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Need Satisfaction, Motivation, and Learning Strategies in Undergraduate Kinesiology Students

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ABSTRACT

The purpose of this study was to examine the influence of basic psychological need satisfaction and motivation on students' use of deep and surface learning strategies across undergraduate kinesiology courses. This study used a survey consisting of demographic questions and three self-report questionnaires assessing basic need satisfaction, motivation, and deep and surface learning strategies. The survey was administered via Qualtrics at the end of two semesters (fall 2020 and spring 2021). The participants consisted of 1,125 undergraduate kinesiology students (81.9% female, 55.3% white, 94.8% non-Hispanic) at a midsize university in the southeastern part of the United States. Path modeling showed that intrinsic motivation was influenced by autonomy, competence, and relatedness, while identified regulation was influenced by autonomy and competence. Relatedness also influenced both introjected regulation and external regulation. Participants' intrinsic motivation and identified regulation negatively predicted surface learning strategies while external regulation positively predicted surface learning strategies. Intrinsic motivation and identified motivation predicted deep learning strategies. Interestingly, all three basic psychological needs predicted deep learning strategies. These findings underscore the importance of satisfying basic needs to influence motivation and, in certain cases, learning strategies. While it is evident that the use of deep learning strategies would be highly beneficial for this group of learners, kinesiology students may not rely on these strategies due to a lack of intrinsic motivation and basic need satisfaction. Although future research is necessary to test the causal links between these constructs, supporting students' basic psychological needs and fostering intrinsic motivation could contribute to the use of deeper learning strategies.

KEYWORDS

Self-determination theory; higher education; exercise science; allied health

As one of the fastest-growing academic fields, kinesiology has seen "a growth of knowledge, and an increase in the breadth of contexts in which this knowledge is applied" (Pennington & Brock, 2021). Kinesiology graduates pursue a variety of careers and work in different settings that include medical, clinical, educational, psychosocial, corporate, and sports environments, as well as pursuing advanced degrees. Because kinesiology graduates may apply their knowledge to a variety of fields and domains, they must gain a deep understanding of course concepts while in college.

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To prepare students for success in kinesiology programs and their later careers, faculty are encouraged to implement high-impact practices, work-integrated learning, and teaching methods that focus on improving important foundational skills (e.g., quantitative literacy, information literacy, teamwork skills) (Nadrljanski et al., 2020). However, the implementation of these practices may not be effective if students do not have the motivation and skills to engage in learning. Indeed, researchers have emphasized the role of study strategies in understanding the material, developing clinical reasoning skills, and applying course concepts in practice upon graduation (Chodzko-Zajko, 2014; Elvén et al., 2019). In addition, researchers have noted that motivation is oftentimes an important precursor to the learning strategies implemented by students (Zimmerman & Schunk, 2012). Thus, to facilitate students' success in kinesiology, it is imperative for researchers and instructors to understand kinesiology students' learning strategies and the motivational precursors to these learning strategies. Developing a deep understanding of motivation and learning strategies in kinesiology is an initial step in developing interventions aimed at improving these characteristics in learners.

Learning strategies

"Approaches to learning," initially described as levels of processing, are one way to conceptualize students' engagement in learning (Marton & Saljo, 1997). They are firmly established in the research literature (Entwistle, 1991; Marton & Saljo, 1997) and are classified as deep and surface learning approaches. For clarity, we will use the terms deep learning strategies and surface learning strategies to better align with the current literature across disciplines. Learning strategies characterize the different ways that students may engage in academic tasks (Biggs et al., 2001; Zusho, 2017), thus, they relate to the learning process (e.g., *how* students engage with the material). Surface learning strategies are those used to meet the minimal requirements of a particular academic task. This usually includes activities such as note-taking, highlighting underlining, and rote memorization (J. Hattie & Donoghue, 2016). Deep learning strategies refers to the strategies that a student uses to gain competence in a particular area. This includes activities such as elaboration and organization and is intended to maximize understanding. J. A. C. Hattie (2009) described students using deep learning strategies as "self-regulated." J. Hattie and Donoghue (2016) argue that if students are to apply knowledge in a new context (transfer), which is the hope for kinesiology graduates, deep learning strategies are necessary. Multiple factors influence whether a student chooses to implement surface or deep learning strategies. They include contextual factors (such as subject, content, discipline, and characteristics of teaching methods), perceived contextual factors (such as workload and relevance to professional practice), and student factors (including age, gender, and year in school) (Baeten et al., 2010).

Although it is hypothesized that students may use different strategies when completing tasks in different disciplines, empirical support is mixed. Some cross-disciplinary (nursing, engineering, medicine, health sciences, and medicinal chemistry) studies did not find significant differences in the use of learning strategies among discipline groups (Salamonson et al., 2013), but other research suggests that class content, subject area, and discipline influence the use of different learning strategies (Baeten et al., 2010; Coertjens et al., 2016). In a previous study, students in content areas like arts and social sciences showed extensive use of deep learning strategies (Baeten et al., 2010), yet there is a paucity of studies exploring these learning strategies in kinesiology students. Additionally, studies focused on kinesiology students tend to examine the outcomes of using effective learning strategies, rather than the antecedents of these strategies, including motivation for learning. For example, some research in anatomy showed that the use of deep learning strategies was associated with successful cadaveric dissection and students' appreciation for working with cadaveric material (Smith et al., 2014; Wang & McWatt, 2023). Graduate allied health students in occupational therapy and physical therapy reported using both surface and deep learning strategies. Interestingly, those with lower mental health ratings were more inclined to employ surface learning strategies (DaLomba et al., 2021). To provide a more comprehensive understanding of the learning process, knowing how kinesiology students are motivated to learn could provide more insight into the process of adopting specific learning strategies.

In general, prior research has found that the types of learning strategies students implement have different relationships with academic performance. For example, deep learning strategies have consistently been found to predict positive academic outcomes including academic performance, achievement, and grade point average (Bonsaksen et al., 2017; Everaert et al., 2017; Liem et al., 2008; Sæle et al., 2017). However, the findings on surface learning strategies are more divergent. While some research has suggested that the use of surface learning strategies negatively predicts academic performance (Bonsaksen et al., 2017; Everaert et al., 2017) and achievement (Liem et al., 2008), others did not find a statistically significant relationship to academic achievement (Sæle et al., 2017).

Taken together, it is clear that the types of learning strategies students adopt are related to academic performance. Thus, it is imperative for researchers to better understand the antecedents to these strategies to begin to identify how to facilitate students' use of effective learning strategies. In identifying potential antecedents to academic performance, basic psychological need satisfaction and motivation, as explained via self-determination theory, have been investigated previously. The vast majority of studies conducted in education tend to show a direct relationship between satisfaction of basic psychological needs and motivation. In turn, motivation tends to influence academic engagement, academic achievement, or general well-being outcomes (Vasconcellos et al., 2020). As an example, Karimi and Sotoodeh (2020) found that basic psychological needs had both direct and indirect relationships with academic engagement among agriculture students. The indirect relationships observed were carried through students' intrinsic motivation. Because of the connections between learning strategies and academic performance, it is possible that basic need satisfaction and motivation could also be tied to learning strategies. If that is the case, there could be concrete suggestions available for instructors in kinesiology to enhance motivation, which might lead to increased use of deep learning strategies throughout a kinesiology program.

Academic motivation and basic psychological need satisfaction

Self-determination theory delineates students' motivation along a continuum of regulatory styles, encompassing both autonomous and controlled forms. On one hand, autonomous motivation comprises intrinsic motivation (engaging in an activity for the sheer enjoyment of it) and identified regulation (engaging because it is personally important; Ryan & Deci, 2019). Individuals driven by autonomous motivation participate in activities out of personal desire and choice. On the other hand, controlled motivation includes introjected regulation (engaging due to internal pressures) and external motivation (engaging to obtain or avoid an external consequence). Those inclined toward more controlling motivation often engage in learning because they feel obligated or seek external rewards (Ryan & Deci, 2019).Though not measured in this study, amotivation could also be incorporated into the continuum, denoting a complete lack of motivation.

These distinct motivational beliefs emanate from the satisfaction of three fundamental psychological needs: autonomy, competence, and relatedness (Ryan & Deci, 2000). Autonomy underscores students' requirement for control and choice in what and how they learn, including their willingness to engage with the belief that the decision to do so originates from within. Instructors foster autonomy by presenting information relevant to students' preferences and goals, alongside providing choices conducive to those goals. Competence pertains to students' need to feel capable of successfully completing tasks, while relatedness addresses their need for connection with peers and instructors. From a student's perspective, autonomy would involve the student seeing and feeling the connection between the material being learned and their personal goals. In addition, being provided with choice and agency could enhance motivation for learning. For example, a kinesiology student could have the opportunity to write lab reports on a topic of their choosing and/or be given options for presenting different concepts in a biomechanics course. Using this same example, competence could be nurtured through a student's feeling of confidence in knowing how to correctly apply biomechanical principles to exercise instruction. Assignment choice could also enhance relatedness, through the students' feeling of connection to other students who might want to work on the same topic or have similar career interests.

Previous research has indicated that students' use of learning strategies is a product of their motivation and can lead to academic engagement and achievement (Entwistle, 2000). Instructors can play a crucial role in actively fostering intrinsic motivation for learning, moving beyond conventional content delivery to create an engaging learning experience for students. Student-centered learning environments are associated with increased use of deep learning strategies and enhanced student need satisfaction (Baeten et al., 2010; Mauldin et al., 2022). Satisfied needs correlate with intrinsic motivation, leading to a greater likelihood of learning and achievement of course objectives (Hsu et al., 2019). Intrinsically motivated students dedicate more time to studying, employ deep learning strategies, and demonstrate superior academic performance (Abdel Meguid et al., 2020; Everaert et al., 2017). Additionally, intrinsic motivation has been identified as a negative predictor of surface learning, while extrinsic motivation positively predicts deep learning, though not surface learning strategies (Everaert et al., 2017). Despite these connections between motivational beliefs and learning strategies, research has yet to comprehensively explore the interplay among need satisfaction, motivational beliefs, and learning strategies in a single study.

In kinesiology clinical education, the adoption of deep learning approaches becomes especially significant. These approaches not only enhance academic understanding, but also contribute to a more effective application of knowledge in real-world clinical scenarios. For a student to properly design an exercise program for a client, they must first know how the body works and moves, in addition to knowing when specific exercises should be applied.

As students engage in critical deep learning, they are better equipped to navigate the complexities of clinical responsibilities, ultimately ensuring a positive impact on their patients. Understanding students' use of learning strategies is vital to designing interventions that teach students *how* to learn in addition to *what* to learn.

Current study

The purpose of this study was to determine if basic need satisfaction and motivation were predictors of deep and surface learning strategies among a large sample of undergraduate students enrolled in a kinesiology program. We examined this through an exploratory path model, focusing on autonomy, competence, and relatedness. Motivation was also investigated via the separate regulatory styles of intrinsic, identified, introjected, and external regulation. Because the model was exploratory, we opted to test the connections between all basic psychological need constructs to all regulatory styles. Similarly, all regulatory styles had paths leading to both surface and deep learning strategies. Figure 1 shows an illustration of the exploratory model. Path modeling was chosen in this instance because of the use of observed variables instead of latent variables, allowing for multiple regression pathways to be tested at once, both direct and indirect, without increasing error.

Methods

Participants

The participants consisted of 1,036 undergraduate kinesiology students at a midsize, southeastern United States university, enrolled in kinesiology core classes. For brevity, the largest percentages of demographics are mentioned here, but the full list of demographic information is listed in Table 1. While age was not collected, students were mostly in their freshman

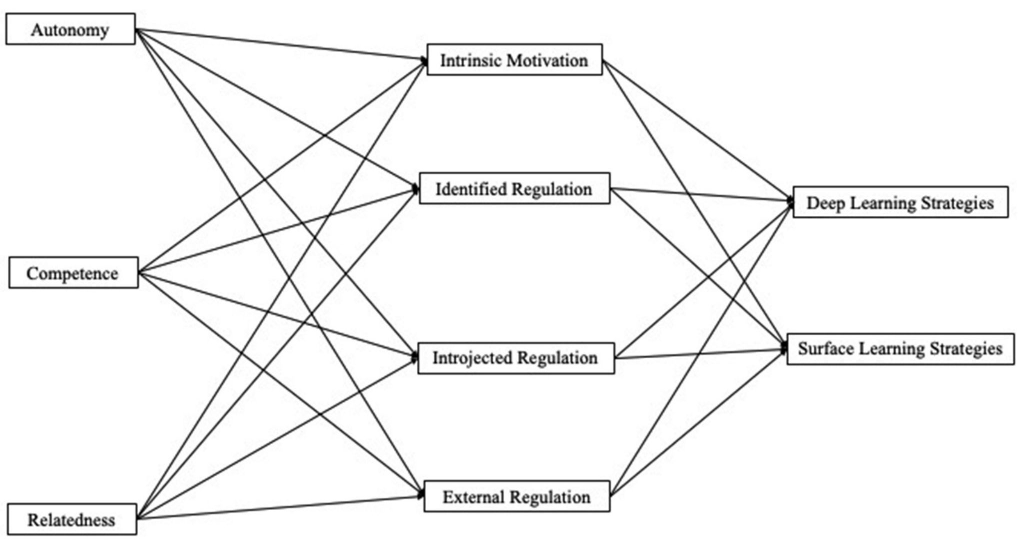

Figure 1. Hypothesized model predicting deep and surface learning strategies. For clarity, covariances are not depicted in the figure.

Table 1. Participant demographics.

Category		N (%)	Category		N (%)
Gender	Male	187 (18.1%)	Current Major	Exercise Science	690 (66.6%)
	Female	848 (81.9%)		Nursing	180 (17.4%)
	Prefer Not to Say	1 (.1%)		Biology	31 (3%)
Race	White	576 (55.9%)		Public Health	20 (1.9%)
	African American	386 (37.4%)		Nutrition	10 (1%)
	Asian	20 (1.9%)		Athletic Training	8 (.8%)
	American Indian/ Alaskan Native	9 (.9%)		Chemistry	8 (.8%)
	Other	35 (3.4%)		Other	76 (7.3%)
Ethnicity	Hispanic or Latino	54 (5.3%)		Health and Physical Education	13 (1.3%)
	Not Hispanic or Latino	971 (94.7%)	Likelihood to Continue with Current Major	Not at all likely	25 (2.4%)
Class Standing	Freshman	277 (26.8%)		Somewhat unlikely	33 (3.2%)
	Sophomore	369 (35.7%)		Neither unlikely nor likely	28 (2.7%)
	Junior	212 (20.5%)		Somewhat likely	185 (17.9%)
	Senior	153 (14.8%)		Very likely	763 (73.8%)
	Other	23 (2.2%)	Desired Career Path	Physical Therapy	172 (16.6%)
Approximate GPA	<2.00	15 (1.5%)		Occupational Therapy	63 (6.1%)
	2.00–2.49	70 (6.8%)		Physician's Assistant	80 (7.7%
	2.50–2.99	210 (20.3%)		Athletic Training	8 (.8%)
	3.00–3.49	410 (39.7%)		Nursing	439 (42.4%)
	3.50–4.00	327 (31.7%)		Personal Training	16 (1.5%)
				Strength and Conditioning	14 (1.4%)
				Coaching	13 (1.3%)
				Other	190 (18.3%)

(26.8%) or sophomore year (35.7%). A majority of the participants identified as female (81.9%), not Hispanic (94.7%), and white (55.9%). The participants' career aspirations included nursing (42.4%), physical therapy (16.6%), and other (18.3%). Within the other category, participants indicated desired careers as doctors, physician's assistants, cardiac rehabilitation specialists, medical/pharmaceutical sales representatives, chiropractors, exercise physiologists, and researchers. Overall, participants reported that they were very likely (92%) to continue with their current major.

Most students were enrolled in lower division kinesiology courses (73.9%), while the remaining 26.1% were in upper division kinesiology major courses. Table 2 outlines the courses surveyed, descriptions of the courses, and the number of students who completed surveys in each course. It is important to note that there was some variation in the structure of the courses students were enrolled in; some of the courses consisted of a lecture and lab component, while others relied solely on lecture format. Courses were also delivered in a variety of modalities, including traditional face-to-face, hybrid, and online.

Instrumentation

This study utilized a survey consisting of demographic questions (nine items) and three measures assessing basic need satisfaction (20 items), motivation (32 items), and learning strategies (20 items). The survey was administered via Qualtrics near the end of the fall 2020 and spring 2021 semesters by providing a link via the classroom management system in the kinesiology courses listed in Table 2. Students completed the survey outside of their scheduled classroom time. Because modifications were made to each instrument to align

Table 2. Course names, descriptions, and participant frequencies.

Course Prefix	Course Name	Description	N (%)
KINS 2531	Anatomy and Physiology I	A two-semester sequence in which human anatomy and physiology are studied using a body systems approach, with emphasis on the interrelationships between form and function at the gross and microscopic levels of organization. Course content includes basic anatomical and directional terminology; fundamental concepts and principles of chemistry and cell biology; histology; the integumentary, skeletal, muscular, and somatic nervous systems and special senses.	484 (46.9%)
KINS 2532	Anatomy and Physiology II	A two-semester sequence in which human anatomy and physiology are studied using a body systems approach, with emphasis on the interrelationships between form and function at the gross and microscopic levels of organization. This course is a continuation of KINS 2531 and includes the endocrine system, autonomic nervous system, cardiovascular system, lymphatic system and immunity, respiratory system, digestive system and metabolism, urinary system, fluid/electrolyte and acid/base balance, and reproductive systems.	278 (27%)
KINS 2535	Intro to Exercise Science	A career-based introduction to the field of Exercise Science and the Exercise Science major. Students will explore resources that can enhance their academic and career goals. Students will also meet medical, health promotion, and fitness professionals, as well as representatives from graduate schools, that can help them learn more about career requirements and opportunities in these fields.	29 (2.8%)
KINS 3130	Research Methods in Kinesiology	Introduces the student to fundamental principles underlying research methods in kinesiology. Included will be basic procedures for conducting experimental, descriptive, correlational, and qualitative research, computer applications, basic measurement concepts, statistical methods, critical thinking, and scholarly writing. Prerequisite(s): KINS 2535 or permission of instructor.	73 (7.1%)
KINS 3132	Introduction to Sport and Exercise Psychology	Introduces the student to how individuals behave in physical activity settings. Psychological antecedents and consequences of primary and secondary involvement in exercise and sport will be explored.	17 (1.6%)
KINS 3541	Structural Kinesiology	This course surveys biological systems and physical principles as applied to human movement and the relationship of these systems and principles to the development of the study of human movement. Prerequisite(s): A minimum grade of “C” in KINS 2511 and KINS 2512 and KINS 2531 and KINS 2532.	36 (3.5%)
KINS 3542	Physiological Aspects of Exercise	Provides an in-depth perspective of the physiological and biochemical responses of the human body when subjected to exercise. Prerequisite(s): A minimum grade of “C” in KINS 2535, KINS 3130, KINS 3541 or permission of instructor.	34 (4.7%)
KINS 3543	Biomechanical Analysis of Movement	Focuses on the study of human motion through an examination of forces acting on the body and the effects produced by these forces.	11 (1.1%)
KINS 3230	Motor Control, Coordination, and Skill	Focuses on the nature of motor skill performance, motor skill learning, and the factors influencing motor skill acquisition.	31 (3%)
KINS 4231	Fitness Evaluation and Exercise Prescription	Provides the student with an in-depth study of fitness appraisal and exercise prescription and the development, interpretation, implementation, and management of fitness programs.	24 (2.3%)

with the study goals and class contexts, we conducted a confirmatory factor analysis (CFA) with our entire sample. Based on the CFA, items were trimmed. The ultimate goal of trimming items was to ensure the items were measuring each construct.

Basic need satisfaction

The Basic Need Satisfaction in Sport Questionnaire (Ng et al., 2011) typically measures how well an athlete's basic needs of autonomy, competence, and relatedness are supported. For the current study, the questionnaire was modified to include "this course" rather than "my sport." CFA was conducted to ensure the validity of the instrument. Items that demonstrated a low factor loading were trimmed, thus items were trimmed from the autonomy subscale. These items tended to reflect the actions students can take in class to guide the activities and assignments (e.g., "I have a say in how things are done."). In addition, one item that was reverse coded was trimmed. The items used in the analysis included 14 items that measured three constructs: autonomy, relatedness, and competence. Students' responses to each item were recorded on a 7-point Likert scale (1 = not true at all, 7 = very true). The questionnaire included statements such as "I can overcome challenges in this course" (competence), "In this course, I feel I am pursuing goals that are my own" (autonomy), and "In this course, I feel close to other people" (relatedness). Competence was measured using five items, autonomy was measured using four items, and relatedness was measured using five items. After trimming items, we examined the internal consistency reliability of each subscale using Cronbach's alpha. All constructs were found to be reliable: competence ($\alpha = .87$), autonomy ($\alpha = .90$), and relatedness ($\alpha = .92$).

Academic motivation

The second questionnaire used was the Academic Motivation Scale (Vallerand et al., 1992). This questionnaire measured four different types of motivation regulatory styles: intrinsic, identified, introjected, and external. Although some versions contain an amotivation subscale, it was not included in the current study. This instrument included four overarching questions that prompted students to reflect on different academic experiences: "Why do I do homework?," "Why do I do classwork?," "Why do I try to answer hard questions in class?," and "Why do I try to do well in the class?" Then, students read statements that coincided with each prompt and rated the extent to which each statement was true of them. Example response statements included "because it's fun" (intrinsic), "because I want to understand the subject" (identified), "So my instructor will think I'm a good student" (introjected), and "because I'll get in trouble if I don't do well" (external). Regulatory styles were scored by averaging the items that correspond to each construct. Validity was confirmed by prior research (Guay et al., 2017). Following trimming, the Academic Motivation Scale included 15 items. Items were trimmed from the Academic Motivation Scale due to their low factor loading and based on either lack of alignment with theoretical constructs or confusing wording. The intrinsic subscale included four items, the identified subscale included four items, the introjected subscale included three items, and the external subscale included four items. The current study's internal consistency reliabilities, calculated using Cronbach's alpha were favorable: intrinsic motivation ($\alpha = .89$), identified regulation ($\alpha = .76$), introjected regulation ($\alpha = .90$), and external regulation ($\alpha = .77$).

Learning strategies

Lastly, the Revised Two Factor Study Process Questionnaire (R-SPQ-2F; Biggs et al., 2001) was used to assess students' deep and surface learning strategies. The questionnaire consists of items that measure four study processes: deep motive, deep strategy, surface motive, and surface strategy. Per published instructions (Biggs et al., 2001), students responded on a 5-point Likert scale using letters A-E. A represents "this item is never or rarely true of me" and was given a score of 1, and E represents "this item is always or almost always true of me" and was given a score of 5. Examples of the items are as follows: "I find that at times studying gives me a feeling of deep personal satisfaction" (deep motive), "I make a point of looking at most of the suggested readings that go with the lectures" (deep strategy), "I see no point in learning material which is not likely to be in the examination" (surface motive) and "I find the best way to pass examinations is to try to remember answers to likely questions" (surface strategy). To score the questionnaire, items corresponding to deep motive and deep strategy are summed to create an overall deep learning strategies score. In addition, items corresponding to surface motive and surface strategy are summed to create an overall surface learning strategies score. Biggs et al. (2001) found acceptable reliability and validity. After trimming based on the initial CFA results, the Two Factor Study Process Questionnaire included 11 items. Items were cut based on low factor loading and specificity of the item. On examining the items closely alongside their factor loadings, the authors realized that items that were too specific or too general may have created challenges for students when completing the survey. The surface learning strategies subscale included four items, while the deep learning strategies subscale included seven items. Further, the internal consistency reliabilities of deep learning strategies ($\alpha = .81$) and surface learning strategies ($\alpha = .71$) were favorable. Because the items in each subscale were reduced, a mean value for each was calculated and used for analysis.

Data analysis

The goal of the CFA was to evaluate the reliability of the modified items. To evaluate model fit, we report results from the Chi-square test along with the CFI, TLI, RMSEA, and SRMR. We used the cutoffs described by Hu and Bentler (1999) to assess model fit. The initial model demonstrated poor fit indices ($\chi2(2448) = 12482.07$, $p < .001$, CFI = 0.72, TLI = 0.71, RMSEA = 0.06, SRMR = 0.08). For an overview of standardized factor loadings for each item prior to trimming, see Tables 3–5. Thus, we examined each item to identify potential reasons for low factor loadings (Brown, 2006). For example, we considered whether items were unintentionally worded in a confusing manner. As another example, we considered the alignment of each item with the latent construct it intended to measure. Based on this examination and results from this confirmatory factor analysis (i.e., fit indices and standardized factor loadings), items were trimmed from each subscale. After trimming items, we re-ran the model and it demonstrated acceptable fit ($\chi2(704) = 2144.91$, $p < .001$, CFI = 0.93, TLI = 0.93, RMSEA = 0.04, SRMR = 0.04).

After running the CFA, we tested all variables against statistical assumptions associated with path analysis, including testing for multicollinearity. Tolerance values were within a normal range, indicating that this assumption had been met. Descriptive statistics and scale reliabilities were also run, using SPSS v. 27 and we calculated the new variables to represent the mean values of all constructs in the model, including autonomy, competence, relatedness, intrinsic motivation, identified regulation, introjected regulation, external regulation, deep learning strategies, and surface learning strategies. Our general approach followed the steps outlined by Kline (2016). Following model identification, we used the

Table 3. Standardized factor loadings from the confirmatory factor analysis of the basic need satisfaction.

	Standardized Factor Loadings		
Item	Competence	Autonomy	Relatedness
1. I can overcome challenges in this course.	0.65		
2. I am skilled at the subject matter in this course.	0.79		
3. I feel I am good at this course.	0.86		
4. I get opportunities to feel that I am good at this course.	0.78		
5. I have the ability to perform well in this course.	0.68		
*6. In this course, I get opportunities to make choices.		0.59	
*7. In this course, I have a say in how things are done.		0.54	
*8. In this course, I can take part in the decision-making process.		0.60	
*9. In this course, I get opportunities to make decisions.		0.63	
10. In this course, I feel I am pursuing goals that are my own.		0.83	
11. In this course, I really have a sense of wanting to be there.		0.87	
12. In this course, I feel I am doing what I want to be doing.		0.84	
13. I feel I participate in this course willingly.		0.72	
*14. In this course, I feel that I am being forced to do things that I don't want to do.		0.14	
*15. I choose to participate in this course according to my own free will.		0.51	
16. In this course, I feel close to other people.			0.79
17. I show concern for others in this course.			0.77
18. There are people in this course who care about me.			0.89
19. In this course, there are people who I can trust.			0.88
20. I have close relationships with people in this course.			0.82

*indicates an item that was trimmed.

Lavaan package in R to test our hypothesized model. Model fit was evaluated using several criteria, including chi-square likelihood ratio (with a ratio of 3:1 deemed acceptable (Gefen et al., 2000), comparative fit index (CFI; acceptable fit greater than .95), Tucker-Lewis index (TLI, acceptable fit greater than .95), and root mean square error of approximation (RMSEA; acceptable fit less than .05) (Hu & Bentler, 1999), and inspection of unstandardized and standardized parameter estimates. Direct and indirect effects were examined as well, with estimates of .50 or higher indicating a large effect, .30–.49 indicating a medium effect, and .10–.29 indicating a small effect (Suhr, 2008). Modification indices were also consulted when needed to improve model fit.

Results

Mean values, Cronbach alpha, and correlations among all constructs are reported in Table 6. Of note are the strong relationships between deep learning strategies and autonomy, competence, intrinsic motivation, and identified regulation. The initial fit for the hypothesized model was poor (χ^2 (9) = 121.81, $p < .001$; $\chi^2/df = 13.53$, CFI = .96, TLI = .83, RMSEA = .11), thus respecification was necessary. Respecification was guided by theory, modification indices, and non-significant parameter estimates (Kline, 2016). Self-determination theory emphasizes a strong connection between psychological need satisfaction and motivation (Ryan & Deci, 2000), thus when respecifying our model we maintained the connection between basic psychological need satisfaction and motivation. In addition, researchers have emphasized that motivation predicts students' use of learning strategies (Zimmerman & Schunk, 2012), thus we maintained the connection between students' motivation, deep learning strategies, and surface learning strategies. When considering how particular psychological needs predicted motivation and, in turn, how specific

Table 4. Standardized factor loadings from the confirmatory factor analysis of the academic motivation questionnaire.

	Standardized Factor Loadings			
Item	External Regulation	Introjected Regulation	Identified Regulation	Intrinsic Motivation
2. Why do I do my homework?: Because I'll get in trouble if I don't.	0.72			
*6. Why do I do my homework?: Because that's what I'm supposed to do.	0.32			
9. Why do I work on my classwork?: So that the instructor won't yell at me.	0.71			
*14. Why do I work on my classwork?: Because that's the rule.	0.57			
*20. Why do I try to answer hard questions in class?: Because that's what I'm supposed to do.	0.43			
24. Why do I try to answer hard questions in class?: Because I want the instructor to say nice things about me.	0.57			
*25. Why do I try to do well in school?: Because that's what I'm supposed to do.	0.42			
28. Why do I try to do well in school?: Because I will get in trouble if I don't do well.	0.67			
*32. Why do I try to do well in school?: Because I might get a reward if I do well.	0.40			
1. Why do I do my homework?: Because I want the instructor to think I'm a good student.		0.85		
*4. Why do I do my homework?: Because I will feel bad about myself if I don't do it.		0.40		
10. Why do I work on my classwork?: Because I want the instructor to think I'm a good student.		0.91		
*12. Why do I work on my classwork?: Because I'll be ashamed of myself if it didn't get done.		0.39		
*17. Why do I try to answer hard questions in class?:Because I want the other students to think I'm smart.		0.47		
*18. Why do I try to answer hard questions in class?: Because I feel ashamed of myself when I don't try.		0.33		
26. Why do I try to do well in school?: So my instructor will think I'm a good student		0.82		
*29. Why do I try to do well in school?: Because I'll feel really bad about myself if I don't do well.		0.32		
*31. Why do I try to do well in school?: Because I will feel really proud of myself if I do well.		0.16		
5. Why do I do my homework?: Because I want to understand the subject.			0.69	
8. Why do I do my homework?: Because it's important to me to do my homework.			0.63	
11. Why do I work on my classwork?: Because I want to learn new things.			0.68	
16. Why do I work on my classwork?: Because it's important to me to work on my classwork.			0.62	
*21. Why do I try to answer hard questions in class?: To find out if I'm right or wrong.			0.49	
*23. Why do I try to answer hard questions in class?: Because it's important to me to try to answer hard questions in class.			0.47	
*30. Why do I try to do well in school?: Because it's important to me to try to do well in school.			0.47	
3. Why do I do my homework?: Because it's fun.				0.77
7. Why do I do my homework?: Because I enjoy doing my homework.				0.82
13. Why do I work on my classwork?: Because it's fun.				0.84
15. Why do I work on my classwork?: Because I enjoy doing my classwork.				0.83
*19. Why do I try to answer hard questions in class?: Because I enjoy answering hard questions.				0.48
*22. Why do I try to answer hard questions in class?: Because it's fun to answer hard questions.				0.53
*27. Why do I try to do well in school?: Because I enjoy doing my school work well.				0.45

*indicates an item that was trimmed.

Table 5. Standardized factor loadings from the confirmatory factor analysis of the revised study process questionnaire.

Item	Standardized Factor Loadings	
	Deep Learning Strategies	Surface Learning Strategies
1. I find that at times studying gives me a feeling of deep personal satisfaction.	0.58	
*2. I find that I have to do enough work on a topic so that I can form my own conclusions before I am satisfied.	0.50	
*5. I feel that virtually any topic can be highly interesting once I get into it.	0.52	
6. I find most new topics interesting and often spend extra time trying to obtain more information about them.	0.68	
9. I find that studying academic topics can at times be as exciting as a good novel or movie.	0.65	
10. I test myself on important topics until I understand them completely.	0.59	
13. I work hard at my studies because I find the material interesting.	0.70	
14. I spend a lot of my free time finding out more about interesting topics which have been discussed in different classes.	0.55	
*17. I come to most classes with questions in mind that I want answering.	0.45	
18. I make a point of looking at most of the suggested readings that go with the lectures.	0.59	
*3. My aim is to pass the course while doing as little work as possible.		0.55
*4. I only study seriously what's given out in class or in the course outlines.		0.38
*7. I do not find my course very interesting so I keep my work to the minimum.		0.53
*8. I learn some things by rote, going over and over them until I know them by heart even if I do not understand them.		0.17
*11. I find I can get by in most assessments by memorizing key sections rather than trying to understand them.		0.52
12. I generally restrict my study to what is specifically set as I think it is unnecessary to do anything extra.		0.63
15. I find it is not helpful to study topics in depth. It confuses and wastes time, when all you need is a passing acquaintance with topics.		0.58
16. I believe that lecturers shouldn't expect students to spend significant amounts of time studying material everyone knows won't be examined.		0.55
19. I see no point in learning material which is not likely to be in the examination.		0.65
20. I find the best way to pass examinations is to try to remember answers to likely questions.		0.50

*indicates an item that was trimmed.

Table 6. Means, standard deviations, cronbach alpha, and correlations among variables.

Variable	M	SD	α	1	2	3	4	5	6	7	8	9
1. Autonomy	5.36	1.41	.90	1								
2. Competence	5.23	1.09	.87	.67**	1							
3. Relatedness	3.52	1.72	.92	.36**	.34**	1						
4. Intrinsic Motivation	2.22	.74	.89	.38**	.32**	.27**	1					
5. Identified Regulation	3.59	.47	.76	.43**	.38**	.15**	.47**	1				
6. Introjected Regulation	2.81	.97	.90	.11**	.10**	.15**	.18**	.13**	1			
7. External Regulation	2.50	.83	.77	.03	.02	.14**	.09**	.03	.70**	1		
8. Surface Learning Strategies	2.35	.81	.71	−.22**	−.19**	−.01	−.22**	−.30**	.14**	.21**	1	
9. Deep Learning Strategies	2.99	.77	.81	.47**	.43**	.28**	.56**	.47**	.09**	.04	−.15**	1

Surface Learning Strategies and Deep Learning Strategies scores were averaged due to trimming of items. This will differ from previous studies using all items. *$p < .05$, **$p < .01$.

motivational beliefs predicted learning strategies, we examined modification indices and non-significant parameter estimates. This included removing paths between deep learning strategies and external regulation and introjected regulation in addition to paths between surface learning strategies and introjected regulation. The path between introjected regulation and relatedness was also removed. For external regulation, all paths were removed except for relatedness. Covariance paths were removed between the basic psychological needs as well as between external regulation and intrinsic motivation, and between deep and surface learning strategies. The modification indices also suggested adding new paths, including a direct path from autonomy, competence, and relatedness to deep learning strategies. These added paths were supported by the correlations run before model fitting. With these modifications, acceptable model fit was achieved, χ^2 (12) = 41.28, $p < .001$; $\chi^2/df = 3.44$; CFI = .96; TLI = .96, RMSEA = .05.

In the case of the final model, the following expected significant paths were confirmed: autonomy and competence to intrinsic motivation and identified regulation and relatedness to intrinsic motivation, introjected regulation, and external regulation. Also confirmed were significant paths from intrinsic motivation, identified regulation, and external regulation to surface learning strategies. Intrinsic motivation and identified regulation had significant paths to deep learning strategies. Covariance paths hypothesized between intrinsic motivation and identified regulation, identified regulation and introjected regulation, and introjected regulation and external regulation were also confirmed.

There were also indirect effects found within the model, with autonomy having an indirect effect on deep learning strategies via intrinsic motivation (B = .08, $p < .05$) and identified regulation (B = .05, $p < .05$). Competence had similar indirect effects via intrinsic motivation (B = .13, $p < .05$) and identified regulation (B = .08, $p < .05$). Relatedness had an indirect effect on deep learning strategies via intrinsic motivation (B = .14, $p < .05$). In total, the model explained 43% of the variance in deep learning strategies and 17% of the variance in surface learning strategies. Figure 2 illustrates the final model with standardized parameter estimates. For ease in visualizing the model, all indirect effects and covariances were removed from the figure.

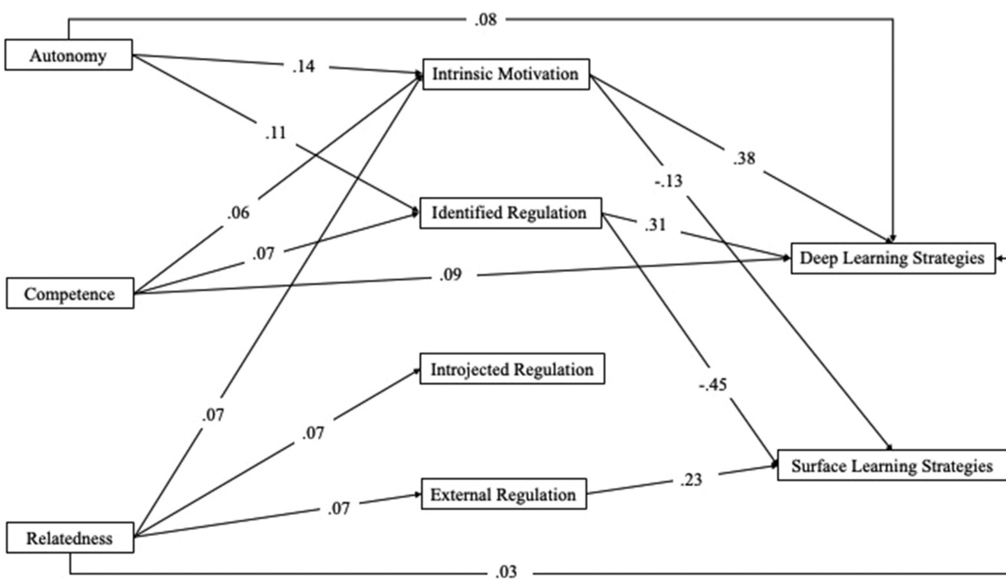

Figure 2. Path model predicting deep and surface learning strategies. All paths included in the figure are significant at $p < .05$. Congruent with assumptions, all variables were allowed to correlate. For clarity, indirect effects and non-significant paths are not depicted in the figure.

Discussion

Based on prior research in understanding how students learn in college courses (Nadrljanski et al., 2020) and the role that study strategies play in the learning process (Chodzko-Zajko, 2014; Elvén et al., 2019), this study extended the understanding of the relationship between learning strategies and their motivational precursors specifically in kinesiology courses by examining the predictors of surface and deep learning strategies in undergraduate students enrolled in major required classes of a kinesiology program. As Baeten et al. (2010) suggested, multiple factors can influence implementation of specific learning strategies. From the perspective of improving teaching, instructors have the ability to directly influence how they interact with students through speech, course design, and teaching methods. All three of these aspects can be modified to influence basic need satisfaction and motivational processes. The results from this study provide a much broader picture of particular learning environments and show initial evidence that can be used to build a framework that encourages the use of more productive learning strategies in college classrooms.

Summary of relationships

We hypothesized that basic need satisfaction would directly influence the motivation regulatory styles, which would then predict deep and surface learning strategies. The model produced partially supported our hypotheses, in that the three basic psychological needs influenced the motivation regulatory styles. While each basic psychological need did not influence all motivation regulatory styles, intrinsic motivation was influenced by autonomy, competence, and relatedness, while identified regulation was influenced by autonomy and competence. Relatedness also influenced both introjected regulation and external regulation. Further, relationships between motivation and learning strategy use that have previously been confirmed were also observed. In addition, there is some evidence that the three basic psychological needs both directly and indirectly influenced the use of deep learning strategies.

In addition to exploring deep and surface learning strategies, the R-SPQ-2F allowed us to identify the reasons that learners opted for these strategies. Mean values across constructs suggest that kinesiology students were interested in the material, wanted to have a thorough grasp of the information, and were willing to put in the work to be successful in the class (deep learning strategies). The data also indicates that kinesiology students in this sample were working on a topic enough to complete the work, but also formed their own conclusions about the material. However, kinesiology students who did not find the material interesting were only completing the minimum work required (surface learning strategies).

Some of the hypothesized connections between the motivation regulatory styles and learning strategies were supported by the final model. This included external regulation as a positive predictor of surface learning strategies. In other words, students tended to learn the information well enough to complete the tasks required as they worked to satisfy external demands such as earning good grades, feelings of duty, and avoiding getting in trouble. Conversely, participants' intrinsic motivation and identified regulation negatively predicted surface learning strategies. In essence, as students' perceptions of the value of learning increased, they were less likely to report using surface learning strategies.

Connection to previous research

Within the model, intrinsic motivation and identified motivation were the only regulatory styles that predicted deep learning strategies. This suggests that students utilized deep learning strategies more often when they felt the material was contributing to their personal goals (intrinsic motivation). In addition, students' feelings of gaining skills and overcoming challenges were indirectly tied to deep learning strategies. Within the literature, this does fall in line with previous studies examining the relationship between motivation and learning strategy use, particularly that of Everaert et al. (2017) who found that intrinsic motivation predicted the use of deep learning strategies. In contrast to their results, however, extrinsic motivation did not predict deep learning strategy use in the current study. In addition, extrinsic motivation was shown to predict surface learning strategy use within the current study, which is in opposition to what Everaert et al. (2017) found among accounting students. There is also support from research by Abdel Meguid et al. (2020), who found a positive correlation between intrinsic motivation and deep learning strategies in addition to higher academic performance. Considering these results within the broader context of learning strategies and academic outcomes (Smith et al., 2014; Wang & McWatt, 2023), encouraging the use of deep learning strategies by activating motivation tied to intrinsic interest and skill attainment could improve overall learning, regardless of course topic or level.

The relationships observed in the current study between basic need satisfaction and motivation match what has already been established in the literature (Fedesco et al., 2019; Liu et al., 2013; Sierens et al., 2009; Yu & Levesque-Bristol, 2020). The significant paths from autonomy and competence to intrinsic motivation and identified regulation were expected, representing the fact that if a student perceives that their need for control, choice, and clarity in instruction is met, they are more likely to internalize the course material as valuable to them, which can have greater impacts on academic performance (Yu & Levesque-Bristol, 2020). Relatedness satisfaction mimics the relationships found in Fedesco et al. (2019), indicating the utmost importance of instructor relatedness support as a way to foster intrinsic motivation among students.

Perhaps more impactful is the direct relationship between basic psychological needs and deep learning strategies. Although we were not able to find a study to directly compare the entire path model to, the direct relationships suggested between basic need satisfaction and learning strategy use mimic paths and relationships established in prior research with other academic outcomes (Makarova, 2021). For example, Ariani (2019) found that basic psychological need satisfaction predicted burnout and academic engagement. More specifically, autonomy satisfaction negatively predicted burnout, while competence satisfaction positively predicted academic engagement. Similarly, Karimi and Sotoodeh (2020) noted moderate predictive relationships between autonomy satisfaction, competence satisfaction, and academic engagement. Taken together, the findings from this study suggest the importance of ensuring basic psychological need satisfaction among students, as they have both direct and indirect impacts on the way students utilize learning strategies. Combined with information from previous studies, this could very likely have a great impact on student achievement and overall well-being.

The results of this study add further explanation to some of the contextual and student factors described by Baeten et al. (2010). In addition, it extends the cross-disciplinary work of Salamonson et al. (2013) and Coertjens et al. (2016). Much like the allied health professions, engineering, and chemistry, the use of deep learning strategies in kinesiology is paramount for knowledge transfer and application. Connecting this to the ideas of Entwistle (2000), the satisfaction of basic psychological needs promotes more autonomous forms of motivation, which can positively influence academic engagement and ultimately, academic achievement. The current study provides a potential direct link to fostering deep learning strategies among kinesiology students; that is, by supporting students' basic psychological needs, in addition to an indirect link by influencing various motivational regulations.

Limitations

Aside from the following limitations, we feel it is important to mention that this study did not consider course content as a moderator of the relationship between motivation and strategy use. While not an inherent limitation of the study, it is possible that the content of each course could have had some influence on the students' use of strategies. Because we did not have enough data to examine this within subjects, we would suggest such an examination be carried out in the future. When interpreting the findings from this study, both the context and sample should be taken into account. First, the COVID-19 pandemic influenced the modality of courses during the two semesters of data collection. The courses were delivered in a variety of formats including in-person, online, and hybrid. Due to the pandemic, students did not have not much choice in the class format, which may have impacted their strategies. Further comparison of these constructs between class formats post-pandemic may highlight differences in study strategies. Second, this study focused on particular major courses that are required within a kinesiology program and did not survey students in elective classes of the program, where student motivation and learning strategies may have been different. Third, the majority of students in the sample identified as female and white which may have resulted in missing racial or gender differences in learning strategies among students. Fourth, extra credit was given inconsistently across classes and may have impacted participation. Future studies should continue to investigate the relationship between basic need satisfaction, motivation, and learning strategies in kinesiology by targeting a more diverse sample of students across different major courses using consistent incentives. Finally, data was observational in nature and collected cross-sectionally. Thus, we cannot make strong causal conclusions about the relationships among study variables. In the future, researchers should adopt intervention or experimental approaches to further investigate the connections between need satisfaction, motivation, and learning strategies in kinesiology students.

Conclusions and practical recommendations

The results of this study provide kinesiology researchers and instructors a glimpse into the minds of kinesiology students and how they view the material they are learning. In general, it is clear that students in kinesiology use different learning strategies and have varying levels of motivation and basic need satisfaction. While it is clear that the use of deep learning strategies would be highly beneficial for this group of learners, kinesiology students may not rely on these strategies because they lack the intrinsic motivation and basic need satisfaction to do so.

From a practical standpoint, while it may not be feasible to survey every student to determine their use of deep and surface learning strategies, results from this study suggest that modifying learning environments that support basic psychological needs and autonomous forms of motivation might have an impact on the learning strategies students choose to use. While it is beyond the scope of this paper to suggest specific modifications, there are studies in education that provide concrete behaviors that can be used in college classrooms to enhance basic need satisfaction and motivation (see Ahmadi et al., 2023 for an example).

In expanding this line of research, future work will need to involve the testing of causal links between these constructs. Because many kinesiology students plan to continue their graduate studies in physical therapy, occupational therapy, or other health specialties, it is imperative for kinesiology undergraduates to gain a good understanding of the material and clinical reasoning skills. Effective learning strategies may support this understanding. Further, investigating specific interventions that include consideration of basic psychological needs and motivation should be conducted to determine if they have a direct effect on the use of specific learning strategies, thereby improving students' readiness for graduate school (Reeve & Cheon, 2021; Reeve et al., 2004).

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