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A cross-classified path analysis of the self-determination theory model on the situational, individual and classroom levels in college education

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ABSTRACT

According to self-determination theory (SDT), the extent to which students' motivation is self-determined is critical for academic performance. SDT also proposes that self-determined academic motivation is facilitated when the learning environment supports the basic psychological needs for autonomy, relatedness, and competence. This model of social support → needs satisfaction → motivation → learning outcomes is termed the general SDT model. Current evidence regarding this general SDT model is limited, in that, to date, no study has examined it in full using within-individual methods, which are critical for understanding inner psychological processes and mechanisms. Using a large and comprehensive college student dataset (total N of responses = 30,765), the current study aims to apply a within-individual analytical approach to the general SDT model. Specifically, we apply a cross-classified path model to account for both the between-student level and between-classroom level nesting structure. This model enables us to explain the relationships between the variables in the general SDT model on three levels: situational (within-student and within-classroom), between-student, and between-classroom.

The results generally support the predictions on all three levels. For a student, a classroom, or a student's specific experience within a classroom, the general SDT model received support. Most importantly, when the same student in the same classroom experiences higher levels of autonomy support, she or he is more likely to have her or his psychological needs satisfied and to study for self-determined reasons, which are associated with higher perceived learning performance. Various unexpected results, such as the direct effects of learning climate and the predominance of the competence need, are also reported. Overall, the current research provides a comprehensive and multilevel understanding of the role of self-determination in college classrooms.

1. Introduction

Self-determination theory (SDT) is a prominent theory in contemporary educational psychology that explains students' motivation and performance. The current research examines the general SDT model by applying cross-classified multilevel analytical methods to a large comprehensive college student dataset. Below, we introduce the general SDT model, followed by cross-classified path analysis.

2. The general SDT model

SDT proposes that self-determined motivation is critical for the positive functioning of all human beings. Self-determined motivation is defined as motivation that is congruent with the self or well-integrated within the human organism. When we do things because they are interesting (intrinsic motivation), because they are congruent with our identity (integrated regulation) or because we identify with the value of the behavior (identified regulation), the motivation is congruent with our self, and we are self-determined. In contrast, when people do things because they feel internal pressure and guilt or shame (introjected regulation), because they are coerced by others (external regulation), or when they simply have no good reason (amotivation), they are non-self-determined. It has been proposed that self-determined motivation contributes to the positive functioning and behavioral and well-being outcomes for human beings (Deci & Ryan, 2000; Ryan & Deci, 2017). For example, research has supported the positive role that self-determined motivation plays in educational achievements (e.g., Fortier, Vallerand, & Guay, 1995; Guay & Vallerand, 1997), engagement (e.g., Bao & Lam, 2008), vitality (e.g., Mouratidis, Vansteenkiste, Sideridis, & Lens, 2011), and well-being (e.g., Vansteenkiste, Zhou, Lens, &

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Soenens, 2005; Yu, Zhang, Nunes, & Levesque-Bristol, 2018).

SDT also proposes that self-determined functioning requires the satisfaction (as opposed to frustration) of certain psychological needs. Decades of empirical research have supported the existence of three basic psychological needs, i.e., for autonomy, relatedness, and competence (Deci & Ryan, 2000). Autonomy refers to people's need to self-organize their experiences and self-regulate their behaviors, while the frustration of this need involves feeling pressured and internally conflicted. Relatedness refers to the need to establish meaningful relationships with others, to care for others and to be cared for, while the frustration of this need involves relational exclusion and feelings of loneliness. Competence refers to the need to feel effective in interacting with the environment, while the frustration of this need involves feelings of failure and doubts about one's efficacy.

In addition, SDT proposes that the extent to which the three basic needs are satisfied depends on the characteristics of the social context (Deci & Ryan, 2000). For example, autonomy support is the style of social context that is most researched in SDT. An autonomy-supportive person (e.g., a teacher) will provide people (e.g., students) with choices, give rationales that help make activities personally relevant to them, and consider their perspectives to ensure that they feel understood and listened to. All of these behaviors contribute to satisfying the need for autonomy.

SDT researchers have also argued that social contexts that support one need also tend to support other needs (e.g., Vansteenkiste, Niemiec, & Soenens, 2010). For example, a parent who is sensitive to her or his children's feelings and needs not only supports the children's autonomy but may also foster a closer relationship with the children and be able to provide information and challenges according to accurate perceptions of the children's conditions. Therefore, although autonomy support may mainly contribute to the need for autonomy, it is also expected to predict higher levels of relatedness and competence satisfaction.

To summarize, according to SDT, we would expect positive relationships among the social context, needs satisfaction, motivation, and behavioral and experiential outcomes. In the current research, this set of propositions is termed the General Model; it is illustrated in Fig. 1. This General Model has generally received empirical support over the last decades (a few examples include Guay & Vallerand, 1997; Jeno & Diseth, 2014; Zhou, Ntoumanis, & Thøgersen-Ntoumani, 2019) and has been recognized as an established model (e.g., Deci, Olafsen, & Ryan, 2017; Yu, Chen, Levesque-Bristol, & Vansteenkiste, 2018). Specifically, in the current research, we focus on examining these propositions on the within-individual level, in a college educational context.

3. Cross-classified multilevel path analysis

3.1. Within-individual analysis

The General Model is posited to function at both the general between-individual level and the situation-specific, within-individual level (Ryan & Deci, 2017; Vallerand, 1997). For example, Vallerand (1997) proposed that the General Model should be valid at the global level (relatively enduring individual differences), contextual level (different life spheres within the person), and situational level (the activity currently engaged in within a personal life sphere). Hence, a student's general perception of others as autonomy-supportive should positively predict the student's general needs satisfaction and self-determined motivation, which then predict outcomes generally (global level). A student's perception of a particular classroom as autonomy-supportive should contribute to the student's needs satisfaction and self-determined motivation towards learning in that particular class, which then predict their outcomes for that course (contextual or situational level).

To date, however, the majority of research evidence has examined the between-individual relationship for the General Model. The between-individual relationships between variables could be different from the within-individual relationships for the same variables (e.g., Borsboom, Mellenbergh, & Van Heerden, 2003; Fisher, Medaglia, & Jeronimus, 2018; Hamaker, 2012; Huta, 2014; Marsh et al., 2008; Molenaar, 2004; Murayama et al., 2017; Stapleton, 2013). To illustrate, suppose that in a dataset, each individual provides multiple data points for both an independent variable (IV) and a dependent variable (DV). These data are illustrated in Fig. 2, in which each circle (individual) contains multiple dots (data points). As can be seen, even when the between-individual relationship between the IV and DV is clearly positive (i.e., circles that are high on IV are also high on DV), at the within-individual level (dots within each circle), relationships between the IV and DV could be either positive, negative, or null and may be greatly variable. Therefore, for example, even though between-individual research can show that individuals who perceive higher levels

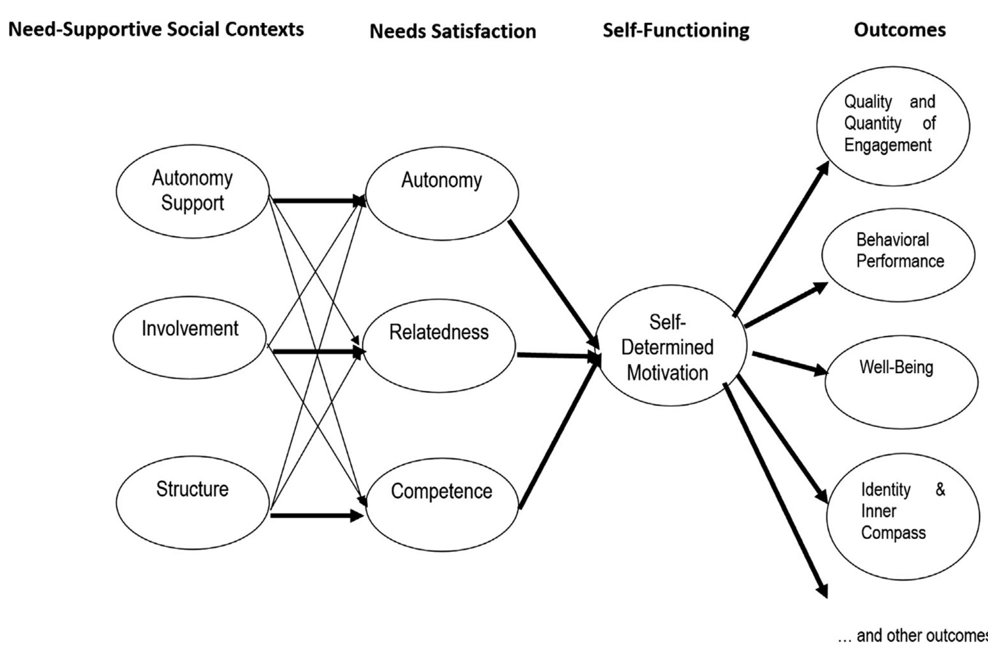

Fig. 1. The General Model.

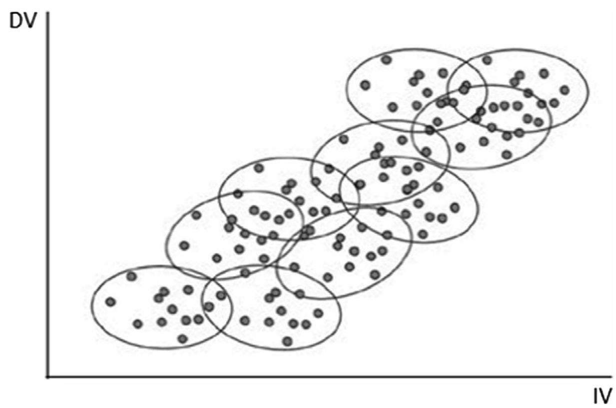

Fig. 2. Relationships of IV and DV at within- and between-individual levels. Each dot represents a data point, and dots within one circle represent data points coming from the same nesting group (e.g., individual or classroom). The Figure is a modification based on Stapleton (2013, p. 527).

of needs satisfaction also tend to exhibit higher self-determined academic motivation and so forth, between-individual research cannot tell us whether, for a particular individual, when they encounter classrooms with higher needs support and satisfaction, they also tend to have higher self-determined motivation and learning outcomes.

In psychological research, very often, we are interested in within-individual psychological processes and mechanisms but not the between-individual differences. For example, researchers interested in the relationship between classroom autonomy support and self-determined motivation may be more interested in how instructional autonomy support makes each student more self-determined in a particular classroom as opposed to how students with different levels of general self-determination differ in terms of their general perception of autonomy support across classrooms. Therefore, within-person designs for the General Model are needed to investigate the behavioral and psychological mechanisms that occur within students and across courses.

Over the last 10 years or so, SDT researchers have realized the limitations of between-individual designs, and they have begun to conduct within-individual studies using repeated-measures surveys and multilevel modeling for analysis. For example, one of the earliest within-individual studies to apply SDT in educational settings is that by Tsai, Kunter, Lüdtke, Trautwein, and Ryan (2008). Focusing on the within-person, lesson-to-lesson variations in classroom experiences, they showed that in classes where 7th grade students perceived teaching involving higher autonomy support (vs. controlling teaching), the students were also likely to experience interest in learning. Similarly, Mouratidis et al. (2011) showed that for a particular student, their vitality and interest-enjoyment tend to be higher in classes that are manipulated to have needs-supportive teaching and self-determined motivation.

Subsequent research in school settings has investigated the within-individual effects of teacher needs support on self-determined motivation and engagement (e.g., Patall et al., 2018; Stroet, Opdenakker, & Minnaert, 2015); of instructional style on perceived autonomy support and positive emotion (Bieg et al., 2017); of basic psychological needs satisfaction vs. frustration on affective, motivational and engagement outcomes (e.g., Vandenkerckhove et al., 2019; Park, Holloway, Arendtsz, Bempechat, & Li, 2012); and of self-determined motivation on affective and behavioral outcomes (e.g., vitality, interest-enjoyment, effort, and procrastination; Mouratidis & Lens, 2015).

Furthermore, in the last two or three years, another more advanced trend in data analysis to be applied in within-individual research in SDT is multivariate multilevel modeling, also referred to as multilevel structural equation modeling (ML-SEM). The methodological advantage of using ML-SEM in SDT research is that the method can holistically examine multiple within-individual relationships in the General Model at the same time. For example, Bartholomew et al. (2017) measured middle school students each trimester over one school year, finding that, at the within-individual level, controlling teaching predicts needs frustration, which predicts self-determined motivation. The within-individual indirect effect of controlling teaching on motivation was also significant.

In summary, over the last 10 years or so, SDT research in educational settings that applies a longitudinal within-person design has burgeoned. However, most research has incorporated only part of the General Model shown in Fig. 1, and no study has incorporated all four stages of the model shown in Fig. 1 using within-individual methods. Thus, in the current research, we propose to apply within-individual analyses (specifically, ML-SEM) to the course-to-course variation in students' self-determined motivation and related variables to answer unexamined research questions derived from the General Model.

3.2. *Cross-classified path model*

Notably, in the current dataset, the responses are nested not only within students but also within classrooms (courses). Just as one student may provide multiple responses, one classroom contains multiple responses. A schematic representation of this data structure is displayed in Table 1. Because one student can take our survey in multiple courses and one course can be taken by multiple students, students and courses are cross-classified (Raudenbush & Bryk, 2002; Ye & Daniel, 2017). Therefore, we aim to use a cross-classified model to account for the nesting structure of both students and classrooms in this cross-classified data.

The use of multilevel modeling to account for either classroom or student nesting structure separately has been a widely applied practice, including in SDT research (e.g., Aelterman et al., 2012; Bartholomew et al., 2017). However, despite recent calls for the use of cross-classified models to account for multiple nesting structures and to obtain more accurate estimations (e.g., Asparouhov & Muthén, 2012; Dunn, Richmond, Milliren, & Subramanian, 2015; Marsh, Martin, & Cheng, 2008), we have found no prior study that uses a cross-classified model to simultaneously control for both between-classroom and between-student level nesting in SDT research. Therefore, we consider it valuable to apply cross-classified models to examine the within-classroom, within-individual experiences of autonomy support, needs satisfaction, self-determination, and academic achievement. Given the prevalence of this structure (multiple students in different multi-classrooms) in institutional datasets of college education, our study also constitutes a valuable contribution to research in college education in general. Our research is also in line with recent calls to combine state-of-the-art analytical methods with complex conceptual issues in large datasets (Marsh & Hau, 2007).

Based on the full model shown in Fig. 1, a model to be tested is shown in Fig. 3. The observed variables are represented by rectangles, and the latent variables modeled by the cross-classified ML-SEM are represented by ellipses. The thinner arrows between the levels denote the measurement relationships between the observed scores and the latent scores. These cross-level thinner arrows do not pertain to

Table 1
Schematic representation of cross-classified data structure.

	Spring 2014			Fall 2014		…	Spring 2017	
	Course A	Course B	…	Course C	…		Course M	…
Student A	√			√				
Student B		√		√			√	
…								
Student N	√	√					√	

Note. Checkmarks in a cell indicate that the student of that row took the course of that column.

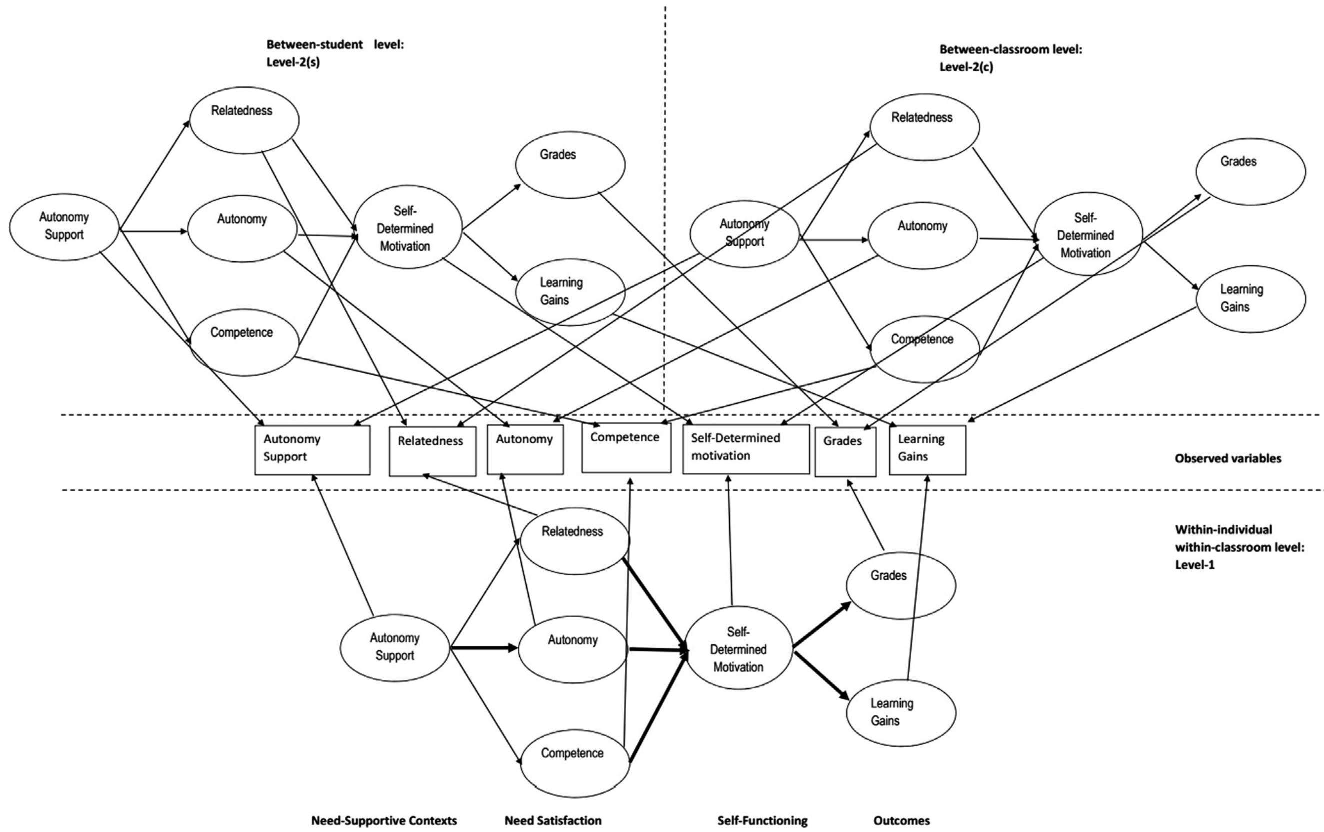

Fig. 3. Structural model tested in this study (simplified diagram). The rectangles represent observed indicator variables, while the ellipses represent latent constructs. The thickened arrows represent core hypotheses. The arrows across levels from the latent to observed variables represent only the measurement relationships between the constructs on different levels and are not estimated or interpreted. The arrows within a certain level represent paths that are estimated with uninformative priors; the effects that are not expected by theory (estimated using small-variance priors centered on zero) are not shown in the diagram. The residual terms and correlations are omitted.

substantive effects and will be neither estimated nor interpreted. Therefore, Fig. 3 shows that the variance in the raw scores can be partitioned into the contribution of the within-student within-classroom level (represented by the latent variables on level-1), the between-student level (represented by the latent variables on the between-student level) and the contribution of the between-classroom level (represented by the latent variables on the between-classroom level). The latent variables on the higher levels are explained by (or explain) other variables in the General Model on that higher level, and the remainder on the within-student within-classroom level is then explained by (or explains) variables in the General Model on the within-student within-classroom level. The thickened arrows between autonomy support → needs satisfaction → self-determined motivation → learning outcomes on the within-individual, within-classroom level (level-1) represent our core research questions.

4. Research in college education

College education is also especially pertinent for examining the research questions related to the General Model. First, unlike secondary education, students' academic experiences no longer fall under a uniform curriculum, and there may be more variations in how they engage in learning activities; thus, the role of motivation may be even stronger for them. Second, college is an important stage in the lives of contemporary youths because it is when they make important career commitments (e.g., Hargrove, Creagh, & Burgess, 2002) and identity formation progress (Arnett, 2000). The college learning experience has profound implications for the rest of their lives. Given that SDT claims universality for its propositions and that college is a critical life stage, it is important to answer the research questions with college samples.

Specifically, a few studies have provided evidence for this model in college students. Some research has shown the positive effects of basic needs satisfaction (Kanat-Maymon, Benjamin, Stavsky, Shoshani, & Roth, 2015) and self-determined motivation (Gillet et al., 2017; Gillet, Morin, & Reeve, 2017; Senécal, Julien, & Guay, 2003) on academic outcomes. A few other studies have applied a more holistic perspective and included multiple paths in this model. For example, several studies have shown that needs support in educational contexts predicts autonomous motivation, which predicts academic outcomes (e.g., Williams & Deci, 1996; Levesque, Zuehlke, Stanek, & Ryan, 2004; Vansteenkiste, Simons, Lens, Sheldon, & Deci, 2004; Vansteenkiste, Sierens, Soenens, Luyckx, & Lens, 2009). In addition, Jang, Reeve, and Halusic (2016) found that perceived autonomy support in the classroom predicts satisfaction of the need for autonomy, which, in turn, predicts engagement and learning outcomes. In short, parts of this model have gained empirical support, although there are still substantial questions about this model that have not been tested with college students. For example, no study has incorporated all four elements (i.e., contextual support, needs satisfaction, self-determined motivation and behavioral outcomes) and demonstrated the validity of this model in its totality with college students. Combining an examination of the general SDT model and the cross-classified analytical framework, our research contributes to a comprehensive understanding of the self-determination dynamics in college education.

5. Current research

The purpose of the current research is to examine the within-person relationships between variables in the general SDT model in a college setting, controlling for between-student level and between-classroom level variances and using cross-classified path analyses. The main research question is as follows: In college students, at the within-student level, do experiences of autonomy support in the learning environment predict needs satisfaction, which, in turn, predicts self-determined motivation, which, in turn, predicts learning outcomes? The main contributions of the current study are that (1) it is by far the most comprehensive (in terms of inclusion of all components of the model) and powerful (in terms of large sample size) testing of the General Model of SDT at the within-individual level; (2) it is by far the most comprehensive and powerful testing of the General Model of SDT in college education; and (3) it is the first study to demonstrate the feasibility of cross-classified ML-SEM to accommodate both between-student level and between-classroom level clustering, thereby providing an important reference for future studies dealing with institutional data in college education.

6. Method

6.1. Data

The data were collected from courses that were part of a campus-wide course-transformation program at the university where the study was conducted. Each semester, as part of their course evaluation survey, thousands of students voluntarily respond to online surveys asking about their experiences of the targeted course (which span most colleges and majors in this university), including the need-supportive learning climate, basic needs satisfaction, and self-determined motivation. The course grades for these students are also available, obtained from the registrar. Because, among the respondents, some students were surveyed repeatedly (in different courses) over the three years preceding our research, we have accumulated a body of repeatedly measured students (up to seven semesters) that is large enough to allow a within-individual analysis (Table 2).

One limitation of the data may be differential attrition. That is, students who supply more repeated measures may be systematically different from those who supply fewer repeated measures. To evaluate the degree of this limitation, the proportion of variance in the variables that can be explained by how many repeated measures are supplied by a particular student is reported on the right-hand side of Table 2. The number of responses explained less than 0.1% of the total variance for most variables, except for gender, age, and external regulation. For gender, it seems that for the majority of respondents (i.e., respondents who responded 5 times or less), the greater the number of responses that the respondent provided, the greater the likelihood that the respondent is female. The reason may be female students' higher agreeableness and, hence, inclination to complete our surveys (e.g., Schmitt, Realo, Voracek, & Allik, 2008). For age, participants who provided more responses tended to have a lower average age when they were surveyed. This tendency is expected because students who are closer to graduation (i.e., older students) tend to have fewer chances to be surveyed than younger students, who still have many future courses to take. For external regulation, students' external regulation appears to increase with the number of responses they provide. Potential explanations for this increase are that students who retake classes have higher external regulation, students who were in earlier cohorts tend to be more externally motivated, and students who are externally motivated tend to take more courses in our transformation program. Overall, the substantive variables do not seem to change systematically with the number of responses provided, but the correlation between age, gender, external regulation and the response counts may limit the validity of our findings.

6.2. Instrumentation

Below, we include information about the measurements used in our survey. The correlations, descriptive statistics and Cronbach alpha coefficients are displayed in Table 3.[1] All the self-report scale scores are computed by averaging all non-missing item scores, which is consistent with conventional practice in psychological research and maximizes the use of available information.

6.2.1. The short-form learning climate questionnaire (LCQ)

This 6-item version of the LCQ (Williams & Deci, 1996) has been used to measure students' perceptions of an autonomy-supportive classroom climate. Participants indicate the extent to which they agree with the statements on a 7-point Likert scale (1 = *strongly disagree*, 4 = *neither agree nor disagree*, 7 = *strongly agree*). The following is an example item: "I feel that my instructor provides me choices and options." Previous research has shown that the need-supportive learning climate measured by this scale is positively associated with the satisfaction of all three needs (e.g., Yu, Traynor, & Levesque-Bristol, 2018). Additionally, the internal consistency is high (alpha = 0.94).

6.2.2. The academic self-determined motivation scale

This 18-item scale (Guay & Vallerand, 1997; Levesque-Bristol, Knapp, & Fisher, 2011) contains six subscales measuring the six types of motivation proposed by SDT (Deci & Ryan, 2000), with three items measuring each subscale. The orienting statements ask students to indicate their "motivation for taking the course;" the following are example items: "Because it's really fun" (intrinsic), "Because acquiring all kinds of knowledge is fundamental for me" (integrated), "Because it allows me to develop skills that are important for me" (identified), "Because I would feel guilty if I didn't" (introjected), "Because I feel I have to" (external), and "I don't know. I wonder if I should continue" (amotivation). Participants indicate the extent to which they agree with the statements on a 7-point Likert scale (1 = *strongly disagree*, 7 = *strongly agree*). The internal consistency for all subscales is high (Cronbach's alpha ranged from 0.80 to 0.94). Additionally, for each participant, we create one single indicator of self-determined motivation by calculating a self-determination index (SDI). Considering recent research findings (e.g., Sheldon, Osin, Gordeeva, Suchkov, & Sychev, 2017; Yu & Levesque-Bristol, 2018), the unweighted SDI is used; the formula is SDI = intrinsic + integrated + identified - introjected - external - amotivation.

6.2.3. The basic psychological needs scale (BPNS)

A version of the 21-item BPNS (Ilardi, Leone, Kasser, & Ryan, 1993), slightly adapted to reflect the classroom setting, was used to measure the satisfaction of the basic psychological needs for autonomy, relatedness, and competence. The following are example items: "I feel like I can make a lot of inputs in deciding how my coursework gets done" (autonomy), "People in this course care about me" (relatedness), and "I often do not feel very capable in this course" (competence, reversed). Participants indicate the extent to which they agree with the statements on a 7-point Likert scale (1 = *strongly disagree*, 7 = *strongly agree*). Consistent with prior research (e.g., Yu, Traynor, et al., 2018), the item "There is not much opportunity for me to decide for myself how to go about my coursework" did not have a sufficient correlation with the other items in the autonomy subscale and is hence removed from the calculation of the autonomy scale score. The Cronbach alpha coefficients are satisfactory for all subscales (0.75 for competence, 0.85 for relatedness, and 0.77 for autonomy).

[1] The Cronbach alpha coefficients of the survey instruments are derived from a non-duplicate dataset in which each of the 18,875 students provided one response to provide a better reflection of the reliability of the instruments by removing the within-individual correlations. All the other statistics in Table 3 are based on the entire dataset to present a better general description of the characteristics of the dataset.

Table 2
Descriptive statistics by the number of responses per student.

No. of Responses per Student		1	2	3	4	5	6	≥7	Variance Explained by No. of Responses
Count of Students		11,625	4441	1742	626	253	109	79	
Percentage of Students		61.59	23.53	9.23	3.32	1.34	0.58	0.42	
% Female		46.63	50.61	52.02	56.32	56.13	48.62	34.62	0.2%
Mean Age when Surveyed		20.30	20.03	19.91	19.88	19.87	19.77	20.04	0.5%
Mean	Learning Climate	5.34	5.35	5.40	5.41	5.27	5.39	5.45	< 0.1%
	Competence	4.56	4.57	4.62	4.62	4.57	4.56	4.59	< 0.1%
	Autonomy	4.60	4.60	4.64	4.70	4.63	4.68	4.72	< 0.1%
	Relatedness	4.73	4.76	4.81	4.82	4.76	4.78	4.85	< 0.1%
	Intrinsic Motivation	4.09	4.08	4.13	4.12	3.98	4.02	4.09	< 0.1%
	Integrated Regulation	4.95	4.97	4.95	4.99	4.94	4.90	5.11	< 0.1%
	Identified Regulation	4.81	4.84	4.90	4.92	4.83	4.87	5.02	< 0.1%
	Introjected Regulation	3.11	3.16	3.14	3.12	3.12	3.22	3.02	< 0.1%
	External Regulation	4.90	4.97	5.04	5.04	5.07	5.19	5.34	0.2%
	Amotivation	2.62	2.63	2.56	2.63	2.65	2.63	2.65	< 0.1%
	Learning Gains	3.64	3.65	3.66	3.66	3.57	3.66	3.68	< 0.1%
Median of Mean Personal Grades		3.30	3.50	3.43	3.43	3.40	3.38	3.28	< 0.1%

Table 3
Correlations, descriptive statistics, alphas, and ICCs of the variables in the entire dataset.

	1 LCQ	2 Competence	3 Autonomy	4 Relatedness	5 Intrinsic	6 Integrated	7 Identified	8 Introjected	9 External	10 Amotivation	11 SDI	12 Grades_Inv	13 SALG
1		0.58	0.70	0.35	0.51	0.38	0.52	0.05	−0.09	−0.36	0.51	0.20	0.50
2			0.73	0.50	0.63	0.43	0.60	−0.09	−0.23	−0.58	0.72	0.33	0.53
3				0.50	0.55	0.39	0.52	−0.05	−0.19	−0.43	0.59	0.28	0.45
4					0.32	0.30	0.35	−0.07	−0.05	−0.33	0.39	0.20	0.27
5						0.59	0.78	0.17	−0.28	−0.37	0.83	0.19	0.55
6							0.72	0.24	−0.12	−0.25	0.64	0.10	0.41
7								0.20	−0.20	−0.43	0.79	0.15	0.57
8									0.25	0.31	−0.16	−0.07	0.08
9										0.22	−0.52	−0.07	−0.15
10											−0.72	−0.18	−0.38
11												0.22	0.56
12													0.16
Alpha	0.94	0.75	0.77	0.85	0.94	0.81	0.87	0.85	0.81	0.81	NA	NA	0.93
M	5.36	4.58	4.62	4.76	4.09	4.96	4.85	3.13	4.98	2.62	6.12	0.70	3.65
SD	1.32	1.05	1.05	0.96	1.61	1.20	1.36	1.50	1.35	1.37	11.22	0.28	0.97
Skewness	−1.02	−0.27	−0.37	−0.07	−0.33	−0.65	−0.80	0.41	−0.61	0.86	−0.18	−0.12	−0.63
Kurtosis	0.77	0.09	0.22	−0.08	−0.77	0.28	0.21	−0.70	−0.08	0.16	−0.26	−1.57	0.20
ICC(s)	0.19	0.25	0.25	0.32	0.23	0.47	0.29	0.55	0.39	0.35	0.30	0.03	0.20
ICC(c)	0.24	0.13	0.21	0.16	0.19	0.06	0.15	0.03	0.10	0.09	0.17	0.15	0.14
ICC(t)	0.42	0.38	0.46	0.49	0.42	0.53	0.43	0.58	0.48	0.44	0.47	0.18	0.35

Note. All correlations significant at the $p < .001$ level. ICC(s) is the ICC of the student level; ICC(c) is the ICC of the classroom level; ICC(t) is the ICC of total level-2 nesting (student plus classroom). Grades_Inv: inverse-transformed grades. SALG: self-assessed learning gains.

6.2.4. Self-assessed learning gains

This 5-point Likert scale measures participants' self-perceived gains in learning knowledge and skills identified by the faculty teaching the class surveyed. The questions were presented in the end-of-semester course evaluation. Notably, only approximately half of the responses are paired with the perceived learning gains measurement. That is, among the 30,765 responses provided by a specific student for a specific course, only 15,520 contained self-assessed learning gains data. The questions share the same structure: "This course helped me learn/acquire ___ knowledge/skills"; however, the specific knowledge/skills that fill in the blank vary by course. For example, the knowledge/skills for a statistics class could include "calculating probabilities under the normal curve," whereas the knowledge/skills for an educational psychology class could include "understanding Bloom's Taxonomy." For each course, the number of perceived learning gains items used ranged from 3 to 8. In the current study, we are interested in how students perceived their gains in the knowledge or skills generally considered important by the instructors. Therefore, we averaged all the items and aggregated them into one self-assessed learning gains score to reflect a general level of perceived learning gains.

This practice (the same variable consists of different items in different situations) may appear to be unconventional; hence, we explain it briefly. In the ML-SEM method we use in the current study, all variables are implicitly group-mean centered (e.g., Marsh et al., 2012; this group-mean centering is in addition to the overall grand-mean standardization mentioned in the Analytical Strategy section below). The latent mean of class j is subtracted from the score of student i in class j. This means that the learning gains on level-1 are the relative level of self-assessed learning gains within that class regardless of what content or expected score those items have. If we observe a positive effect of self-determined motivation on self-assessed learning gains on level-1, it can be interpreted as the self-determined motivation of a student in a course positively predicts that student's perceived learning gains compared to other students in that course. Therefore, the multilevel method helps make the within-individual, within-classroom effects comparable across courses, even though the items are different for each course and the expected scores vary by course. For the between-course level, because each course has different items, the perceived learning gains may not be comparable, and higher perceived learning gains in a given course may reflect a combination of students' truly higher learning gains and the fact that the items for a given course may elicit higher responses. These two confounds are not separable; hence, on the higher levels the effects on perceived learning gains should be interpreted with caution.

We also calculated Cronbach's alpha using all the available items on and responses to the self-assessed learning gains scale. The overall Cronbach's alpha was 0.93. Because the alpha coefficient can be interpreted as the average inter-item covariance (per unit of total score variance; e.g., Raykov & Marcoulides, 2011), this result means that, if we look beyond the differences in the specific knowledge/skills that the items target and treat them all as items that assess the general perception of learning gains, then the items strongly correlate with each other. Self-assessed learning gains also had a weak positive correlation of 0.19 with course grade ($p < .001$). On the one hand, the high alpha and the weak correlation coefficient with course grades provide evidence for the reliability and validity of the self-assessed learning gains measure. On the other hand, they indicate that self-assessed learning gains are sufficiently different from course grades, meaning that the scale may provide incremental value as a more subjective measurement for learning performance.

6.2.5. *Course grades*

Course grades were obtained from the registrar. The distribution of grades showed a strong negative skew (skewness = -1.35, $SE = 0.02$; kurtosis = 1.60, $SE = 0.04$). After inverse transformation (Tabachnick & Fidell, 2001), the skewness is reduced to -0.123, but the kurtosis is still high (-1.57). Nevertheless, this high kurtosis should not substantially threaten the validity of the current analyses given that research has shown that ML-SEM is generally robust against normality violations (e.g., Norman, 2010; Zhang, 2006).

The course grades are also subject to the limitations discussed above for perceived learning gains. That is, although grades appear to be a unitary variable, their equivalence or equating relationship has never been established for college courses. Each college course may use a different set of evaluation methods that are not comparable with each other. Our multilevel analyses with group-mean centering aligns the grades in different courses on the same level and make them comparable on the within-individual, within-classroom level, but the effects on grades on higher levels require extra caution to interpret.

6.3. *Analytical Strategy*

Our multilevel cross-classified path model analyses are performed using *Mplus* software (Muthén & Muthén, 2004). The data analysis proceeds in three general steps. First, basic statistics are examined to ensure that the data meet the assumptions and requirements. Apart from the independent observations assumption, which is explicitly modeled using multilevel modeling, we also check the other assumptions of linear modeling, such as normality, linearity, and constant variance. Specific to multilevel modeling, one prerequisite is to examine the clustering effect, i.e., how much within-cluster (i.e., students and classrooms) responses correlate with each other and how much variance is explained by between-cluster effects (e.g., Raudenbush & Bryk, 2002). The intraclass correlation coefficient (ICC) is calculated as an indicator of the clustering effect. In two-level cross-classified models, the total variance of each variable can be partitioned into variances that can be explained by level-1 and each level-2, and the ICCs can be obtained by calculating the proportion of total variance that can be explained by each level-2 as well as by all level-2 combined (e.g., Snijders & Bosker, 1999). ICCs can thus be interpreted as the average agreement between any two data points in the same nesting structure (in our case, student or classroom). There is no consensus regarding the cutoffs for ICCs as they greatly vary depending on the constructs and the substantive nature of the nesting structure, although, from a statistical perspective, ICCs lower than 0.10 may cause estimation difficulties (e.g., Brunner, Keller, Wenger, Fischbach, & Lüdtke, 2017).

The second step is to run the main cross-classified multilevel path analysis. As mentioned in the previous section, group-mean centering is implicitly applied to all variables (e.g., Marsh et al., 2012). We approach the analysis of the main model in two sub-steps. Before running the full-scale model depicted in Fig. 3, in a first sub-step, we test a model with one general need satisfaction variable (derived from averaging the satisfaction of all three needs) to estimate the mediating effect of overall needs satisfaction. In the second sub-step, we differentiate these three needs into their respective variables and run the full model depicted in Fig. 3 to take a more refined look at the unique effects of each need satisfaction.

For the estimation of our cross-classified SEM, the Bayesian estimation is used because it is the only estimation method currently available in *Mplus* for cross-classified models. The Bayesian method differs from traditional frequentist methods, which we briefly explain here. In traditional frequentist methods, the sample estimate (i.e., the information derived from data) is used to infer the population parameter. In Bayesian methods, a prior distribution of parameters is also taken into consideration, such that the prior distribution and the information that is derived from the data (i.e., the likelihood of data given the prior distribution) are combined by taking their product to determine the posteriori distribution of a parameter. In the current study, consistent with previous conventions pertaining to the use of Bayesian methods (e.g., Muthén & Asparouhov, 2012; Asparouhov, Muthén, & Morin, 2015), all variables are standardized at the individual response level before any model specification to ensure that the priors are set to a standardized scale for the coefficient estimates. Additionally, and also consistent with the abovementioned authoritative writings regarding Bayesian modeling, the paths estimated according to theoretical prediction (Fig. 3) are set as having uninformative priors (i.e., with infinite variances), which will essentially yield the same estimate results as the traditional frequentist methods. The paths that are not expected by theory (i.e., the connections that are not drawn in Fig. 3 between variables on the same level) are set as having small-variance informative priors, conforming to a distribution of $\sim N(0, 0.01)$. This essentially means that 95% of the standardized coefficient estimates for these non-hypothesized paths are expected to fall between -0.2 and 0.2, which is considered small. Compared to the exact zero setting for cross-loadings and the non-hypothesized structural paths used in traditional structural equation modeling (SEM), this setting of small priors serves the same function of restricting the paths that are not expected by theory but are more flexible and realistic (Muthén & Asparouhov, 2012). Using these settings, the posterior distribution of all parameters (both hypothesized and not) is reported. We also report the significance levels of the posterior estimates, although, under the Bayesian context, the significance levels have a somewhat different meaning (e.g., $p < .05$ suggests that the 95% credibility interval does not contain zero; see Muthén & Asparouhov, 2012; Zyphur & Oswald, 2015). The fit of the models is examined using the posterior predictive p values (PPP). A PPP of approximately 0.50 is considered a good fit; the lower the PPP is, the poorer the fit, and PPPs lower than 0.05 indicate a poor fit (Muthén & Asparouhov, 2012; Zyphur & Oswald, 2015).

Finally, after the estimation of the main models, the last step involves several additional complementary analyses. First, consistent with Muthén & Asparouhov (2012), in case the model estimates show clearly non-zero atheoretical paths, these paths are re-specified with uninformative priors, and the model is re-estimated. That is, although some paths are not theoretically expected and are given a prior of $\sim N(0, 0.01)$, the model may produce results that are substantively different from zero. To obtain estimates that are more reliable, we re-run the model with the priors for these paths adjusted to be uninformative. Second, we re-run models excluding those students who provided only one-time responses to our survey. This procedure is to obtain model estimations that are more relevant to the within-individual research question and is intended also as an additional robustness check for our original results. In addition, as will be shown in the following section, unexpected observations of our main results led us to conduct follow-up suppressor analyses and contextual effect analyses.

7. Results

7.1. Basic statistics

An inspection of the histograms and bivariate scatterplots generally supported the assumptions. Except for course grades, all variables generally conformed to a normal distribution. As mentioned in the Instrumentation section, the course grade variable has high skewness and kurtosis, even after inverse transformation. To some extent, a range restriction for learning climate is also observed: Consistent with the previous literature (Yu, Traynor, et al., 2018), the LCQ does not sufficiently reflect highly autonomy-supportive classrooms. All the bivariate scatterplots appear to support linear relationships with constant variance.

Table 3 also presents the ICCs of the variables, which are generally greater than 10% for all variables. In general, the current variables showed substantial clustering effects on both the between-student and the between-classroom levels.

7.2. Path models

7.2.1. Model results with one single needs satisfaction variable

The results of the multilevel cross-classified path model with an overall basic psychological needs satisfaction variable are shown in Fig. 4. The path model had a good fit: PPP = .539. The path coefficient estimates generally support our model: On all levels, including the within-individual, within-classroom level (which is our central concern), autonomy-supportive learning climate significantly positively predicts students' satisfaction of the basic psychological needs, which significantly predicts their self-determined motivation to study, which positively predicts their perceived learning gains. A few paths that were not hypothesized in our model also turned out to be significant. Most notably, autonomy-supportive learning climate has significant direct effects on self-determined motivation and on perceived learning gains, beyond the mediation path specified in our model. Another notable contradiction to our expectation is that grades are not significantly related to self-determined motivation on any level.

7.2.1.1. Follow-up models. Next, as introduced above, we followed up these findings with additional analyses. Given that the paths from autonomy-supportive learning climate to perceived learning gains is

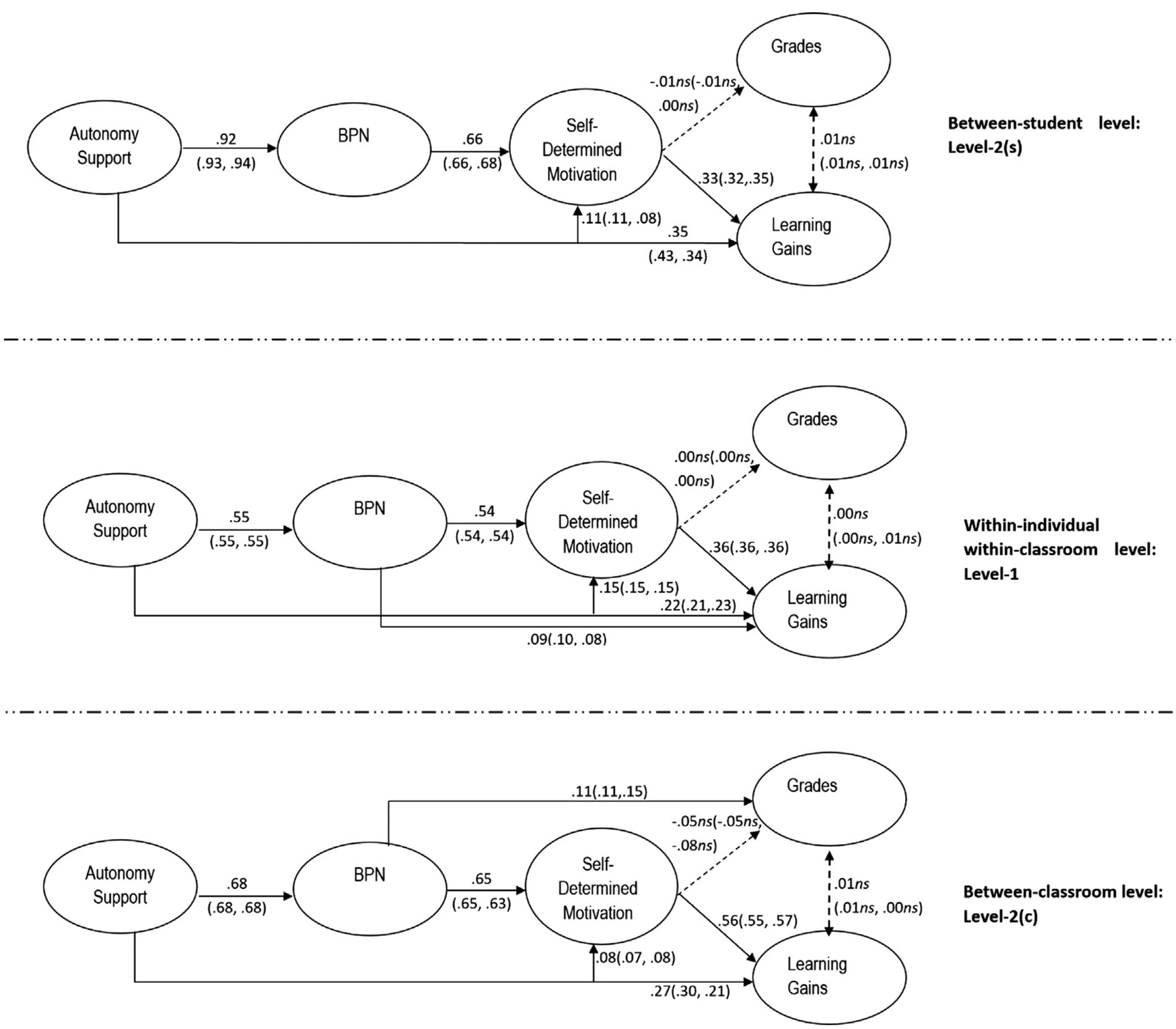

Fig. 4. Results of the cross-classified multilevel path model with one overall basic needs satisfaction variable in each level. BPN = overall basic psychological needs satisfaction. Estimates outside parentheses are from the original analyses; first estimates inside the parentheses are from follow-up analyses that adjusted the priors of clearly non-zero non-hypothesized paths; second estimates inside the parentheses are from follow-up analyses that excluded one-time respondents. All solid paths are significant at the $p < .05$ level. Dashed arrows are hypothesized relationships that are non-significant. Relationships that are not shown on the diagram are non-significant.

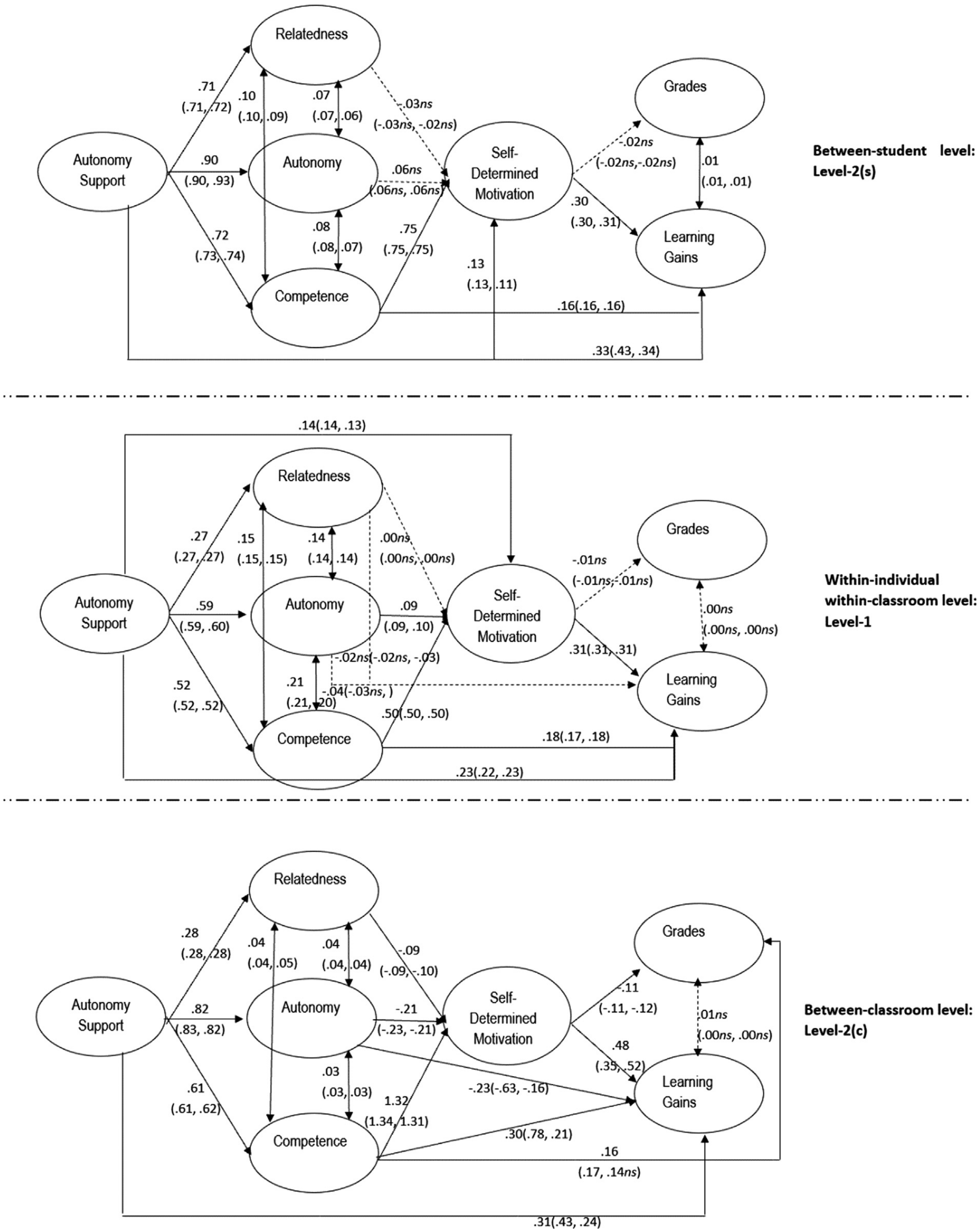

Fig. 5. Results of the cross-classified multilevel path model. Estimates outside the parentheses are from the original analyses; first estimates inside the parentheses are from follow-up analyses that adjusted the priors of clearly non-zero non-hypothesized paths; second estimates inside the parentheses are from follow-up analyses that excluded one-time respondents. All solid paths are significant at the $p < .05$ level. Dashed arrows are hypothesized paths that are non-significant or significant paths that are very weak (< 0.10). Relationships that are not shown on the diagram are non-significant.

clearly non-zero (i.e., > 0.20), we re-specified their priors to be uninformative and re-run the model. In addition, we re-run the model after removing one-time respondents. Both models showed good fits (PPP = .533 and 0.462, respectively). As shown in Fig. 4, the estimates outside the parentheses are the original results, the re-run results with adjusted priors are the first estimates in parentheses, and the re-run results with the dataset that excluded one-time respondents are the second estimates in parentheses. These additional models did not result in any change of the significance level of coefficient estimates, and all the changes are minimal in magnitude (< 0.10).

7.2.2. Model results with three separate needs satisfaction variables

The multilevel cross-classified path model results are shown in Fig. 5. The path model had a good fit: PPP = .451. As shown, on the within-individual, within-classroom level, which is our focus, many of the hypothesized effects are supported. For example, an autonomy-supportive learning climate has statistically significant positive effects on all three needs. Both autonomy and competence significantly positively predict self-determined motivation, which significantly positively predicts perceived learning gains. A few hypothesized effects are non-significant: Relatedness does not contribute to self-determined motivation, and grades are not predicted by any other variable. In addition, autonomy support seems to have statistically significant effects on self-determined motivation and perceived learning gains, and competence also has a statistically significant positive effect on perceived learning gains.

On the between-student level, the results are highly similar. Students who generally perceive higher autonomy support in the classroom also tend to perceive higher needs satisfaction. The only need that is statistically significant in predicting motivation is competence, such that students who generally feel competent in their classrooms are also generally self-determined with regard to taking those classes. Self-determined motivation significantly positively predicts higher perceived learning gains but not grades. Additionally, there appear to be direct effects of autonomy support on perceived learning gains and on motivation, such that students who generally perceive higher autonomy support also tend to have higher self-determined motivation and perceived learning gains across courses beyond those that can be accounted for by needs. Competence also has a statistically significant direct effect on perceived learning gains.

On the between-classroom level, the effects are less expected or interpretable. First, consistent with the other levels, learning climate predicts needs satisfaction; in other words, courses that have higher aggregated student ratings of autonomy support also tend to have higher aggregate student ratings of autonomy, relatedness, and competence satisfaction derived from these courses. However, while the effect of competence on self-determined motivation is statistically significant and positive, the effects of autonomy and relatedness on motivation are statistically significant (though weak) and negative. Competence also has a statistically significant positive effect on grades, whereas self-determined motivation has a statistically significant negative effect on grades. Competence and learning climate have positive effects on perceived learning gains, whereas autonomy has a negative effect on perceived learning gains.

7.2.2.1. Follow-up models. Again, we followed up the analyses with additional analyses that (1) adjust for the priors of clearly non-zero non-hypothesized paths and (2) use the dataset that excludes one-time respondents. Both models showed good fits (PPP = .492 and 0.465, respectively). The estimates from both additional analyses are shown in parentheses in Fig. 5. Most estimates did not have substantial differences between these additional models and the original model (changes in coefficient estimates < 0.10). The only exceptions are the effects of autonomy, competence, self-determined motivation and autonomy-supportive learning climate on perceived learning gains, on the between-classroom level. When the priors are adjusted to be uninformative for the non-hypothesized effects of learning climate, autonomy and competence on learning gains, the effect of competence changes from 0.30 to 0.78, the effect of autonomy changed from -0.23 to -0.63, the effect of autonomy support changed from 0.31 to 0.43, and the effect of motivation changed from 0.48 to 0.35.

7.2.2.2. Suppressor analysis. In the findings on the between-classroom level, although all the bivariate correlations are positive, as expected, some of the regression coefficients are negative, whereas others (e.g., the effect of competence on self-determined motivation) are larger than 1. This result is even more noticeable in the follow-up model where these unusual paths are given uninformative priors. This phenomenon is called the *suppression effect* (for more detailed explanations, see Maassen & Bakker, 2001).

When the suppressor effect occurs, it is suggested that one could identify the variables responsible for the unexpected negative predictive relationships (Maassen & Bakker, 2001). In the case of the current findings on the between-classroom level, three outcome variables demonstrated suppression effects: self-determined motivation, perceived learning gains, and grades. Because grades are positively predicted only by competence in addition to the negative effect of motivation, it is apparent that the stronger association between competence and grades has suppressed the effect of motivation on grades. Indeed, after removing competence from the model, the coefficient of self-determined motivation predicting grades changed from -0.11 to -0.03 ($p > .05$). This case is similar for motivation: Competence is the only positive (and very strong) predictor of motivation, while the other needs are negatively associated with motivation (-0.21 for autonomy and -0.09 for relatedness). Thus, the dominant effect of competence has clearly suppressed the effects of autonomy and relatedness. Indeed, after removing competence from the model, the coefficients of autonomy and relatedness became significantly positive (0.51 and 0.10, respectively, both $ps < 0.05$). For perceived learning gains, after removing the predictors one by one, we found that competence and learning climate are jointly responsible for the negative association between autonomy and perceived learning gains. After removing both variables, the coefficient of autonomy predicting learning gains changed from -0.23 to 0.22 ($p < .05$).

7.2.2.3. Contextual effects. Interestingly, for the paths that are statistically significant in the predicted direction on both level-1 and level-2 (i.e., learning climate to three basic needs and self-assessed learning gains, competence to self-determined motivation, and self-determined motivation to learning gains), the strengths of these paths on level-2 are generally stronger than those on level-1. For example, the relationships between learning climate and needs satisfaction are 0.27, 0.59, and 0.52 for relatedness, autonomy and competence, respectively, on level-1. However, these values are, respectively, 0.71, 0.90, and 0.72 on the between-student level and 0.28, 0.82, and 0.61 on the between-classroom level.

Given this discrepancy in the effects on different levels, we followed the recommendation made in multilevel research (e.g., Raudenbush & Bryk, 2002; Marsh et al., 2012) to test for the significance of contextual effects, which are the effects of the level-2 independent variables on the level-1 dependent variables, even after controlling for the corresponding effect of the level-1 independent variables. The effects on level-1 are subtracted from the corresponding effects on level-2, and the discrepancy effects are tested against the standard errors produced in *Mplus*. The results showed that many contextual effects are significant. For the between-classroom level, the effects of the classroom learning climate on the satisfaction of the three basic needs in a particular situation and the effect of classroom overall competence on self-determined motivation in a particular situation are significantly positive, after removing the corresponding level-1 effects. For the between-student level, the effects of the individual overall perception of learning climate on autonomy and competence satisfaction in a particular situation, the effect of overall individual competence on self-determined motivation in a particular situation, and the effect of overall self-determination on perceived learning gains in a particular situation, are significant, after removing the level-1 effects.

8. Discussion and conclusion

The main findings of the current study answered the main research question: After controlling for between-student and between-classroom level variations, at the within-student within-classroom level, the classroom climate predicts college students' satisfaction of the basic psychological needs for autonomy, relatedness, and competence, which in turn predict self-determined motivation, which in turn predicts self-assessed learning gains. The current findings highlight the importance of the need support, needs satisfaction (especially regarding competence), and self-determined motivational processes in the college learning context with a degree of methodological rigor (in terms of sample size, analytical framework, etc.) unprecedented in the previous literature.

8.1. Unexpected results

Although the main conclusion is largely consistent with our predictions, we also found several unexpected results. First, throughout our models and on almost all levels, learning climate also has a statistically significant direct effect on motivation and perceived learning gains, indicating that some of the effects of learning climate on motivation and learning outcomes are not explained by the three basic needs. This finding may be explained by recent research that attempts to identify additional need factors contributing to motivation (e.g., González-Cutre, Sicilia, Sierra, Ferriz, & Hagger, 2016; Martela, Ryan, & Steger, 2018). For example, González-Cutre et al. (2016) showed that there might be a fourth need beyond what has been suggested by SDT, namely, novelty. Human beings also need to experience something that they have not previously experienced or that deviates from their everyday routine. A more recent study (Jeno, Vandvik, Eliassen, & Grytnes, 2018) has also shown that this novelty factor may mediate the relationship between the learning environment and autonomous motivation and learning outcomes. In addition, competence predicts perceived learning gains beyond the effect of self-determined motivation. This result may be explained by the positive relationship between actual competence and actual learning gains.

Second, in our most comprehensive model involving all three needs, we found that competence has a dominant effect on self-determined motivation (whereas the effects of autonomy are weak, and the effects of relatedness are non-significant). This finding is consistent with previous suggestions by SDT researchers that the need for competence may be especially important for the educational setting (e.g., Jang, Reeve, Ryan, & Kim, 2009; Ryan & Deci, 2017). More generally, our finding of the importance of competence is also consistent with the view of competence as taking a central role in education by various traditions in educational psychology (Schunk, Meece, & Pintrich, 2012). In our view, this phenomenon does not mean autonomy and relatedness are unimportant for college education. Rather, the finding can be related to the proposition that motivation towards an activity could benefit from need satisfaction processes beyond the specific activity. That is, although autonomy and relatedness supported by the classroom may not be as important as competence for our college students, we posit that autonomy and relatedness support from other life domains (e.g., families, friends, or general life circumstances) may still play crucial roles. For example, a student would be likely to be self-determined in studying French if they have a French lover or if they appreciate the French cultural heritage and they have a life goal of living in France in the future. Indeed, previous research has supported the cross-domain effect of needs support (e.g., Hagger & Chatzisarantis, 2016; Legault, Green-Demers, & Pelletier, 2006; Milyavskaya et al., 2009; van der Kaap-Deeder, Vansteenkiste, Soenens, & Mabbe, 2017).

The third unexpected result is that course grades are not significantly associated with any other variable in the level-1 model. We do not believe that this result challenges the positive effects of self-determined motivation, given considerable previous evidence showing the effect of self-determined motivation on behavioral engagement and performance in specific learning tasks (e.g., Bao & Lam, 2008; Deci, Spiegel, Ryan, Koestner, & Kauffman, 1982; Jang, Reeve, & Deci, 2010; De Naeghel, Van Keer, Vansteenkiste, & Rosseel, 2012; Vansteenkiste et al., 2004; Vansteenkiste et al., 2005). Rather, we posit that this result may be because self-determined motivation is mostly predictive of deep learning and high-quality performance (as opposed to mechanistic rote learning; e.g., Benware & Deci, 1984; Vansteenkiste, Simons, Lens, Soenens, & Matos, 2005), but grades are frequently a mix of both or not quite reflective of high-level learning (e.g., Soenens, Sierens, Vansteenkiste, Dochy, & Goossens, 2012). As a result, grades cannot reliably positively associate with self-determined motivation. Indeed, past research has shown the relationship between grades and self-determined motivation to be largely inconsistent (e.g., Baker, 2004; Black & Deci, 2000; Chen & Jang, 2010; Conti, 2000; Guay, Ratelle, Roy, & Litalien, 2010; Guay & Vallerand, 1997; Hardre & Reeve, 2003; Soenens et al., 2012; Soenens & Vansteenkiste, 2005; Svanum & Aigner, 2011; Vansteenkiste et al., 2009).

8.2. General SDT model on the student and classroom levels

On the between-student and between-classroom levels, the patterns found on the within-student within-classroom level are generally replicated: Learning climate statistically significantly predicts all three needs, competence is the dominant predictor for motivation, and self-determined motivation is a relatively strong predictor of perceived learning gains.

One unexpected finding on the between-classroom level is the suppression effects. Because of the high multicollinearity between variables, the coefficient estimates of some predictors become negative, whereas others become larger than usual. Once again, this result highlights the importance of competence need satisfaction in college learning. In addition, the fact that the suppression effect is found only on the between-classroom level is consistent with the phenomenon discussed previously, i.e., the multicollinearity between independent variables may be especially strong at some higher levels. Overall, while results are reported for the higher levels, they are not the main results of the current study and should be interpreted with caution because of the non-equivalence of learning gains and grades (as introduced in the Instrumentation section) as well as other limitations noted below in the Other Considerations section.

We observed that the strength of the relationships at the higher levels is generally stronger than those on the within-student within-classroom level. This phenomenon may have several possible explanations. First, this result may be a statistical artefact. Hutchison (2007) suggested that, given measurement errors, in multilevel models, the regression coefficient estimate on level-2 may be biased, giving rise to spuriously larger estimates on higher levels compared to level-1. When the constructs have higher reliability on level-2 than on level-1 (which may be true in our analyses given our latent aggregations on level-2), the measurement errors largely reside within level-1, and they will bias downwards the estimates at level-1 and upwards the estimates at level-2.

A second explanation is that the effects considered in the current analyses may be inherently more about individuals and classrooms than about within-individual behaviors and psychological experiences. Indeed, recent research pointed out that the different mechanisms of how variables relate to each other may give rise to higher effects on the group-level than on the individual psychological level (e.g., Fisher et al., 2018; Na et al., 2010). For example, it is possible that self-determination processes are inherently concerned more with general individual needs satisfaction than with fluctuations for one individual in a specific situation (i.e., classroom). To use the diagram of multilevel data shown in Fig. 2, imagine each circle is an individual and each dot a situation within that individual. When the IV and DV are variables in the General Model, persons scoring high on the IV may also score high on the DV, but the relationship is weaker within the circles.

Another way to interpret the stronger effects on the higher levels is to consider the contextual effects. For example, on the between-classroom level, we found that being in a classroom with a high overall learning climate contributes to a students' basic psychological needs satisfaction in that classroom, even after considering the fact that the student's experience of autonomy support tends to be high in that particular situation. Similarly, being in a classroom with high overall competence predicts a student's self-determined motivation in that classroom, even after considering the fact that the student's experience of competence tends to be high in that particular situation. These contextual effects highlight the important influence that overall course environment has on individual student's self-determination, beyond the influence mediated by individual psychological mechanisms. Similarly, the significant contextual effects we found on the between-student level show that individual-difference level perceptions of autonomy support, competence and self-determination affect outcome variables in particular classrooms, even after accounting for the fact that the students tend to be higher on these independent variables in particular classrooms.

The current multilevel findings also provide support for the hierarchical model of motivation (Vallerand, 1997). Certainly, our model does not exactly examine Vallerand's (1997) model: We examine a between-classroom level model that is not covered in Vallerand's hierarchical model, and we could not examine the proposition for a recursive relationship between motivation at different levels. Nonetheless, our results on individual and classroom levels do provide support for Vallerand's proposition that the General Model functions on different levels of generalizability. Additionally, although Vallerand's hierarchical model is multilevel in nature, as empirical support he provided only between-individual level data, which could not disentangle the between-individual and within-individual effects. To our knowledge, we are also the first to provide truly multilevel testing for Vallerand's hierarchical model (relationships between context, needs satisfaction, motivation and outcomes on individual and classroom levels).

8.3. Other considerations

To the best of our knowledge, the current study is one of the first to apply a cross-classified ML-SEM framework to educational research; it is also the first to apply cross-classified ML-SEM to examine SDT propositions. The current research provides some implications for the use of this method. First, the current research demonstrated the feasibility of using cross-classified SEM to simultaneously control for individual student and classroom variations and to estimate relatively complex models. However, this feasibility seems to be limited to path models only. We also tried full models in which the level-1 variables are represented by latent variables; however, the latent measurement models could not be replicated on higher levels. This result suggested that the observed items may not factor into the same latent constructs the same way on different nesting levels. Second, the path models on different levels showed substantial similarity, although it is uncertain whether this similarity is limited to the characteristics of only the current dataset. Third, one limitation suggested by the current findings is that, on some levels, the correlations between constructs may be so high that the multicollinearity will cause suppressor effects to occur. Thus, future studies that aim to apply this method should do so with caution.

The current study has several limitations. First, the data are collected from courses that underwent a transformation project in one university in the Midwestern US, and how much of an impact this aspect has on the generalizability of our findings to all courses in all universities is unknown. Nonetheless, we believe that these limitations are minimal because, otherwise, we would observe a large difference between students who participated in a large number of our transformed courses vs. those who participated in the transformed courses only once. This is not the case, as is demonstrated in Table 2 and in the Data section. Future studies may run this model in non-transformed courses and compare the results with the current findings.

Second, although the model intended to incorporate all variables typically examined in SDT, a few variables of important conceptual interest, such as well-being and vitality, are not included. In particular, as a learning outcome, course grades did not function well in the current analyses; future studies should incorporate other types of learning outcomes, such as behavioral engagement, using real learning assignments. Similarly, we found the need for competence to be the most important need in college classrooms; however, the current model does not examine classroom environments that are supposed to specifically contribute to satisfying this need (e.g., by providing structure). Future studies should also incorporate measurements of classroom support that are directly related to competence. Third, relatedly, learning climate is measured by student self-reports. Future studies should use more objective or multi-informant measures to reduce common method bias. Fourth, the model itself cannot differentiate the temporal precedence between variables, and longitudinal models that are more specialized for testing temporal precedence should be employed in the future. Fifth, the model emphasizes the relationships between need support, needs satisfaction, motivation, and normative or positive learning outcomes, whereas recent research has started to differentiate the negative side of the model, in which need-thwarting environments make a unique contribution to needs frustration, which, in turn, contributes to non-self-determined motivation and negative outcomes (e.g., Cheon et al., 2018). Future studies could aim to differentiate these different sides of the model.

Sixth, although we interpreted the statistically significant effects, some of the effect sizes are small. For example, although the effects of autonomy on self-determined motivation are significant on the within-individual and between-classroom levels, both are below 0.30, which can be considered small. The practical significance of the effects should be considered when interpreting our results. Relatedly, the interpretation of the practical significance of the higher-level effects is especially difficult, given that they explain only the variance that is partitioned to that level (e.g., Raudenbush & Bryk, 2002). Hence, for example, even a large effect on a higher level may not have substantial significance if the ICC of that variable on that level is particularly low. Seventh, the focus of our research is on the within-individual, within-classroom level. Although we also provide estimations for the between-student and between-classroom levels, the estimates on the higher levels need to be interpreted with caution because the higher-level models have their own confounding factors. For example, the courses themselves are nested in majors, which systematically differ in how they organize the courses. One example is that science courses may tend to curve their grades more than courses in social sciences or humanity majors, which causes clustering of course grades on the between-classroom level. We are unable to account for these more complex issues in our analysis because, first, our focus is on the within-individual, within-classroom level, and second, the modeling software currently does not have the computing power to consider more confounding factors on higher levels.

8.4. Concluding remarks

The current study supports various propositions in the general SDT model at the within-individual, within-classroom level. We find that a given student's perception of the classroom as autonomy-supportive predicts that student's higher level of autonomy, relatedness, and competence need satisfaction within that classroom; the satisfaction of these basic psychological needs (especially autonomy and competence) in turn predicts higher levels of self-determined motivation towards learning for that course, which explain higher levels of self-reported learning gains compared to other students in that course. Unexpected findings that may be illuminating of college education include the unique importance of competence in college learning experiences and the direct effects of learning climate. Overall, our study contributes to the literature by providing insights into the dynamics of self-determination at the within-individual level and especially in college classrooms; our research also serves as a reference point for future investigations using the cross-classified modeling approach in education.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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