve as an informative basis for theory building in future integrative work on motivation. Below we note some of the observations.

One of the most important goals of education is to promote learners' self-regulation (Boekaerts, 1996), that is, supporting students in a way that enables them to learn and independently motivate themselves without relying on any extrinsic pressures. Research on motivation has proposed a number of theoretical frameworks and concepts to facilitate such learners, including intrinsic motivation, expectancy belief, positive affective experiences, etc. (Eccles & Wigfield, 2002). The current findings show that these theoretical components form a large cluster of networks, which suggest they may indeed be interacting with each other to support people's autonomous motivational engagement as a whole. It is also interesting to see that this main body of the network was further subdivided into two clusters: one comprising affective experiences and the other comprising a mixture of other motivational components such as reasons, goals, and expectancy belief (hereafter called "core motivational components"). These results indicate that while the affective process constitutes an important part of autonomous motivational engagement, core motivational components may form a separate coherent system, thus supporting the idea that affective and motivational processes should be portrayed as separate processes (Linnenbrink-Garcia et al., 2016). Of course, this does not mean that affective experiences and core motivational components are independent; as our data suggested, these two clusters of nodes are closely connected and perhaps have reciprocal relations (Linnenbrink & Pintrich, 2002).

It is worth noting that the linking nodes that bridge affective experiences and core motivational components were the feeling of curiosity and intrinsic reasons for engagement. Previous research has suggested that curiosity has both emotional and motivational aspects: while curiosity is often conceptualized as an emotional feeling triggered by the awareness of a knowledge gap or uncertainty (Loewenstein, 1994), it has also been described as a motivational concept given its strong function of initiating behavior (FitzGibbon et al., 2020). In addition, its conceptualizations are debated (Hidi & Renninger, 2019), the feeling of curiosity is a precursor or important component of developing interest or autonomous task engagement (Murayama et al., 2019). Similarly, intrinsic reasons refer to motivational engagement for the inherent pleasure or enjoyment of a task (Ryan & Deci, 2000). This means that the

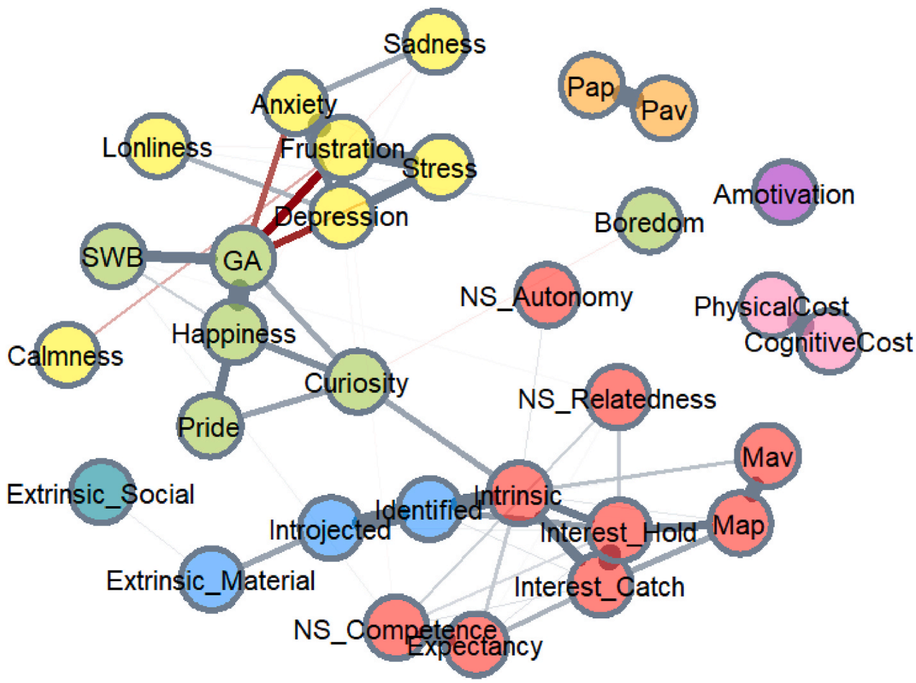

Fig. 2. The estimated contemporaneous network of motivational engagement
Note. The negative edges were represented by red color. Node colors represents the result of the walk-trap community finding algorithm. NS = need satisfaction; Map = mastery-approach goals; Mav = mastery-avoidance goals; Pap = performance-approach goals; Pav = performance-avoidance goals; SWB = subjective well-being; GA = general affective valence. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

intrinsic reasoning for a task already includes positive affective experience as one of its definitive characteristics. Therefore, it is sensible that both curiosity and intrinsic reasons play a bridging role in the observed network of autonomous motivational engagement. Using these key components, future studies should examine more detailed mechanisms to explore how core motivational components influence affective experience and vice versa.

Centrality analysis also identified some core components in the autonomous motivational engagement process: intrinsic reason, interest-hold and general emotional valence. Interpretation of these central nodes depends highly on the causal directions of associated edges. However, if they can be considered as antecedents of or having bidirectional effects on other nodes, these central nodes can be an effective target of intervention (Contreras et al., 2019; Fried et al., 2017), as they are likely to influence many other components in the motivational engagement process. In that respect, it is illuminating that nodes that represent the internalization of value (i.e., intrinsic reason and interest-hold) were identified as some of the most central nodes in the current network analysis. This observation is consistent with a recent successful application of an intervention on values to support students' autonomous engagement (Gaspard et al., 2015; Hulleman, Godes, et al., 2010) and provides another piece of evidence from a different angle that this is a promising avenue for future intervention studies.

Another interesting observation from the current study is that nodes that were not included in the main part of the network showed relatively small, isolated clusters rather than forming a single network of non-autonomous motivational engagement. These results indicate that non-autonomous motivational engagement is not a uniform process. These components—performance goals, cost value, amotivation, and boredom—are still important to explain people's motivated behavior but they seem to act on engagement independently of each other and independently of whether one is autonomously engaged. The fact that these components emerged as isolated nodes means that the mechanisms underlying such non-autonomous forms of motivational engagement might not have been sufficiently covered by the current set of variables included in the network model. In fact, in comparison to the autonomous motivational engagement, theoretical development of these motivational components is still at a nascent stage (Murayama & Elliot, 2011; Nett et al., 2011). Future studies should examine and identify causal mechanisms underlying these types of motivational engagement in more detail.

Despite these generative ideas from the current findings that could be tested in the future, it is important to add that the current findings are based on a fixed-effects model in which parameter estimates are assumed to be the same across all participants. We deliberately selected a fixed-effects model to ensure stable parameter estimates, given the large number of nodes (Mansueto et al., 2020), and our analysis showed that individual network structures seem to be consistent with the overall network structure. However, future studies would benefit considerably by examining potential individual differences in individual networks. With more participants and perhaps more time points (to ensure the stability of individual networks), within-person data have great potential to examine both commonalities and individual differences in within-person causal relations. Such information could be useful to consider personalized and adaptive interventions in educational settings, which is one of the imminent topics in research on education.

One important limitation of the current manuscript is that we only examined four participants working on psychological research projects based on convenient sampling, all of whom are relatively mature and motivated learners. This fact restricts generalizability to a broader participant population. In fact, although both contexts involve people's learning, academic research work and school lessons have very different task structures (e.g., research jobs require a more autonomous learning style). Nevertheless, we believe that the underlying fundamental learning and motivational processes are the same; indeed, research in the work domain tends to show similar findings with that in the academic domain (Gagné & Deci, 2005; Sadri & Robertson, 1993). It should also be noted that there is an inherent tradeoff between the studies of hypothesis confirmation, which normally test a few (often a single)

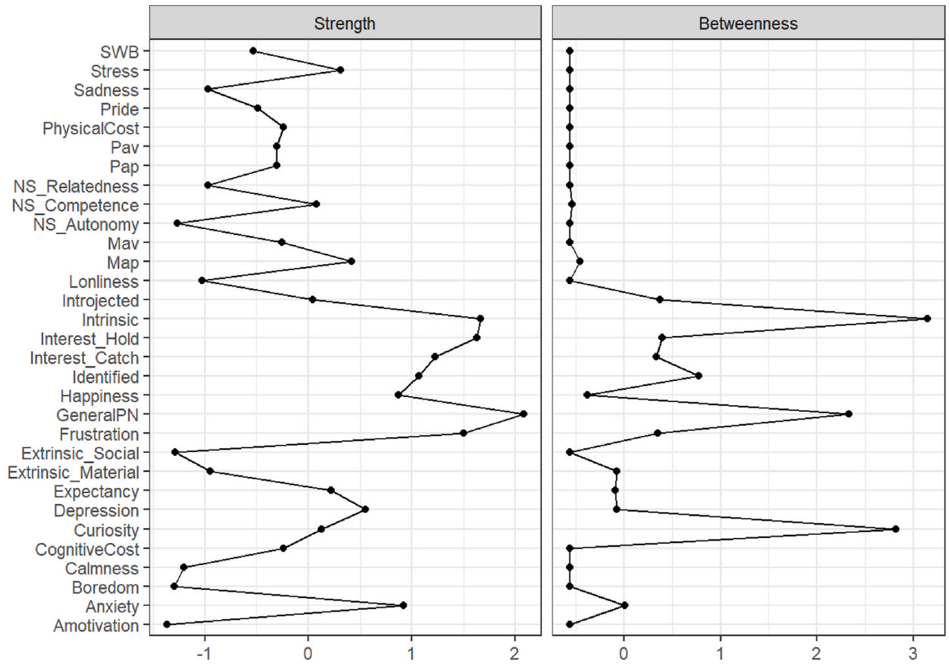

Fig. 3. The centrality indices of each component
Note. Standardized scores are shown on horizontal axis. SWB = subjective well-being; Pav = performance-avoidance goals; Pap = performance-approach goals; NS = need satisfaction; Mav = mastery-avoidance goals; Map = mastery-approach goals; GA = general affective valence.

hypothesized relations with a large sample, and the studies of hypothesis generation, which often inspect rich intensive data from a relatively small number of participants in a bottom-up manner (this also includes qualitative research). The focus of the current study is on the latter. As such, while it is true that our work has limited generalizability, the findings still contribute to the advancement of motivation theories by complementing a number of hypothesis-driven studies, which are currently predominant in the field of motivation studies. Nevertheless, future research should test the generalizability of the findings and generated hypotheses by examining other types of learning and instructional settings with a relatively larger sample.

Another critical limitation of the current research is the reliance on self-report questions. This means that the current research deals only with subjective interpretations associated with underlying motivational processes. However, we believe it is still useful to understand whether and how different motivational components are distinctly experienced and how they are related to each other—a vast amount of past research has demonstrated the predictive utility of these self-reported measures of motivation. At the same time, we agree that such subjective feelings at most provide a coarse picture about the underlying psychological process (Fulmer & Frijters, 2009; Murayama et al., 2019). Therefore, the findings should be interpretated with caution.

5. Conclusion

Motivational engagement is a dynamic process. Values, goals, expectancy beliefs, affective experiences, and other components dynamically interact with each other. “Being motivated” for learning can be seen as an emergent property of these dynamics. Such a dynamic systems perspective has been put forward in the motivation literature (e.g., Op 't Eynde & Turner, 2006), but there has been little empirical research aiming to address complex dynamic interactions in a scientific rigorous manner. Psychological network analysis, although still at a nascent stage of development, provides a promising tool to approach such challenging dynamics (Dalege et al., 2016; Lange et al., 2020). However, with a more fine-grained longitudinal intensive or experimental design, researchers should be able to identify the causal direction of the motivational components, thus providing a more accurate picture of the dynamics of motivational engagement process in learning. We hope that the current exploratory investigation serves as a springboard for future systematic studies.

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Declaration of competing interest

The authors declare no competing interests.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.learninstruc.2022.101649.

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