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Using the Selection, Optimization, and Compensation Model of Action-Regulation to Explain College Students' Grades and Study Satisfaction

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Statistics on study disruptions and delays and their negative impact on academic performance call for action-regulation strategies that students can use to manage their performance and well-being. In the present research, we rely on the action-regulation model of selection, optimization, and compensation (SOC), which was developed in the life span developmental literature. The aim of the present study was to establish indirect links between two specific SOC components (i.e., elective selection and optimization) and study outcomes (i.e., end-of-first-year average grade and study satisfaction) through higher self-efficacy beliefs. In 2 prospective studies conducted during 2 subsequent academic years, we tested our research model with first-year undergraduate students ($n = 366$ in Study 1 and $n = 242$ in Study 2). Results of both studies indicate that there are positive indirect relations between optimization, but not elective selection, and favorable study outcomes through self-efficacy beliefs. The present study contributes to SOC theory and the educational sciences by showing that the SOC model of action-regulation can be helpful in explaining college students' grades and study satisfaction.

Educational Impact and Implications Statement
Statistics on study disruptions and delays and their negative impact on academic performance call for action-regulation strategies that students can use to manage their performance and well-being. In the present research, we apply the action-regulation model of selection, optimization, and compensation (SOC), which was developed in the life span developmental literature, to the educational context. We argue that students can use these action-regulation components to manage their academic performance and satisfaction. In two studies, we demonstrate that first-year college students' grades and study satisfaction can be explained by the action-regulation component of optimization through self-efficacy beliefs. Based on these findings, we recommend teaching students optimization techniques and provide them with the means that they need to facilitate their goal pursuit.

Keywords: action-regulation, self-efficacy, goal-setting, SOC, academic outcomes

The first year of college can be challenging. Students have to adapt to a new environment, possibly live far away from family and friends, create new social networks, and face new academic challenges. The American College Health Association (2017) reported that reasons for prolonged study disruptions or decreased academic performance in over 63,000 students include stress (30.6%), anxiety (24.2%), depression (15.9%), and homesickness (4%). Many first-year students suffer from burnout and withdrawal intentions because they feel that their efforts remain unrewarded (Williams, Dziurawiec, & Heritage, 2018). These disquieting numbers call for a greater focus on action-regulation strategies—strategies to monitor performance in the form of goal-setting and goal-pursuit—that students can use to manage stressful life and study situations, and to maintain satisfactory levels of grades and study satisfaction. Study satisfaction and grades have received a great deal of attention in educational research. For instance, academic performance in the form of grades is considered a relevant predictor of future academic performance beyond grades

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(e.g., research productivity or faculty evaluations of students; Kuncel & Hezlett, 2007), the number of job interviews students will be invited to after graduation (Ming Chia, 2005), and future job performance (Roth, BeVier, Switzer, & Schippmann, 1996). Furthermore, it has been established that study satisfaction is associated with general psychological well-being (Winefield, 1993) and better performance (e.g., Douglas, McClelland, & Davies, 2008; Horton & Snyder, 2009).

Given the importance of these study outcomes, the predictors of grades and study satisfaction have also been the focus of many previous studies. Academic performance is often attributed to environmental factors, such as a supportive and communicative study environment (e.g., Douglas et al., 2008) or service quality at the college (e.g., Clemes, Gan, & Kao, 2008). Yet, it is also influenced by individual difference variables, such as personality (e.g., Poropat, 2009), achievement motivation (e.g., Harackiewicz, Barron, Tauer, Carter, & Elliot, 2000), or self-regulation defined as metacognition and self-monitoring (e.g., Duckworth, White, Matteucci, Shearer, & Gross, 2016; Pintrich & De Groot, 1990; B. J. Zimmerman & Pons, 1986).

Notably, self-regulation in academic settings has often been defined within the framework of self-regulated learning, including aspects such as following instructions, setting learning goals, managing time, seeking help when needed, and monitoring performance (e.g., Hiemstra & Van Yperen, 2015; Schunk & Ertmer, 2000). A related approach is the action-regulation model of selection, optimization, and compensation (SOC; Baltes, 1997; Baltes & Baltes, 1990). The SOC model was developed within the life span context, but to date, it is considered a more general model of action-regulation in different life and achievement domains (Freund & Baltes, 2000). This coherent and well-established model states that the use of four groups of strategies can help people maintain performance and well-being in demanding situations, especially in situations that are marked by a mismatch between demands, resources, and selected goals. Specifically, the SOC model proposes that individuals can actively allocate their personal resources to achieve their goals by making use of elective selection (prioritization of some goals over others in line with preferences), loss-based selection (reorganization of goal hierarchies in response to resource losses), optimization (resources investment and goal pursuit), and compensation (resources substitution in case of a loss; Freund & Baltes, 2000).

Remarkably, to date, the SOC model has been largely neglected in the educational sciences. However, as shown in Figure 1 and elaborated below, we argue that the action-regulation components of elective selection and optimization (but not loss-based selection and compensation) are also useful for explaining college students' grades and study satisfaction, which is assumed to be channeled through their self-efficacy beliefs. Self-efficacy beliefs are personal judgments of one's capabilities to engage in certain actions to attain self-selected or designated goals (Bandura, 1993). In line with our research model (see Figure 1), self-efficacy beliefs have consistently been identified as a positive predictor of academic performance and well-being (Judge & Bono, 2001).

Applying life span and action-regulation models such as SOC in the educational domain may not only benefit students in terms of their academic performance and study satisfaction. Having learned to successfully apply action-regulation strategies may also facilitate students' school-to-work transition (see Heckhausen & Farruggia, 2003). At the same time, by applying SOC theory in the educational domain, SOC theory itself can benefit immensely, for example, by adding to the importance of the theory in the literature on life span motivation and the organizational sciences.

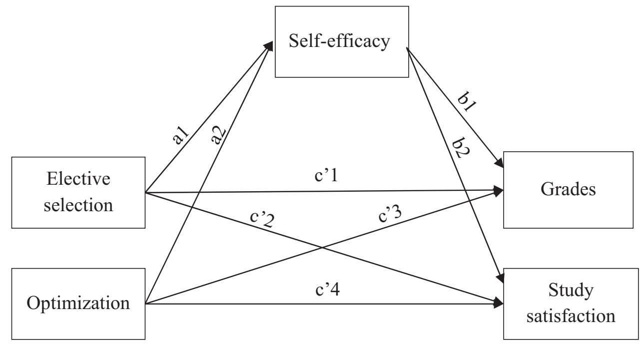

Figure 1. Hypothesized research model (coefficients are presented in Tables 2 and 4).

In the past, there have been theoretical arguments for incorporating life span and developmental psychology theories to higher education and adult learners (e.g., Haase, Heckhausen, & Wrosch, 2013; Heckhausen, Wrosch, & Schulz, 2010). For instance, Sutherland (1999) argued that Piaget's stage theory, originally developed to understand thinking and learning in children, is also relevant to adult learners. Specifically, Sutherland argued that applying this theory of child development to adults could both lead to a better understanding of adults and help further develop theory by testing it in different contexts. In the present study, we have similar intentions and argue that our study contributes to the educational and action-regulation literatures in three ways.

First, by testing our research model (see Figure 1), we sought to replicate and extend studies that showed that the use of SOC components is positively associated with performance and well-being in education (e.g., Gestsdottir & Lerner, 2007; S. M. Zimmerman, Phelps, & Lerner, 2007), work (e.g., Müller et al., 2013; Schmitt, Zacher, & Frese, 2012), and life-management contexts (e.g., Chou & Chi, 2002). Second, we extend previous research on SOC by exploring the underlying mechanisms that take place when students engage in SOC. That is, we tested whether the use of elective selection and optimization is indirectly and positively associated with college students' grades and study satisfaction through self-efficacy beliefs. Currently, the mechanisms through which SOC unfolds its beneficial effects are not well-understood (Moghimi, Zacher, Scheibe, & Van Yperen, 2017). Third, we combined the life span model of SOC with the motivational concept of self-efficacy in the educational context to gain new insights into the generalizability of the SOC model to other contexts. It has been shown that regulatory processes are subject to growth and changes during adolescence. There have been empirical studies showing that goals change throughout the life span, which implies that also the motivation to engage in certain actions changes throughout the life span (Moghimi, Scheibe, & Freund, 2019). For instance, a study by Penningroth and Scott (2012) confirms the need for situating motivational processes in the life span context by showing that younger adults reported goals that were focused on knowledge acquisition in the future, whereas older adults were more likely to adopt goals that focused on maintenance and loss-prevention (also see Ebner, Freund, & Baltes, 2006). By incorporating the action-regulation model of SOC in the college context, this study bridges the gap between life span research and motivation research among younger adults.

The Selection, Optimization, Compensation (SOC) Model

The SOC model is a metatheory of human development (Baltes, 1997; Baltes & Baltes, 1990). The theory states that at each stage of the human life span, individuals are at times confronted with mismatches between the resources that are available to them, the goals that they have set for themselves, and the demands that are imposed on them (e.g., new environment, increased learning requirements, social pressure to fit in). While some stages of life are marked by greater mismatches than others, at all developmental stages (e.g., toddler, adolescence, adulthood), individuals can manage their lives and actively master the mentioned mismatches by engaging in SOC strategies (Baltes & Baltes, 1990; Freund & Baltes, 2000).

In the present study, our main focus is on the preference-based strategies of elective selection and optimization. Individuals who engage in these strategies pursue a goal or a strategy that they have selected based on preference and act as proactive agents in the pursuit of their goal (Li, Lindenberger, Freund, & Baltes, 2001). More specifically, elective selection refers to the prioritization of some goals over others based on personal preference, for instance, in the form of goal hierarchies, as opposed to pursuing several goals at the same time. Successful elective selection further requires the adequate contextualization of goals by choosing goals that make sense in a certain context (Freund & Baltes, 2002). An example of well-contextualized daily elective selection in the college setting would be having a to-do list every day which includes the most relevant tasks that need to be done. An example of longer-term elective selection could be a goal hierarchy for the upcoming study years or a vision board (e.g., mainly focusing on studies, engaging in meaningful social activities, and joining a sports team). The other preference-based strategy, optimization, refers to actions that help the individual achieve previously set goals. This includes allocating resources such as time and attention to relevant tasks, being persistent, and acquiring new skills or new resources that will help in achieving these goals. For a student, this could mean focusing time, effort, and financial resources on achieving the goal of acquiring study-relevant skills and eventually finishing the studies successfully. With reference to the previous example, monitoring the progress of the activities listed on a to-do list or a vision board could also be seen as optimization.

The other two SOC components are motivated by losses rather than preferences (Freund, Li, & Baltes, 1999). When engaging in loss-based selection or compensation, individuals have to engage in reactive behavior and respond to resource losses (e.g., loss of time, health, money, important study partners; Freund & Baltes, 2000). Loss-based selection mainly refers to the reorganization of one's goal hierarchy after the experience of a loss in resources. To do so successfully, one needs to adapt personal standards to the new situation and search for possible new goals (Freund & Baltes, 2002). A student whose goal was to finish undergraduate studies in 3 years but is facing a period of severe illness (i.e., loss of health), could engage in loss-based selection by changing the goal hierarchy and prioritizing health over study time. The student could further adapt the standards to the new situation, for instance, by trying to finish the studies in 4 rather than 3 years. It is important to note that both elective and loss-based selection entail the act of setting goals. The difference between these two SOC components is that they are preceded either by preference or a loss in resources. Compensation includes the substitution of means, activation of unused or new skills, asking others for help, and changing resource allocation in response to a resource loss (Freund & Baltes, 2002). Taking the previous example of the sick student, after feeling better, the student could refocus on successfully finishing the studies by working with a tutor (i.e., activating new means), investing more time than before in studying (i.e., reallocating resources), or asking friends for help and study support.

In the following, we refer to *SOC*, the *SOC model*, and *selection, optimization, and compensation model* synonymously. Note that the term "selection" refers to two components: elective selection and loss-based selection.

SOC, Grades, and Study Satisfaction

Empirical support for the positive relationship between the overall use of SOC and both performance and satisfaction is found in studies across a diversity of life and achievement contexts. For instance, studies with young children and adolescents confirm that SOC components are associated with beneficial performance outcomes in the context that the SOC is applied to (Gestsdottir, Lewin-Bizan, von Eye, Lerner, & Lerner, 2009; Lerner et al., 2005). Furthermore, a meta-analysis regarding SOC use in the work context demonstrates that SOC components are positively associated with objective and subjective indicators of occupational performance as well as job satisfaction (Moghimi et al., 2017).

However, most of these studies only provide information on the overall use of all SOC components and disregard the effects that each component may have independently. The beneficial effects of SOC components can possibly only be attributed to certain components in certain situations and not to their combined use at all times. The combined use of SOC components is supposed to yield the best outcomes according to SOC theory (Freund & Baltes, 2000). Despite this claim, more and more studies are considering the effects of each component separately. These studies show that effects on outcomes can indeed differ depending on the component used (Demerouti, Bakker, & Leiter, 2014; Yeung & Fung, 2009; Zacher, Chan, Bakker, & Demerouti, 2015). In the present study, we suggest that the links between SOC components and both grades and study satisfaction can mainly be attributed to preference-based components (i.e., elective selection and optimization) and not to loss-based components (loss-based selection and compensation); this is discussed in more detail below.

The components of loss-based selection and compensation result from a resource loss, whereas elective selection and optimization are components that are used based on personal preference. Major resource losses are often observed in older individuals (Salthouse, 1996), which is the reason why the SOC model was originally described as a model of successful aging. Previous studies have shown that, due to these resource losses, there are differences in goal orientation between younger and older adults. While young adults are normatively growth-oriented, older adults are oriented toward maintenance and loss-prevention (De Lange, Van Yperen, Van der Heijden, & Bal, 2010; Ebner et al., 2006; Penningroth & Scott, 2012). Experiencing a loss in resources requires reactive behavior and disrupts the active selection and pursuit of goals. Reactive behavior constitutes a deviation from self-concordant behavior, which is defined as actions and goals that are in line with personal values and preferences (Sheldon & Kasser, 2001). Nonconcordant goal pursuit exhausts personal resources, which eventually diminishes well-being and thriving (Sheldon, 2002). We argue that the present sample is too young to normatively experience severe losses that affect the selection and pursuit of academic goals. Therefore, in the present study, we focus on preference-based components (i.e., elective selection and optimization) rather than loss-based components (i.e., loss-based selection and compensation).

We argue that being able to select and pursue preferred goals (as in elective selection and optimization) is positively associated with grades and study satisfaction because students can act in an active and self-concordant manner and are oriented toward growth rather than loss-prevention. While elective selection helps to allocate available resources to goal-relevant means, optimization allows full-hearted goal pursuit without compromises. Individuals who pursue self-concordant goals invest more sustained effort, attain their goals more successfully, and are more satisfied with the process (Sheldon & Kasser, 2001). Furthermore, self-concordant behavior creates a feeling of control and is, therefore, associated with positive outcomes. In line with these ideas, we expected that the components of elective selection and optimization are positively associated with grades and study satisfaction (see Figure 1).

Some empirical support for these ideas is provided by studies in the work and educational context. For instance, Wiese, Freund, and Baltes (2000) found that selection and optimization were positively related to job satisfaction, while compensation was not. Similarly, Abraham and Hansson (1995) found positive relationships between selection and optimization and goal attainment as an indicator of performance. It should be noted that in both studies, elective and loss-based selection were combined as a global indicator of goal selection. In a meta-analysis of academic performance, Richardson, Abraham, and Bond (2012) reported positive relationships between (among other things) effort regulation and time management (as indicators of regulation) and academic performance. These self-regulation strategies are similar to the activities that are attributed to optimization; this provides additional support for the notion that active, preference-based goal-pursuit is associated with favorable outcomes.

SOC and Self-Efficacy

Bandura (1977) defined self-efficacy beliefs as personal judgments of one's skills and capabilities to execute certain actions to attain personally set or designated goals. Self-efficacy beliefs are assumed to be domain and task specific. For instance, one can believe oneself to be highly capable in verbal tasks but less capable in arithmetic tasks. Self-efficacious individuals consider their options to be broader than individuals who do not believe in their abilities. Self-efficacy beliefs are acquired from four main subjective sources of information regarding one's skills and capabilities: physiological reactions (e.g., stress and anxiety), vicarious experiences (e.g., comparing own performance with others' performance), persuasion (e.g., verbal encouragement), and mastery experiences (e.g., previous performance; Bandura, 1977). In this sense, self-efficacy beliefs have two important characteristics: on the one hand, the nature and topic of goals are important because they seem to be the reference point for self-efficacy beliefs. On the other hand, self-efficacy beliefs not only affect behavior, but are also influenced by one's actions and environmental conditions (Schunk & Meece, 2006). Based on this idea, we suggest that the strategies of elective selection and optimization might increase self-efficacy beliefs because they provide positive personal and environmental information regarding potential goal achievement.

Across domains, several correlational studies have confirmed a positive relationship between general self-regulatory skills and self-efficacy beliefs (e.g., Bouffard-Bouchard, Parent, & Larivee, 1991; Magogwe & Oliver, 2007; for a review see: Schunk & Ertmer, 2000). However, studies focusing on SOC and self-efficacy beliefs are scarce. In a study of women returning to work after maternity leave, Wiese and Heidemeier (2012) reported positive relationships between the overall use of SOC components and self-efficacy beliefs. The authors argue that self-efficacy beliefs are not observable but rather beliefs that favor the implementation of actions. In contrast to Wiese and Heidemeier, we argue that observable actions (i.e., elective selection and optimization) favor self-efficacy beliefs because they create a feeling of control. Furthermore, we expect that the reported positive relationship between SOC and self-efficacy beliefs can primarily be ascribed to the two preference-based SOC components that involve self-concordant goal-setting and intentional resource allocation.

Previous studies often focused on the link between self-regulation and self-efficacy beliefs (e.g., Anderson, Wojcik, Winett, & Williams, 2006; Senécal, Nouwen, & White, 2000), but not on the links between action-regulation in the form of SOC and self-efficacy. In addition, the results were mostly based on cross-sectional studies that did not allow causal interpretations of the observed links. Some studies incorporated self-efficacy beliefs as a mediator between self-regulated behavior and favorable outcomes (Frayne & Latham, 1987; Prussia, Anderson, & Manz, 1998), while others assumed a reversed causal relationship. That is, self-efficacy beliefs increase self-regulated behavior (for instance, as described by B. J. Zimmerman, 2000a), which, in turn, leads to desired outcomes (e.g., Rovniak, Anderson, Winett, & Stephens, 2002). Our nonexperimental data do not allow causal inferences either. However, to consider all possibilities, we also tested an alternative model in which self-efficacy beliefs were indirectly related to our outcome variables through the SOC components optimization and elective selection.

Self-Efficacy, Grades, and Study Satisfaction

One reason why academic self-efficacy beliefs are suggested to precede academic outcomes is that they specifically refer to future functioning and are usually assessed before a certain task is executed (Marsh, Martin, Yeung, & Craven, 2017; B. J. Zimmerman, 2000b). The literature on self-efficacy shows that self-efficacy beliefs in different domains are consistently associated with better performance and greater satisfaction (for meta-analyses, see Judge & Bono, 2001; Multon, Brown, & Lent, 1991; Stajkovic & Luthans, 1998). Indeed, individuals who believe that they will be able to achieve the goals that they have set for themselves are likely to perform better and feel more satisfied with their achievement context (Bandura, 1977; B. J. Zimmerman, Bandura, & Martinez-Pons, 1992). Specifically, it has been shown that self-efficacy beliefs in junior high school predict academic performance over and above the effects of socioeconomic status or previous academic performance (Caprara, Vecchione, Alessandri, Gerbino, & Barbaranelli, 2011). Similarly, students' academic self-efficacy has been associated with their academic performance and personal adjustment in the first academic year (Chemers, Hu, & Garcia, 2001). Hsieh, Sullivan, and Guerra (2007) found that self-efficacy is positively related to academic standing (i.e., grade point average of 2.0 and higher). Finally, the positive effects of self-efficacy beliefs on performance have also been replicated in migrant and minority students where academic self-efficacy was associated with two measures of academic success, grade point averages and credits earned (Zajacova, Lynch, Espenshade, Sep, & Espenshadet, 2005).

Many studies have also confirmed the positive links of self-efficacy with study and life satisfaction. For instance, college self-efficacy has been associated with all five dimensions of the College Student Satisfaction Questionnaire (Betz, Betz, & Menne, 1989): namely, compensation (receiving adequate returns for one's efforts), social life, working conditions, recognition, and quality of education (DeWitz & Walsh, 2002). In a study of eustress and life satisfaction in students, it was shown that hope and self-efficacy together explained a significant proportion of variance in life satisfaction among undergraduate students (O'Sullivan, 2011). Finally, the positive relationship between self-efficacy beliefs and satisfaction has also been found in other domains. In a study of over 2,000 teachers in Italian high schools, teachers' self-efficacy beliefs were highly correlated with their job satisfaction (Caprara, Barbaranelli, Steca, & Malone, 2006). As shown in Figure 1, and in accordance with SOC and self-efficacy theories, we hypothesized that elective selection and optimization are indirectly related to both grades and study satisfaction through self-efficacy beliefs.

Method

Participants and Procedure

The data used in this study were collected in two studies with first-year undergraduate psychology students from a Dutch university over the course of 2 academic years. Note that in the Dutch system students select their area of study when they sign up for college. Thus, one can assume that first-year students are pursuing a study that is in accordance with their preferences.

Participants were recruited through the faculty's participant pool and spent approximately 30 min completing an online questionnaire in exchange for course credit. The students were first asked for permission to retrieve their grades at the end of the academic year. After agreeing to share their grades, students were asked a number of questions regarding their action-regulation strategies, self-efficacy beliefs, and study satisfaction. Grades were retrieved at the end of the academic year, after all exams had been completed. After the grades had been retrieved, student numbers were deleted and replaced by anonymized participant numbers to assure that grades could not be traced back to students. Students gave written informed consent, and both studies were approved by the Ethics Committee Psychology of the University (IDs 16,055-S-NE for Study 1 and 17,198-S-NE for Study 2).

Study 1. Participants were 455 students. However, 87 responses had to be excluded due to double entries, incomplete data, or missing student numbers, which meant that grades could not be retrieved. In the case of double entries, we always kept the first entry based on the date and time variables, and deleted the second entry. In total, 368 complete responses were recorded. Two students indicated that their gender was other than male or female. In our analyses, we control for gender based on studies that indicate that male students feel more efficacious than females (e.g., Wilson, Kickul, & Marlino, 2007). Given the lack of studies regarding other gender orientations, we excluded the two students whose gender could not be identified in a binary manner. The final sample consisted of 366 students, of whom 62.2% were female and 37.8% were male, with an age range of 17 to 52 ($M = 20.41$, $SD = 3.09$). Students followed their studies in Dutch (22%) or in English (78%). It should be noted that the courses that students attend in the first year are identical in terms of content and often even in the exams across the Dutch and English tracks. This allowed us to regard all students as one group and compare grades across programs. Because the survey was administered in English, we also asked the students to rate their language skills on a 7-point scale ranging from 1 (*very low*) to 7 (*very high*). In total, 94.5% of the students rated their English language skills with a 4 or higher.

Study 2. In Study 2, we aimed to replicate our results from Study 1 to avoid conclusions based on results that occurred by chance or due to a rather large sample size. The data collection procedure and measures were identical to those in Study 1. After double entries were excluded, there were 248 unique responses. Two participants indicated a wrong student number for which the grades could not be retrieved. Four participants indicated that their gender was "other" than male or female and were excluded from the analyses. The final sample consisted of 242 students, of whom 69.4% were female and 30.6% were male, with an age range from 18 to 54 ($M = 20.56$, $SD = 3.15$). A total of 68.2% were enrolled in the English track and 31.8% were enrolled in the Dutch track; 96.3% of the students evaluated their English skills with a 4 or higher on the 7-point Likert scale.

Measures

Unless indicated otherwise, items of all measures were rated on 7-point Likert response scales ranging from 1 (*strongly disagree*) to 7 (*strongly agree*). Note that SOC components, self-efficacy, and study satisfaction were assessed during the academic year, whereas grades were obtained at the end of the academic year.

Selection, optimization, compensation strategies. The action-regulation strategies of SOC were assessed using 12 items from the commonly used SOC questionnaire (Baltes, Baltes, Freund, & Lang, 1999). The items were adapted to the college setting by adding the words "during my studies" at the beginning of each sentence. This approach has often been used in the work and organizational literature, by adding the words "at work"; this generally yields good reliabilities (e.g., Schmitt et al., 2012; Zacher et al., 2015). Elective selection, optimization, loss-based selection, and compensation were assessed using three items each. Example items are: "During my studies, I concentrate all my energy on a few things" (elective selection; $\alpha_{Study1} = .71$;

$\alpha_{\text{Study2}} = .76$), "During my studies, I keep working on what I have planned until I succeed" (optimization; $\alpha_{\text{Study1}} = .76$; $\alpha_{\text{Study2}} = .74$), "When things during my studies don't go as well as they have in the past, I choose one or two important goals" (loss-based selection; $\alpha_{\text{Study1}} = .51$; $\alpha_{\text{Study2}} = .68$), and "When things during my studies don't go as well as they used to, I keep trying other ways until I achieve the same result I used to" (compensation; $\alpha_{\text{Study1}} = .57$; $\alpha_{\text{Study2}} = .60$).

It should be noted that other studies have found similar low reliabilities for some SOC scales (e.g., Bajor & Baltes, 2003; Demerouti et al., 2014). The authors argued that each item is meant to tap into a different component of the respective scale, which can explain the low reliabilities. A better estimate of reliability of the SOC scale should be test–retest reliability, which has been shown to reach satisfactory levels in previous studies ranging between $r_{tt} = .56$ to .75 (e.g., Wiese et al., 2000).

Self-efficacy. The belief in one's own skills and abilities was assessed using a questionnaire developed and validated by Chen, Gully, and Eden (2001). The eight general self-efficacy items ($\alpha_{\text{Study1}} = .90$; $\alpha_{\text{Study2}} = .88$) were adapted to the study setting by adding the words "in my studies" or "study," depending on the specific item. A sample item of the questionnaire is "I will be able to achieve most of the study goals that I have set for myself."

Study satisfaction. A validated single-item measure by Dolbier, Webster, McCalister, Mallon, and Steinhardt (2005) that is often used in organizational research was adapted to the educational context to assess study satisfaction: "Taking everything into consideration, how do you feel about your studies as a whole?" Responses ranged from 1 (*extremely dissatisfied*) to 7 (*extremely satisfied*). The use of single-item measures to assess (job) satisfaction has been validated by Wanous, Reichers, and Hudy (1997), who reported an average correlation of .67 between single-item job satisfaction measures and reliability-corrected multi-item scales of overall job satisfaction. More recently, Fisher, Matthews, and Gibbons (2016) investigated the test–retest reliability of a single-item job satisfaction measure and reported reliability coefficients of .70 for a 1-month time lag and .60 for a 3-month time lag.

Grades. We used students' end-of-first-year average grade as an index of study success. Students' grades were obtained, with students' permission, from the exam committee after the completion of all exams at the end of the academic year. With only the first attempts (either pass or fail), we calculated the average grade per student for all exams in the first year ($\alpha_{\text{Study1}} = .88$; $\alpha_{\text{Study2}} = .89$). On average, students participated in 9.41 exams ($SD = 1.59$) in Study 1 and in 9.85 exams ($SD = 0.77$) in Study 2. Note that grades in the Dutch system range from 1 to 10, with 10 being the best possible outcome.

Statistical Analyses

To test our research model (see Figure 1), we employed regression-based path analyses in Mplus 7 (Muthén & Muthén, 2007). For this purpose, we used syntax that translated Model 4 of the PROCESS macro (Hayes, 2017) to Mplus language (Stride, Gardner, Catley, & Thomas, 2016). In each model, age, gender, and study track (Dutch or English) were included as covariates. Age is argued to be an important predictor of SOC use (Freund & Baltes, 1998) and was, therefore, controlled in the analyses. Gender is often related to self-efficacy beliefs in different domains (Wilson et al., 2007). Finally, at the university where the study was conducted, it is often observed that there is a trend for the English-speaking track to perform better than the Dutch-speaking track, which is why we also controlled for study track.

For our analyses, we followed recommendations by Hayes (2017) and consistently used 10,000 bootstrapped samples to construct bias-corrected 95% confidence intervals for indirect effects. All covariates were included for the prediction of both the dependent variable and the mediator. Additionally, all continuous predictors were mean-centered and dichotomous variables were dummy-coded.

Results

Study 1

Preliminary analyses. Table 1 shows the means, standard deviations, and correlations (below the diagonal) between all study variables, including the covariates of age, gender (0 = male, 1 = female), and study track (0 = English, 1 = Dutch). Except for elective selection, all SOC components were positively correlated with gender, with correlations ranging from $r = .11$ to $r = .21$ ($ps < .05$), which suggests that women reported using SOC more

Table 1
Means, Standard Deviations, and Correlations for Study 1 (Below the Diagonal) and for Study 2 (Above the Diagonal)

	Study 1		Study 2											
Variable	*M*	*SD*	*M*	*SD*	1	2	3	4	5	6	7	8	9	10
1. Elective selection	4.80	1.08	4.80	1.01	—	.39**	.46**	.39**	.15*	.11	.24**	.05	.03	−.02
2. Loss-based selection	4.79	0.88	4.81	1.00	.32**	—	.33**	.41**	.15*	.11	.17**	.05	.17**	−.03
3. Optimization	5.13	1.05	5.16	0.98	.50**	.18**	—	.51**	.37**	.28**	.30**	−.02	.17**	.03
4. Compensation	5.08	0.92	5.02	0.99	.31**	.24**	.55**	—	.30**	.21**	.24**	.02	.16*	−.03
5. Self-efficacy	5.18	0.83	5.07	0.81	.18**	.11*	.41**	.25**	—	.32**	.43**	.10	−.16*	−.08
6. Grades	6.35	1.25	6.58	1.13	.12*	−.06	.16**	.04	.15**	—	.44**	.01	.14*	−.27**
7. Study satisfaction	5.02	1.32	5.05	1.25	.20**	.07	.27**	.21**	.43**	.35**	—	.03	−.02	.05
8. Age	20.41	3.09	20.56	3.15	−.04	−.03	−.10*	−.01	−.05	−.04	−.10	—	−.15*	−.05
9. Gender	0.62	0.49	0.69	0.46	.08	.11*	.18**	.21**	−.15**	.08	.00	−.19**	—	.03
10. Study track	0.22	0.41	0.32	0.47	−.07	.04	−.06	−.15**	−.04	−.06	.10*	−.07	.08	—

Note. $N_{\text{Study1}} = 366$; $N_{\text{Study2}} = 242$. Coding gender: 0 = male, 1 = female; Coding study track: 0 = English, 1 = Dutch.
* $p < .05$. ** $p < .01$.

than men. Furthermore, in line with other research (e.g., Wilson et al., 2007), gender was negatively correlated with self-efficacy beliefs, $r = -.15$, $p = .003$, indicating that female students felt less efficacious than male students. More importantly, the correlations reported in Table 1 provide preliminary support for our research model (see Figure 1). There were positive correlations of (a) elective selection and optimization with self-efficacy beliefs, (b) elective selection and optimization with grades, (c) elective selection and optimization with study satisfaction, and (d) self-efficacy beliefs with study satisfaction and grades.

Test of the research model. Figure 2 depicts the tested research model, including direct and total effects. The fit indices suggested a good model fit ($\chi^2 = 16.546$, $df = 6$, $p = .01$; root mean square error of approximation = .070; comparative fit index = .951; Tucker–Lewis index = .852; standardized root mean square residual = .044). As can be seen in Table 2, the indirect effects of optimization on grades ($B_{a2b1} = .07$, $p = .03$) and study satisfaction ($B_{a2b2} = .22$, $p < .001$) through self-efficacy beliefs were significant, which suggests mediation (Hayes, 2017). Also the total effects of optimization on grades ($B = .15$, $p = .04$) and study satisfaction ($B = .30$, $p < .001$) were significant (see also Figure 2, footnote). The nonsignificant direct effects suggest that optimization did not have effects on grades and study satisfaction independent of self-efficacy beliefs.

Our analyses did not support the assumption of indirect relationships of elective selection with grades and satisfaction through self-efficacy beliefs. These results only partially support our model.

To provide a complete picture of all SOC components and the outcomes of interest, we tested another model that additionally included loss-based selection and compensation. Table 2 shows that there were no significant indirect relationships of loss-based selection and compensation with the outcome variables grades and study satisfaction. While none of the components was significantly associated with self-efficacy beliefs and study satisfaction, loss-based selection was negatively related to grades ($B = -.15$, $p = .04$). Finally, analyses of the reversed model (see Figure 3) in which self-efficacy beliefs were linked to grades and study satisfaction through elective selection and optimization did not yield significant indirect effects (see Table 3).

Study 2

Preliminary analyses. Table 1 shows the means, standard deviations, and correlations (above the diagonal) between all study variables. Consistent with the findings of Study 1, female students engaged more in loss-based SOC than male students, with correlations ranging from $r = .16$ to $r = .17$ (ps $< .05$). Also in line with previous results, Table 1 shows that self-efficacy beliefs were negatively correlated with gender, $r = -.16$, $p = .01$, again indicating that female students had lower self-efficacy than male students. Furthermore, in line with our model and again consistent across both studies, we observed positive correlations of (a) all SOC components with self-efficacy beliefs, (b) optimization with grades, (c) elective selection and optimization with study satisfaction, and (d) self-efficacy beliefs with study satisfaction and grades. However, in contrast to Study 1, the anticipated positive correlation between elective selection and grades was not significant.

Test of the research model. Figure 2 depicts the results of our research model. The fit indices suggested an excellent model fit ($\chi^2 = 8.499$, $df = 6$, $p = .20$; root mean square error of approximation = .042; comparative fit index = .987; Tucker–Lewis index = .962; standardized root mean square residual = .036). Table 4 reveals that, in line with our research model and consistent with Study 1, there were significant indirect relationships between optimization and both grades ($B_{a2b1} = .13$, $p = .001$) and study satisfaction ($B_{a2b1} = .20$, $p < .001$) via self-efficacy beliefs. Also

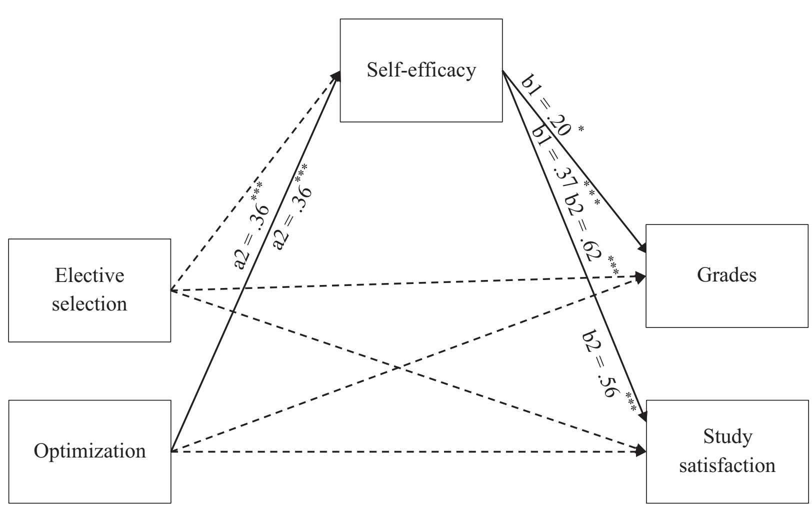

Figure 2. Results of the hypothesized research model for Study 1 ($N = 360$) and Study 2 ($N = 241$). Estimates above the arrows correspond to Study 1. Estimates below the arrows correspond to Study 2. Dotted lines represent nonsignificant paths. The coefficients are unstandardized. Study 1: Total effect optimization → grades: c = .15*. Study 1: Total effect optimization → study satisfaction: c = .30***. Study 2: Total effect optimization → grades: c = .34***. Study 2: Total effect optimization → study satisfaction: c = .38***. * $p < .05$. *** $p < .001$.

Table 2
Unstandardized Coefficients of the Path Model for Study 1

Model	Estimate	*SE*	*p*	95% Bootstrap CI Lower bound	95% Bootstrap CI Upper bound
Elective selection → Self-efficacy ($a1$)	−0.02	0.05	.65	−0.11	0.07
Optimization → Self-efficacy ($a2$)	0.36*	0.05	<.001	0.26	0.46
Self-efficacy → Grades ($b1$)	0.20*	0.09	.03	0.02	0.38
Self-efficacy → Satisfaction ($b2$)	0.62*	0.10	<.001	0.41	0.81
Elective selection → Grade ($c'1$)	0.06	0.07	.45	−0.09	0.20
Elective selection → Satisfaction ($c'2$)	0.13 (.14*)	0.07	.07 (.05)	−0.01	0.28
Optimization → Grades ($c'3$)	0.07	0.08	.35	−0.08	0.22
Optimization → Satisfaction ($c'4$)	0.07	0.08	.35	−0.08	0.22
Indirect effect ($a1 \times b1$)	−0.00	0.01	.69	−0.03	0.01
Indirect effect ($a1 \times b2$)	−0.01	0.03	.66	−0.08	0.04
Indirect effect ($a2 \times b1$)	0.07*	0.03	.03	0.01	0.15
Indirect effect ($a2 \times b2$)	0.22*	0.05	<.001	0.14	0.33
Covariates					
Track → Self-efficacy	−0.01	0.09	.94	−0.18	0.16
Gender → Self-efficacy	−0.41*	0.09	<.001	−0.57	−0.24
Age → Self-efficacy	−0.02	0.02	.22	−0.04	0.02
Track → Grades	−0.14	0.15	.38	−0.45	0.17
Gender → Grades	0.21	0.15	.16	−0.08	0.50
Age → Grades	−0.00	0.02	.86	−0.04	0.05
Track → Satisfaction	0.40*	0.14	.01	0.11	0.67
Gender → Satisfaction	0.06	0.14	.66	−0.21	0.33
Age → Satisfaction	−0.03	0.02	.25	−0.06	0.02
Supplementary analyses					
Loss-based selection → Self-efficacy ($a3$)	0.05	0.05	.36	−0.05	0.16
Compensation → Self-efficacy ($a4$)	0.08	0.06	.13	−0.03	0.19
Loss-based selection → Grade ($c'5$)	−0.15*	0.08	.04	−0.30	0.00
Loss-based selection → Satisfaction ($c'6$)	−0.07	0.07	.37	−0.21	0.08
Compensation → Grades ($c'7$)	−0.15	0.08	.07	−0.31	0.01
Compensation → Satisfaction ($c'8$)	0.16	0.08	.06	−0.00	0.32
Indirect effect ($a3 \times b1$)	0.01	0.01	.43	−0.01	0.05
Indirect effect ($a3 \times b2$)	0.03	0.03	.38	−0.03	0.11
Indirect effect ($a4 \times b1$)	0.02	0.02	.22	−0.00	0.06
Indirect effect ($a4 \times b2$)	0.05	0.04	.16	−0.01	0.13

Note. $N = 360$. CI = confidence interval. Numbers within parentheses indicate effect sizes of effects that became significant after including loss-based selection and compensation in the model. Significant coefficients are marked with an asterisk (*).

in line with Study 1, yet contradictory to our research model, the indirect links of elective selection with both grades and study satisfaction via self-efficacy were *not* significant. And again, the total effects of optimization on grades ($B = .34$, $p < .001$) and study satisfaction ($B = .38$, $p < .001$) were significant (see also Figure 2, footnote). In contrast to Study 1, however, the direct effect of optimization on grades was significant ($B = .21$, $p = .01$), indicating that there was a link between optimization and grades independently of self-efficacy beliefs.

Again, for the sake of completeness, we tested the same model including all SOC variables and confirmed that loss-based selection and compensation were not indirectly related to grades and study satisfaction through self-efficacy beliefs. Only the relationship between compensation and self-efficacy beliefs was significant ($B = .13$, $p = .05$). Hence, in both studies, optimization was the only component that was positively related to grades and study satisfaction through self-efficacy beliefs. Unexpectedly, the analyses of the reversed model (see Figure 3), in which self-efficacy beliefs were linked to grades and study satisfaction through elective selection and optimization, resulted in a significant indirect path between self-efficacy beliefs and grades through optimization ($B_{a2b3} = .11$, $p = .02$, see Table 5).

Discussion

The goal of the present study was to investigate the indirect links between the two preference-based SOC components (i.e., elective election and optimization) and study outcomes (i.e., grades and satisfaction) through self-efficacy beliefs (see Figure 1). We based our ideas on the self-concordance model (Sheldon, 2002), which claims that individuals who select goals that are in line with their preferences, attain better outcomes. However, we also conducted supplementary analyses in which we tested the indirect relationships between loss-based components and study outcomes through self-efficacy beliefs. As expected, we did not find indirect relationships between the two loss-based components (i.e., loss-based selection and compensation) and favorable study outcomes through self-efficacy beliefs. These results are in line

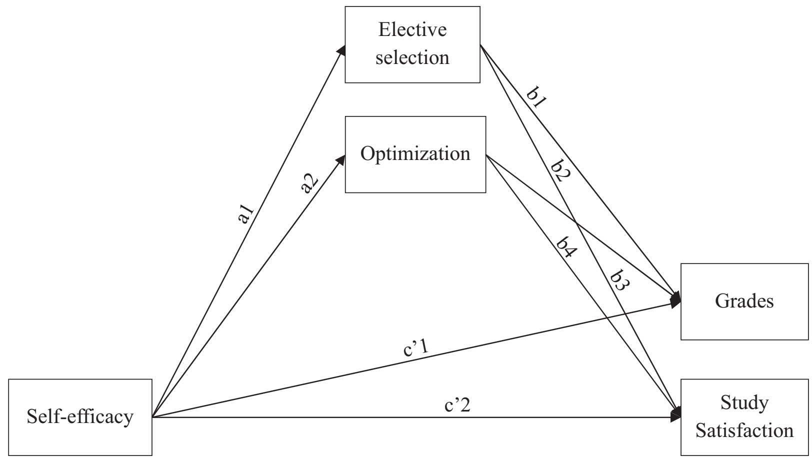

Figure 3. Reversed research model (coefficients are presented in Tables 3 and 5).

with previous studies that showed that young adults are focused on growth-oriented goals (Ebner et al., 2006; Penningroth & Scott, 2012). We conclude that in a sample of relatively young students who presumably still have many resources at their disposal, loss-based regulation is not an effective strategy.

Our main findings were consistent across both studies. That is, in both studies, we observed the expected indirect links between the use of optimization and both outcome variables (i.e., end-of-first-year average grade and study satisfaction) through self-efficacy beliefs. Similarly, in the work domain, studies report positive relationships between SOC components and self-efficacy beliefs, on the one hand, and performance and well-being outcomes, on the other (Judge & Bono, 2001; Moghimi et al., 2017). However, these previous studies have often focused on the overall use of SOC components and not on optimization and elective selection separately. It is possible that in previous studies, the positive effects of the overall use of SOC components were mostly driven by the positive effect of optimization on favorable out-

Table 3
Unstandardized Coefficients of the Reversed Path Model in Study 1

Model	Estimate	*SE*	*p*	95% Bootstrap CI Lower bound	95% Bootstrap CI Upper bound
Self-efficacy → Elective selection (*a*1)	0.26*	0.08	.002	0.09	0.42
Self-efficacy → Optimization (*a*2)	0.55*	0.08	<.001	0.40	0.70
Elective selection → Grades (*b*1)	0.06	0.07	.45	−0.09	0.20
Elective selection → Satisfaction (*b*2)	0.13	0.07	.07	−0.01	0.28
Optimization → Grades (*b*3)	0.07	0.08	.35	−0.08	0.22
Optimization → Satisfaction (*b*4)	0.07	0.08	.35	−0.08	0.22
Self-efficacy → Grade (*c*′1)	0.20*	0.09	.03	0.02	0.38
Self-efficacy → Satisfaction (*c*′2)	0.62*	0.10	<.001	0.41	0.81
Indirect effect (*a*1 × *b*1)	0.01	0.02	.49	−0.02	0.06
Indirect effect (*a*1 × *b*2)	0.03	0.02	.13	0.00	0.10
Indirect effect (*a*2 × *b*3)	0.04	0.04	.36	−0.04	0.13
Indirect effect (*a*2 × *b*4)	0.04	0.04	.37	−0.04	0.13
Covariates					
Track → Elective selection	−0.21	0.14	.13	−0.47	0.05
Gender → Elective selection	0.26*	0.12	.04	0.02	0.51
Age → Elective selection	−0.00	0.03	.89	−0.07	0.04
Track → Optimization	−0.18	0.12	.15	−0.42	0.63
Gender → Optimization	0.53*	0.11	<.001	0.32	0.74
Age → Optimization	−0.01	0.03	.76	−0.06	0.04
Track → Grades	−0.14	0.16	.38	−0.45	0.17
Gender → Grades	0.21	0.15	.16	−0.08	0.50
Age → Grades	−0.00	0.02	.86	−0.04	0.05
Track → Satisfaction	0.40*	0.14	.01	0.11	0.67
Gender → Satisfaction	0.06	0.14	.66	−0.21	0.33
Age → Satisfaction	−0.03	0.02	.25	−0.06	0.02

Note. $N = 360$. CI = confidence interval. Significant coefficients are marked with an asterisk (*).

Table 4
Unstandardized Coefficients of the Path Model for Study 2

Model	Estimate	*SE*	*p*	95% Bootstrap CI Lower bound	95% Bootstrap CI Upper bound
Elective selection → Self-efficacy (*a*1)	−0.03	0.06	.54	−0.15	0.08
Optimization → Self-efficacy (*a*2)	0.36*	0.06	<.001	0.24	0.47
Self-efficacy → Grades (*b*1)	0.37*	0.09	<.001	0.19	0.54
Self-efficacy → Satisfaction (*b*2)	0.56*	0.12	<.001	0.32	0.79
Elective selection → Grade (*c*′1)	−0.03	0.08	.74	−0.17	0.13
Elective selection → Satisfaction (*c*′2)	0.17	0.09	.06	−0.01	0.35
Optimization → Grades (*c*′3)	0.21*	0.08	.01	0.05	0.37
Optimization → Satisfaction (*c*′4)	0.14	0.09	.13	−0.03	0.32
Indirect effect (*a*1 × *b*1)	−0.01	0.02	.55	−0.06	0.03
Indirect effect (*a*1 × *b*2)	−0.02	0.03	.54	−0.08	0.04
Indirect effect (*a*2 × *b*1)	0.13*	0.04	.001	0.07	0.22
Indirect effect (*a*2 × *b*2)	0.20*	0.05	<.001	0.11	0.32
Control variables					
Track → Self-efficacy	−0.16	0.10	.12	−0.35	0.04
Gender → Self-efficacy	−0.38*	0.10	<.001	−0.57	−0.18
Age → Self-efficacy	0.02	0.01	.20	−0.01	0.05
Track → Grades	−0.62*	0.14	<.001	−0.88	−0.35
Gender → Grades	0.39*	0.14	.01	0.11	0.67
Age → Grades	−0.00	0.02	.96	−0.05	0.04
Track → Satisfaction	0.19	0.15	.20	−0.12	0.47
Gender → Satisfaction	0.07	0.16	.67	−0.26	0.37
Age → Satisfaction	−0.00	0.03	.98	−0.04	0.07
Supplementary analyses					
Loss-based selection → Self-efficacy (*a*3)	0.03	0.06	.62	−0.08	0.14
Compensation → Self-efficacy (*a*4)	0.13*	0.07	.05	0.01	0.26
Loss-based selection → Grade (*c*′5)	−0.02	0.08	.82	−0.17	0.14
Loss-based selection → Satisfaction (*c*′6)	0.05	0.09	.60	−0.12	0.22
Compensation → Grades (*c*′7)	0.03	0.09	.75	−0.15	0.21
Compensation → Satisfaction (*c*′8)	0.01	0.09	.92	−0.16	0.18
Indirect effect (*a*3 × *b*1)	0.01	0.02	.65	−0.03	0.06
Indirect effect (*a*3 × *b*2)	0.02	0.03	.64	−0.04	0.09
Indirect effect (*a*4 × *b*1)	0.05	0.03	.08	0.01	0.11
Indirect effect (*a*4 × *b*2)	0.07	0.04	.08	0.01	0.17

Note. $N = 241$. CI = confidence interval. The significance levels of the variables included in the main analyses did not change after including loss-based selection and compensation. Significant coefficients are marked with an asterisk (*).

comes. Similar to this unique optimization effect, in a recent study among high school students, Muenks, Yang, and Wigfield (2018) found a positive link between perseverance of effort (a component of grit) and grades at the end of the semester. Perseverance or persistence is one of the most important aspects of optimization and requires the investment of sustained effort over time toward the same, preferred goal (Freund & Baltes, 2000). Furthermore, in line with our finding that being able to pursue goals in a preferred manner positively relates to favorable study outcomes through self-efficacy beliefs, Koestner et al. (2006) found that goal progress was only achieved when goal implementation (similar to optimization) was combined with an actual implementation plan and a subsequent self-efficacy boosting exercise.

Unexpectedly, we also found some support for the reversed relationship. That is, only in Study 2, there were indirect relationships between self-efficacy beliefs and grades through optimization. This finding suggests a reciprocal relationship between optimization and self-efficacy beliefs, which is in line with the notion of feedback systems that regulate functioning (Carver & Scheier, 1990; B. J. Zimmerman, 1989). Carver and Scheier (1990) proposed that feedback loops serve the purpose of monitoring goal progress by comparing current behavior with a reference point (e.g., a set goal). This periodical comparison with the reference point serves the purpose of decreasing any discrepancy between the current state and the desired state. Translated to the current findings, optimization and self-efficacy beliefs might affect each other reciprocally in this loop in the sense that effort investment (i.e., optimization) increases the feeling that one can achieve a certain goal (i.e., self-efficacy). In turn, the elevated self-efficacy beliefs increase effort investment toward goal achievement because one feels efficacious enough to engage in goal pursuit. However, it should be noted that we found more consistent results for the indirect relationships between optimization and outcomes through self-efficacy beliefs than the reverse.

Contrary to our predictions, we did not find significant indirect relationships between elective selection and beneficial outcomes through self-efficacy beliefs. Similarly, Muenks et al. (2018) did not find a link between consistency of interest (a component of

Table 5
Unstandardized Coefficients of the Reversed Path Model in Study 2

Model	Estimate	*SE*	*p*	95% Bootstrap CI Lower bound	95% Bootstrap CI Upper bound
Self-efficacy → Elective selection (*a*1)	0.20*	0.09	.02	0.03	0.38
Self-efficacy → Optimization (*a*2)	0.51*	0.08	<.001	0.35	0.66
Elective selection → Grades (*b*1)	−0.03	0.08	.74	−0.17	0.13
Elective selection → Satisfaction (*b*2)	0.17	0.09	.06	−0.01	0.35
Optimization → Grades (*b*3)	0.21*	0.08	.01	0.05	0.37
Optimization → Satisfaction (*b*4)	0.14	0.09	.13	−0.03	0.32
Self-efficacy → Grade (*c*′1)	0.37*	0.09	<.001	0.19	0.54
Self-efficacy → Satisfaction (*c*′2)	0.56*	0.12	<.001	0.32	0.79
Indirect effect (*a*1 × *b*1)	−0.01	0.02	.77	−0.05	0.02
Indirect effect (*a*1 × *b*2)	0.03	0.02	.12	0.00	0.10
Indirect effect (*a*2 × *b*3)	0.11*	0.04	.02	0.03	0.21
Indirect effect (*a*2 × *b*4)	0.07	0.05	.14	−0.02	0.17
Control variables					
Track → Elective selection	−0.01	0.14	.94	−0.28	0.28
Gender → Elective selection	0.13	0.15	.38	−0.14	0.45
Age → Elective selection	0.01	0.04	.75	−0.09	0.05
Track → Optimization	0.12	0.13	.36	−0.14	0.38
Gender → Optimization	0.48*	0.13	<.001	0.23	0.76
Age → Optimization	−0.01	0.02	.71	−0.07	0.02
Track → Grades	−0.60*	0.14	<.001	−0.88	−0.35
Gender → Grades	0.39*	0.14	.01	0.11	0.67
Age → Grades	−0.00	0.02	.96	−0.05	0.04
Track → Satisfaction	0.19	0.15	.20	−0.12	0.47
Gender → Satisfaction	0.07	0.16	.67	−0.26	0.37
Age → Satisfaction	−0.00	0.03	.98	−0.04	0.07

Note. $N = 241$. CI = confidence interval. Significant coefficients are marked with an asterisk (*).

grit) and high school students' grades at the end of the semester. Similar to elective selection, consistency of interest concerns sustained focus on a preferred goal. Muenks et al. (2018) argued that in high school students, pursuing many goals simultaneously, as opposed to being selective, is the norm rather than the exception. Indeed, it has been shown that elective selection increases with age and peaks in late adulthood (Freund & Baltes, 2002). Other life span models also support the idea that young adults need to keep their options open to successfully pursue their goals and plans (Heckhausen & Schulz, 1993).

Theoretical Implications

In the present study, we ventured a first attempt at uncovering the underlying mechanisms between certain SOC components and beneficial outcomes in the educational context. A few studies have considered the conjoint effects of SOC components and self-efficacy beliefs (Wiese & Heidemeier, 2012) or related constructs such as self-esteem (Wiese et al., 2000) on beneficial outcomes. However, none of those studies were aimed at explaining how SOC components affect beneficial outcomes. Furthermore, none of those studies were conducted in the educational context. The present study was a first attempt at explaining how action-regulation in the form of effort investment is positively related to grades and study satisfaction, that is, through self-efficacy beliefs.

Furthermore, by looking at the use of all SOC components separately, we empirically tested more fine-grained predictions of the SOC model than most previous studies. Our results challenge SOC theory, which claims that it is the combination (or "orchestration") of all components that positively affects functioning and well-being (Baltes, 1997; Freund & Baltes, 2000). In the present study, we found a positive indirect effect on our outcome variables through self-efficacy beliefs only for optimization. As discussed earlier, during young adulthood, loss-based selection and compensation may be unrelated to favorable outcomes because the negative notion of a resource loss overshadows the positive outcomes of resource-preservation. In line with this, Ebner and colleagues (2006) showed that among young adults, focusing on loss-prevention is negatively associated with well-being.

Finally, we contribute to educational, motivation, and life span research through the consideration of key constructs drawn from two different and rarely connected theoretical perspectives to explain academic performance and study satisfaction. Specifically, in the present study, we combined the motivational concept of self-efficacy with a general model of action-regulation that defines and explains successful life span development. In doing so, we not only provided yet another context to which SOC components can be applied, and hence, tested the generalizability of the model, but also aimed at empirically bridging the gap between motivation and life span research in the educational context.

Practical Implications

Given the alarming number of students who are unhappy or have difficulties achieving satisfactory outcomes during their studies (American College Health Association, 2017), the present results can be used to guide educators in helping students increase their academic performance and well-being by showing them how to engage in optimization activities. Freund and Baltes (2000) argued that equifinality is an essential component of optimization, because goals can always be achieved in many different ways (Kruglanski, 1996). Accordingly, to engage in efficient goal pursuit (i.e., optimization), it is of the utmost importance to know what to do, when to do it, and in what situation (Freund & Baltes, 2000). Applied to the educational context, we recommend that educators (a) help students identify their goals and the means that are needed for goal pursuit and eventual goal achievement, (b) provide students with the right tools and skills, and (c) teach students to read and recognize situational cues to act on certain goals. The ultimate goal of optimization training is that students become active agents of their personal goals and resources that are needed to optimize goal pursuit, and learn to apply optimization activities without the help of educators.

Additionally, building on our finding that there are indirect links between optimization and academic outcomes through self-efficacy beliefs, we recommend self-efficacy-enhancing training that refers to optimization. We believe that in college, students themselves can best administer this training given that college students are often taught in large groups that exceed the capacities of a single educator to train each student individually. For example, Koestner and colleagues (2006) implemented self-efficacy-boosting training with the following steps: (a) formulating a goal that had already been achieved similar to the goal that is currently being pursued, (b) thinking of someone similar to oneself who has already attained the goal that is being pursued (i.e., has successfully optimized), and (c) thinking of an individual who could offer support for the goal. These steps are based on the four sources of information that can help to determine one's own skills and capabilities (i.e., physiological reactions, vicarious experiences, persuasion, and performance; Bandura, 1977; Schunk & Meece, 2006). Interestingly, by engaging in this self-administered training, students already take the first steps toward successful optimization. As mentioned earlier, goal implementation in combination with the self-efficacy boosting training resulted in goal progress. Thus, we recommend that additional to training students to use optimization in the best way, students should be encouraged to engage proactively in these self-efficacy-boosting steps to perform at their best.

Limitations and Future Directions

A number of limitations of our study should be considered. First, the prospective nature of the present study does not allow any causal inferences. While we partially addressed this issue by assessing grades at the end of the academic year and by testing reversed models, SOC components, self-efficacy beliefs, and study satisfaction were assessed at the same time. In future research, the experimental-causal-chain approach to mediation may be adopted to test the causality of the indirect relations (Spencer, Zanna, & Fong, 2005). This approach requires a SOC intervention aimed at increasing students' self-efficacy beliefs, and subsequently, a self-efficacy intervention aimed at increasing students' grades and study satisfaction. This latter training may aim at improving persuasion, vicarious learning, and performance (e.g., Koestner et al., 2006; Luzzo, Hasper, Albert, Bibby, & Martinelli Jr, 1999). A promising SOC intervention has recently been developed in a group of nurses, with the main steps being the introduction to the SOC model and the development of a limited number of main goals (Müller, Heiden, Herbig, Poppe, & Angerer, 2016; Müller, Weigl, Heiden, Rudolph, & Angerer, 2017). A second module consisted of the practical implementation of and possible adjustments to the action-plan. The training course ended after eight weeks with reflection and discussion of possible future applications of SOC components. Similar steps could be implemented in a student sample by having students specify their academic goals at the beginning of the academic year, asking them to develop an action-plan with regard to those goals, and revising the action-plan after several weeks to see whether the goals have been achieved. Finally, the action-plan could be revised and improved throughout an entire academic year and goal achievement could be measured at the end of the academic year. Another suggestion for future research is to examine SOC interventions at a more microlevel, for example, from one exam to the next. Studies at such a specific level may reveal that action-regulatory strategies other than optimization might be effective as well.

Second, in a review of students' achievement values, goal orientation, interests, and performance outcomes, Wigfield and Cambria (2010) showed that in college students, there were clear relationships between (among other things) intrinsic motivation, interests, and performance outcomes. Other researchers found that college students engaged in more self-regulation strategies in their favorite courses (Ben-Eliyahu & Linnenbrink-Garcia, 2015) and in tasks that had a self-directed instructional strategy (Hiemstra, Van Yperen, & Timmerman, 2019). However, college students do not attend university for intrinsic reasons only. They may also be at college because they want to increase their job opportunities and earning power, or they may feel pressured by their parents. Future studies may aim at investigating SOC use in relation to intrinsic versus extrinsic goals. Researchers may first ask students to list their most important intrinsic and extrinsic goal, and next, ask them to respond to the SOC questionnaire with respect to each specific goal.

Third, as expected, we showed that loss-based components were not related to beneficial outcomes through self-efficacy beliefs. Future studies could elaborate on these nonfindings. For instance, under what conditions may loss-based regulation be beneficial to young college students? Loss-based regulation is possibly relevant only in populations that have to manage a great deal of losses, such as students who have to manage chronic illnesses, or students who have experienced high-impact life events such as parenthood. Furthermore, college students in general might not have many opportunities to develop loss-oriented regulation because normatively they come from families with higher socioeconomic status and therefore have a larger pool of resources compared to their low-socioeconomic-status mates. Additionally, the use of SOC components might be dependent on the environmental context and the resources and demands that each environment provides and poses on the students.

Finally, we recommend that future research focuses on developing a SOC instrument that measures each component more reliably. As noted earlier, some SOC components only reach mediocre levels of reliability which leaves room for improvement in future endeavors to improve the assessment of SOC. Relatedly, these measures should be further developed in different languages and countries to test the generalizability of our findings. The present study was conducted in one particular university in the Netherlands. In future studies different colleges and environments may be included and/or different groups of students within the same college (e.g., based on socioeconomic status, gender, age, ethnicity) may be taken into account. We are, however, confident that our theory-based findings can largely be replicated in other college environments, both within and outside the Netherlands.

Conclusion

The present study was one of the first attempts at combining life span and motivational theories in the educational context and explaining academic outcomes with specific SOC components. The results consistently showed that investing effort, time, and attention in selected goals (i.e., optimization) was positively related to college students' end-of-first-year average grade and study satisfaction through self-efficacy beliefs. Based on these findings, we recommend that practitioners and educators teach students how to identify goals, the means that are needed for goal pursuit, strategies that can be employed to achieve goals, and how to recognize situational cues that allow goal pursuit. These optimization-oriented strategies together with self-efficacy-boosting training have the potential to increase grades and satisfaction in students.

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