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GOAL SETTING AND GOAL ORIENTATION AS PREDICTORS OF LEARNING SATISFACTION AND ONLINE LEARNING BEHAVIOR IN HIGHER EDUCATION BLENDED COURSES

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ABSTRACT

This study investigated how goal setting and goal orientation are related to student learning behavior and engagement in an online learning environment, and how learning behavior, goal setting, and goal orientation are related to student satisfaction with the course they are studying. A total of 882 students from 76 different courses participated in this study, which used both self-reported data from a questionnaire and indicators based on digital traces in an online learning environment. The results of multilevel regression analyses showed that student ability to set learning goals (i.e., goal setting) was positively related to both student learning satisfaction and student learning behavior. Intrinsic goal orientation positively predicted student satisfaction with the course. Extrinsic goal orientation did not show a significant effect in any of the observed relationships. The analyzed indicators of student learning behavior showed no statistically significant association with learning satisfaction. Possible explanations for these findings are discussed, and limitations and directions for future research are suggested.

KEYWORDS

self-regulated learning; goal setting; goal orientation; learning engagement; online learning behavior; course satisfaction

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Introduction

Self-regulated learning (SRL) entails processes that empower learners to regulate their cognition, emotions, and behavior as they engage in learning tasks (Pintrich, 2004). Although these processes are employed cyclically throughout the learning process, it is possible to distinguish three phases of SRL: forethought, performance, and self-reflection (Panadero, 2017). In the forethought phase, SRL involves goal setting and strategic planning, incorporating motivational beliefs such as self-efficacy, outcome expectations, goal orientation, and the intrinsic value of the learning task. The performance phase encompasses self-control and self-observation during learning (Zimmerman & Campillo, 2003). In the self-reflection phase, learners engage in self-judgment by comparing their learning outcomes with their expectations, making causal attributions for their results, and responding emotionally to their learning outcomes (Zimmerman, 2002). The extent to which learners engage in SRL during their studies is associated with their academic achievement and satisfaction (Broadbent & Poon, 2015). In our study, we focus on two SRL processes that relate to how learners set their goals in the first phase of their SRL.

Engagement in SRL is essential in online learning environments, including the learning management systems (LMS) that are widely used in higher education, as such environments put high demands on student ability to structure, process, and evaluate their online learning (Wong et al., 2019). In recent years, there has been a shift in the way online learning is studied, with researchers looking for new ways to explore and measure the online learning process, attempting to move away from self-report questionnaires toward new indicators based on capturing digital traces of student learning behavior in online learning environments (Winne, 2010). In this approach, learning engagement in online learning environments may be measured in terms of the number and frequency of visits or learning time spent in the online learning environment (Kim, et al., 2016; Kim et al., 2018; Kovanović et al., 2015a; Kovanović et al., 2015b). Learning analytics, the broader research area that specifically focuses on capturing and investigating online learning processes through the collection and analysis of data available in online learning environments, appears to be a promising approach to studying online learning behavior (Vieira et al., 2018; Winne, 2017). However, in the context of learning in blended courses, learning analytics can provide only a limited insight into student learning processes, as not all learning takes place in online learning environments (Ifenthaler & Schumacher, 2016; Wilson et al., 2017). Digital traces of student learning behavior offer useful insights into the actions that students take while learning; on the other hand, these data can suffer from the ambiguity of interpretation (Gašević et al., 2016; Wise & Shaffer, 2015). This study combines subjective data (i.e., self-reports) and data of an objective nature (i.e., logs) to gain further insight into the relationship between student SRL, online learning behavior, and satisfaction with the course.

We aim to answer the question of how goal setting and goal orientation are related to student engagement within the online learning environment, as demonstrated by the number of visits, regularity of visits, and total time spent. At the same time, we aim to answer the question of how learning behavior, goal setting, and goal orientation are related to student satisfaction with the course.

1 Theoretical background

1.1 Goal setting and goal orientation within self-regulated learning

Setting learning goals for one's own learning is an essential part of SRL processes across the different theoretical approaches to describing the SRL model (Panadero, 2017). In Zimmerman's model, goal setting and goal orientation are processes that fall within the first of three phases of SRL. In this first phase, learners focus on forethought and planning their learning process. The forethought phase consists of task analysis, including goal setting and strategic planning, and self-motivation beliefs consisting of self-efficacy, outcome expectations, intrinsic interest, and goal orientation (Zimmerman, 2002; Zimmerman & Moylan, 2009). Pintrich (2004) argued that the first phase of SRL covers forethought, planning, and activation; it involves cognitive, affective, and behavioral processes, as well as the perception of the learning task and context. In this SRL model, the learner sets goals at the cognitive level and adopts goal orientation at the motivational and affective levels. According to Winne (2013), these processes follow task definition and consist of setting goals and planning how to achieve them, linking goals and tactics before the learner starts working on the task itself. To sum up, goal setting and goal orientation cover the cognitive as well as the motivational and affective aspects of how learners deal with goals in learning.

Goal setting is the process of identifying goals and deciding what outcomes one wants to achieve (Zimmerman & Moylan, 2009). Setting goals is linked to various aspects of student learning at university. Goal setting, along with other SRL behaviors, is associated with the perception of online courses (Barnard et al., 2008) and with the quality of learning resources (Ballouk et al., 2022). Students with higher levels of goal setting are more likely to adopt a deep learning approach to learning (Soyer & Kirikkanat, 2019). Goal setting is also associated with academic achievement (Ballouk et al., 2022; Barnard et al., 2008).

Goal orientations describe the broader purposes of achievement behavior and explain how people behave in achievement situations and why (Kaplan & Maehr, 2007). It is possible to distinguish mastery and performance goal orientations. Students applying mastery goal orientations focus on achieving task-based or intra-personal competence; those applying performance goal orientations focus on being well perceived by others (Miller et al., 2021). Similarly, based on goal content theory, we can distinguish between extrinsic and intrinsic goal orientations (Kasser & Ryan, 1996). Intrinsic goal orientation focuses on personal growth and learning itself; extrinsic goal orientation is associated with the fulfilment of goals such as achievement, recognition from others, and obtaining material benefits (Zhang et al., 2018). Goal orientations influence how students perceive different components of the learning environment, such as course assessment (Kaur et al., 2018), and their behavior, such as task selection (Lindfors, 2021).

1.2 Online learning behavior and course satisfaction

Learning satisfaction is understood as an affective dimension of learning outcomes (Klein et al., 2006). Course satisfaction can then be viewed as the satisfaction arising from studying a particular course. In the context of online and blended learning, learning satisfaction seems to be one of the key factors that determine learning retention and academic success when learning in an online learning environment (Ke & Kwak, 2013; She et al., 2021). Huang (2023) stated that effective goal setting promotes learning motivation and higher learning satisfaction, which in turn leads to better performance and well-being. At the same time, Klein et al. (2006), in their research on blended learning environments, found a significant positive relationship between goal orientation and learning satisfaction. Similar results were found in relation to goal orientation among college students (Sánchez-Cardona et al., 2021). Another study (Ma & She, 2023) found a positive correlation between goal orientation and learning satisfaction, while also focusing on a mediating effect in this relationship, with academic self-efficacy and learning engagement acting as intervening factors. Thus, our first hypothesis is as follows:

- **H1** Goal setting and goal orientation positively correlate with student course satisfaction.

The relationship between student learning behavior and their learning engagement was assumed in Pintrich's SRL model (Pintrich, 2004), in which learning goal orientation was seen as a kind of motivational process within the forethought phase, which lays the foundation for the subsequent performance phase, within which students regulate their learning behavior (i.e., it affects student learning engagement). Several studies have concluded that student online learning behavior is influenced by their affective characteristics. An important implication of a study by Schwam et al. (2021) was that students who lack confidence in their ability to navigate the online learning environment may not use SRL techniques as effectively as their more proficient peers. This discomfort has the potential to impede the learning process, as students not only have to engage with the course content, but also have to invest considerable effort in familiarizing themselves with the intricacies of the online learning environment. Similarly, Zhang & Liu (2019) suggested that student learning behavior and learning engagement are driven by their learning goals and plans. Therefore, we propose the following hypothesis:

- **H2** Goal setting and goal orientation positively correlate with student behavior in the online learning environment.

Pintrich's SRL model (Pintrich, 2004) also proposes a relationship between student learning behavior (in other words, their learning engagement) and learning satisfaction. In the context of online learning environments, learning engagement is manifested by, for example, the frequency of course visits, the regularity of completing assignments, and the number of posts in discussion forums. Learning engagement is a determinant of the learning experience and thus subsequent course satisfaction (Rajabalee & Santally, 2021). Research has suggested that learning behavior and learning engagement are among the strongest predictors of learning satisfaction (Murillo-Zamorano et al., 2019). A study by El-Sayad et al. (2021) focused on online learning during the COVID-19 pandemic found a significant relationship between student behavioral engagement and their learning satisfaction. At the same time, students who are not sufficiently engaged in the learning process tend to experience low levels of learning satisfaction (Gao et al., 2020). Thus, we propose the last hypothesis as follows:

- **H3** Student behavior in the online learning environment positively correlates with student course satisfaction.

2 Methods

2.1 Sample and procedure

This study focuses on goal-related aspects of SRL and their relationship to student satisfaction and behavior in an online learning environment used to support student learning in blended university courses. The study combines data from two different sources: data from a questionnaire survey that the students completed during the semester and data extracted from the database of the online learning environment that the students used during the semester as part of their coursework.

Participants in this study were recruited from 76 different courses taught at the Faculty of Arts, Masaryk University (Czech Republic) during three different semesters. In each of the three semesters, students of different courses were approached to complete a questionnaire focusing on various dimensions of SRL and other relevant factors. After the end of the semester, relevant data on student behavior in the online learning environment were extracted for those students who agreed to participate in the research. All of the research, the distribution of the questionnaire and the extraction of data from the online learning environment, was carried out in cooperation with the teachers of the selected courses.

A total of 882 student responses were analyzed. Only courses with responses from at least five different students were included in the sample. Students from both bachelor's (77.55%) and non-follow-up master's fields (21.77%) were approached to complete the questionnaire. The mean age of the respondents was 21.98 years (med = 21). Regarding gender, 76.87% of the respondents were female and 21.77% were male, which corresponds to the gender distribution of the students at the Faculty of Arts (1.02% of the students chose the option "other"). The vast majority of students in the sample were full-time students (94.56%).

2.2 Measures

Goal setting was measured using a five-item scale developed by Barnard, Lan, To, Paton, & Lai (2009) and used as one of six subscales within the *Online Self-Regulated Learning Questionnaire* (OSLQ). The goal setting scale consisted of five-point Likert scale items such as: "I set standards for my assignments in online courses," "I set short-term (daily or weekly) goals as well as long-term (monthly or for the semester) goals," and "I set goals to help me manage study time for my online courses." The wording of the items was slightly modified to suit the context of this study (e.g., blended courses using online support in an online learning environment to varying degrees in combination with in-class instruction). The Cronbach's alpha in the original study (i.e., Barnard et al., 2009) was 0.95; in our sample, the Cronbach's alpha is 0.763, which can probably be explained by the use of the scale in the context of blended courses.

Student goal orientation was measured using two subscales from the *Motivated Strategies for Learning Questionnaire* (MSLQ) developed by Pintrich et al. (1991). In this questionnaire, the authors distinguish between **intrinsic and extrinsic goal orientation** when measuring student goal orientation. Both the intrinsic and extrinsic goal orientation scales consist of four seven-point Likert scale items. The intrinsic goal orientation scale consisted of items such as: "In a class like this, I prefer course material that really challenges me so I can learn new things" and "The most satisfying thing for me in this course is trying to understand the content as thoroughly as possible." The Cronbach's alpha of the intrinsic goal orientation scale reported in Pintrich's manual for the MSLQ (Pintrich et al., 1991) was 0.74; in our sample, the Cronbach's alpha is 0.815. The extrinsic goal orientation scale consisted of items such as: "I want to do well in this class because it is important to show my ability to my family, friends, employer, or others" and "If I can, I want to get better grades in this class than most of the other students." The wording of the items was slightly modified to fit the context of Czech university studies (for example, the items related to grade point average (GPA) have been modified as GPA is not a highly used indicator in the Czech context compared to other countries). The Cronbach's alpha of Pintrich's manual for the MSLQ was 0.62; in our sample, the Cronbach's alpha is 0.82.

To measure student learning satisfaction when studying a blended course with online support in an online learning environment, we used the five-item **course satisfaction** scale used by Lee, Srinivasan, Trail, Lewis, & Lopez (2011), which included items such as: "This course increased my interest in the subject," "I felt comfortable in this course," and "I would recommend this course to others." Respondents answered on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The Cronbach's alpha in the original study (i.e., Lee et al., 2011) was 0.94; in our sample, the Cronbach's alpha is 0.9.

Table 1
Basic descriptive statistics and Cronbach's alpha for the questionnaire scales

	Min–Max	Mean	Median	SD	Skewness	Kurtosis	Alpha
Goal Setting	1–5	3.28	3.20	0.86	–0.15	–0.25	0.76
Intrinsic goal orientation	1–7	4.91	5.00	1.22	–0.56	0.26	0.82
Extrinsic goal orientation	1–7	4.16	4.25	1.53	–0.12	–0.63	0.82
Course satisfaction	1–5	4.03	4.20	0.94	–1.11	0.61	0.90

The second set of variables used in the analyses were related to online learning behavior. The variables were created based on student log records extracted from the database of the online learning environment that served as the main online learning support for each course. After pre-processing the student log records, three proxy indicators were used to measure and describe student learning behavior in the online learning environment (OLE): 1) number of course visits in OLE, 2) irregularity of visits in OLE, and 3) total time spent in online course support in OLE.

For the **number of course visits** in OLE, a visit was conceptualized as a situation where a student enters a course in OLE, spends some time in the course, and then leaves the course. If the student returns to the course after a period of time (e.g., a week), this is counted as a new visit. In most online learning environments, it is not possible to distinguish exactly between visits, because the end of a visit is usually not explicitly recorded in the system (i.e., the student does not explicitly log out of the system, but simply stops working in the system and closes the browser window). Therefore, an inactivity threshold is usually used to distinguish between individual visits (cf. Kovanović et al., 2015a). For this analysis, an inactivity threshold of 30 minutes was chosen, which means that a 30-minute period of inactivity was used as an indicator of the end of the visit.

The **irregularity of visits** captures another aspect of student learning behavior in OLE. To measure the degree of irregularity of visits, we used the approach suggested by Jo et al., 2015 and Kim et al., 2018, who calculate the irregularity of visits using the standard deviations of the time intervals between individual visits in the course. In general, the lower the value of this variable, the more regularly the student attends the course. For example, a student who regularly attends a course at the same time every week will have a low value for this variable, while a student who attends a course sporadically will have a high value for this variable.

The final variable used to capture student online learning behavior was the **total time spent in the course** in OLE. Similar to the number of visits, a threshold of 30 minutes of inactivity was used to signal the end of a student's visit to the course. The duration of the visit (in minutes) was then calculated as the time from the first log record within that visit to the last log record within that visit (i.e., the last log record preceding the 30-minute period of inactivity). However, for each visit, the estimated time spent on the last activity was added to the time difference between the last and first log within a visit. Following other studies (cf. Kim et. al., 2016; Kovanović et al., 2015b), we estimated the time spent on the last activity as the average time spent on the other activities within the same visit.

As all three variables related to student online learning behavior showed a non-normal distribution, a logarithmic transformation was performed before using the variables in the regression models. The table below shows the descriptive statistics of the variables before and after transformation.

Table 2
Basic descriptive statistics for the student online learning behavior variables

	Min	Max	Mean	Median	SD	Skewness	Kurtosis
Before transformation							
Number of visits in OLE	0	179	37.7	33	27.2	1.39	3.05
Irregularity of visits in OLE	0.02	47.3	4.84	3.14	5.07	3.68	18.9
Total time spent in OLE	0.10	2485.1	402.2	307.5	349.3	2.04	6.00
After transformation							
Number of visits in OLE	0	5.19	3.31	3.5	0.93	–1.16	1.70
Irregularity of visits in OLE	0.03	3.86	1.30	1.15	0.70	0.86	0.55
Total time spent in OLE	0.87	7.82	5.62	5.73	0.97	–0.81	1.10

2.3 Data analysis

Given the hierarchical nature of the data analyzed (i.e., students nested within individual courses), multilevel modelling was used for data analysis (cf. Heck & Thomas, 2015; Hox, 2010; Snijders & Bosker, 2012). The main reason for using multilevel modelling was that we did not control for the learning design of the courses in the study. On the contrary, our aim was not to focus only on a specific learning design of the courses, but to cover a wide range of different types of courses that are commonly used in online learning environments at universities.

First, basic descriptive statistics (see Tables 1 and 2) and correlations between all analyzed variables (see Table 3) were calculated. Then, for each of the dependent variables, a null model was estimated as a basis for calculating the intra-class correlation coefficient (ICC). Finally, separate multilevel models were estimated for each of the hypotheses tested. All preprocessing and analyses were performed using the R statistical software (Posit team, 2023; R Core Team, 2023). The *lme4* library (Bates et al., 2015) was used for multilevel modelling.

3 Results

Initially, descriptive statistics and correlations were calculated (see Tables 1, 2, and 3). Among the descriptive statistics, the higher skewness of course satisfaction is worth mentioning, which showed that in our sample there were rather high values of course satisfaction. As far as correlations are concerned, there was a very strong correlation between all three indicators of student learning behavior. While the strong positive correlation between the number of visits and the total time spent in the course is probably to be expected, the strong negative correlation between the number of visits and the irregularity of visits is perhaps not immediately expected, but it follows from the way the irregularity of visits is calculated. In addition, we calculated the intra-class correlation coefficient for all dependent variables in the following models. The ICC for course satisfaction was 0.241, which means that about 24.1% of the variance in student course satisfaction was due to differences between courses. The ICCs for the indicators of student online learning behavior are as follows: number of visits = 0.533, irregularity of visits = 0.473, total time spent = 0.479. These ICCs can be considered relatively high and further indicate the need to estimate multilevel models.

Table 3
Correlations between all analyzed variables

	1)	**2)**	**3)**	**4)**	**5)**	**6)**
1) Goal setting	1					
2) Intrinsic goal orientation	0.444	1				
3) Extrinsic goal orientation	0.486	0.414	1			
4) Course satisfaction	0.342	0.575	0.267	1		
5) Number of visits in OLE	0.212	0.025	0.105	0.099	1	
6) Irregularity of visits in OLE	−0.196	0.012	−0.061	−0.039	−0.860	1
7) Total time spent in OLE	0.214	0.047	0.080	0.120	0.794	−0.612

To address the first hypothesis, which focused on goal setting and goal orientation and their relationship to student course satisfaction, a model was constructed with goal setting and intrinsic and extrinsic goal orientation as independent variables and course satisfaction as the dependent variable. The resulting model is presented in Table 4, which shows that both goal setting and goal orientation are significant factors in student course satisfaction. However, within goal orientation, only the intrinsic dimension was statistically significant; the extrinsic dimension of goal orientation did not seem to have an effect on student course satisfaction. In both cases, the identified significant relationship was positive: higher goal setting and higher intrinsic goal orientation led to higher student satisfaction with the course.

Table 4
Effects of goal setting and goal orientation on student course satisfaction

	Course satisfaction		
	Coef.	**SE**	**p**
Fixed Effects			
(Intercept)	1.73	0.12	
Goal setting	0.13	0.03	**<0.001**
Intrinsic goal orientation	0.36	0.02	**<0.001**
Extrinsic goal orientation	0.01	0.02	0.584
Random Effects			
Residual variance	0.47		
Intercept variance	0.13		
Fit statistics			
Marginal R^2 / Conditional R^2	0.304 / 0.458		
Deviance	1923.8		
AIC	1957.1		

Subsequently, three models were created in relation to the second hypothesis, which dealt with the relationship between goal-related variables and student behavior in the online learning environment. Thus, a separate model with goal setting, intrinsic goal orientation, and extrinsic goal orientation as independent variables was created for each dependent variable related to student online learning behavior (i.e., number of visits to the course in OLE, irregularity of visits to the course in OLE and total time spent in the course in OLE). The data for all three models are presented in Table 5, which shows that of the three independent variables, only goal setting had a statistically significant effect on student online learning behavior. At the same time, the variable appears to have had a significant effect on all three observed indicators of student behavior. For the number of visits and total time spent, the effect of goal setting was positive, i.e., the better a student was able to set their own goals, the more often they attended the course and the more total time they spent on the course in OLE. For the irregularity of course visits, the observed effect is negative, indicating a positive relationship between goal setting and regularity of course visits. So, similarly to above, the better a student was able to set their learning goals, the more regularly they visited the online learning support of the course being studied.

Table 5
Effects of goal setting and goal orientation on indicators of student online learning behavior

	Number of visits			**Irregularity of visits**			**Total time spent**		
	Coef.	**SE**	**p**	**Coef.**	**SE**	**p**	**Coef.**	**SE**	**p**
Fixed Effects									
(Intercept)	2.90	0.13		1.59	0.11		5.06	0.14	
Goal Setting	0.10	0.03	**0.002**	–0.11	0.03	**<0.001**	0.11	0.04	**0.003**
Intrinsic goal orientation	–0.01	0.02	0.607	0.03	0.02	0.129	0.01	0.02	0.658
Extrinsic goal orientation	0.03	0.02	0.056	–0.01	0.01	0.455	0.03	0.02	0.164
Random Effects									
Residual variance	0.40			0.27			0.49		
Intercept variance	0.45			0.23			0.45		
Fit statistics									
Marginal R^2 / Conditional R^2	0.015 / 0.536			0.016 / 0.469			0.016 / 0.485		
Deviance	1872.5			1441.7			2022.3		
AIC	1905.2			1476.1			2054.4		

The last hypothesis dealt with the relationship between student online learning behavior and student course satisfaction. To test the first hypothesis, we started from the model presented in Table 4 and added the indicators of student learning behavior as three additional independent variables. Similarly to the first model, student course satisfaction served as the dependent variable. The results for this model are presented in Table 6 and show that none of the three indicators of student behavior had a statistically significant relationship with student satisfaction with the course. At the same time, the fit statistics for this model do not appear to be significantly different from those of the original model (cf. Table 4). This further confirms that the addition of indicators of student online learning behavior does not help explain the variability in student course satisfaction.

Table 6
Effects of goal setting, goal orientation, and indicators of online learning behavior on student course satisfaction

	Course satisfaction		
	Coef.	**SE**	**p**
Fixed Effects			
(Intercept)	1.56	0.36	
Goal Setting	0.12	0.03	**<0.001**
Intrinsic goal orientation	0.37	0.02	**<0.001**
Extrinsic goal orientation	0.00	0.02	0.935
Number of visits	–0.00	0.09	0.965
Irregularity of visits	–0.01	0.07	0.910
Total time spent	0.04	0.05	0.405
Random Effects			
Residual variance	0.46		
Intercept variance	0.11		
Fit statistics			
Marginal R^2 / Conditional R^2	0.313 / 0.445		
Deviance	1802.8		
AIC	1854.3		

4 Discussion and conclusion

The aim of this study was to investigate the relationship between goal-related SRL processes (goal setting and goal orientation) and student learning behavior in the online learning environment, and how goal setting, goal orientation, and student online learning behavior are related to student satisfaction with the course. In order to fulfil these aims, we formulated three hypotheses and tested them with multilevel regression analysis.

The first hypothesis predicted a positive relationship between goal setting and goal orientation and student course satisfaction. Based on the analysis conducted, we can confirm the proposed hypothesis. However, for goal orientation, the analyses carried out in this study distinguished between intrinsic and extrinsic goal orientation, which allowed us to reveal that the positive relationship between goal orientation and student course satisfaction occurs only with intrinsic goal orientation. In contrast, no statistically significant relationship was found between extrinsic goal orientation and student course satisfaction.

These findings are consistent with earlier research showing a positive association with learning satisfaction for both goal setting and goal orientation (Huang, 2023; Klein et al., 2006; Ma & She, 2023; Sánchez-Cardona et al., 2021). On the other hand, our findings highlight the importance of distinguishing between intrinsic and extrinsic goal orientation, as the relationship between these two types of goal orientation and student satisfaction appears to be very different. Existing studies have not always distinguished between these two types of goal orientation and have dealt with goal orientation in general, which may obscure important differences. For example, the study by Sánchez-Cardona et al. (2021), which reported a positive relationship between goal orientation and learning satisfaction, actually focused specifically on intrinsic goal orientation (as can be inferred from a close reading of the methodology and measures used), meaning that their findings are quite consistent with our results. The same is true for a number of other studies that report a positive relationship between goal orientation and student learning satisfaction (Klein et al., 2006; Ma & She, 2023). Many other researchers (Kasser & Ryan, 1996; Lee et al., 2010; Miller et al., 2021; Zhang et al., 2018) have distinguished between intrinsic and extrinsic goal orientation, showing that these are indeed two very different dimensions of goal orientation and that their relationship to student learning satisfaction may be distinct and more complex.

Our second hypothesis focused on the relationship between goal setting and goal orientation and student behavior in an online learning environment, predicting that higher levels of goal setting and goal orientation would lead to higher levels of student activity and engagement in the online learning environment. In dealing with the second hypothesis, we focused our attention on three different indicators of student online learning behavior: the number of student visits in the course, the irregularity of student visits in the course, and the total time spent in the course within the online learning environment. The results of the analysis suggest that only goal setting has a statistically significant positive effect on student learning behavior. That is, a greater ability of students to set goals for their own learning is associated with more frequent course attendance, higher regularity of course attendance, and overall greater time spent in the course. On the other hand, goal orientation was not found to be statistically significantly related to any of the three indicators of student behavior in the online learning environment. This was the case for both intrinsic and extrinsic goal orientation. Thus, the second hypothesis is only partially supported.

The fact that no significant relationship was found between goal orientation and student online learning behavior is surprising, as previous research (Miller et al., 2021; Pintrich, 2004; Zhang & Liu, 2019) suggested that goal orientation and the motivational dimension of SRL in general should influence the subsequent performance phase: the level of student activity in the online learning environment or their engagement in actual learning. At the same time, no significant association with learning satisfaction was found for either intrinsic or extrinsic goal orientation, supporting the explanation that the main reason for these findings may be the way in which student online behavior was measured in our study. In a study by Miller et al. (2021), which found a significant relationship between mastery-approach orientation and a variety of learning engagement indicators, the engagement indicators were designed as self-report measures. On the other hand, a study by Zhang & Liu's (2019), like ours, worked with indicators based on digital traces (e.g., number of logins, assignments submitted, number of posts) and found a significant effect of goal orientation on learning engagement. Thus, it seems that this relationship between goal orientation and student online learning behavior and engagement requires further detailed research to uncover which specific indicators of learning behavior are affected by student goal orientation.

The last tested hypothesis focused on the relationship between online learning behavior of students and their course satisfaction. For this relationship, we predicted a positive association: that higher student activity and learning engagement in the online learning environment would be associated with higher satisfaction with the studied course. However, our results showed no statistically significant relationship between the observed indicators of student learning behavior and their learning satisfaction. That is, the number of visits, the regularity of visits, and the total time spent on the course do not appear to be related to course satisfaction.

This finding was very surprising to us, given that a number of earlier studies (El-Sayad et al., 2021; Gao et al., 2020; Murillo-Zamorano et al., 2019; Rajabalee & Santally, 2021) reported that learning behavior and learning engagement were expected to be significant predictors of learning satisfaction. On the other hand, a closer look at the previous studies on this topic reveals that, in the vast majority of cases, the studies measured student perceived engagement using a self-report method (i.e., a questionnaire) rather than proxy indicators that capture actual student behavior in online courses (i.e., indicators based on digital traces in the online learning environment). Thus, it appears that existing research on the relationship between student learning behavior and learning satisfaction may be largely influenced by the measurement approach used. Therefore, one might be inclined to support the views of some researchers (Winne, 2010, 2017; Zeidner & Stoeger, 2019) who expressed concerns that self-reports and questionnaires capture student learning preferences rather than their actual learning behavior. These views, as well as the results of our study, support the thesis that it is necessary to pay more attention to the use of digital traces in researching student learning behavior and engagement in online learning environments, as indicators based on digital traces seem to measure something different from traditional self-report measures.

4.1 Limitations and future research

The research presented in this study has several limitations that need to be addressed and taken into account when interpreting the findings. The main set of limitations arises from the fact that the data analyzed in this study relate to university courses that are blended by design. That is, only part of the teaching of individual courses takes place in an online learning environment; the other part of the teaching takes place in the "traditional" setting, in the form of either face-to-face lectures or seminars. Relatedly, each course may combine traditional and online teaching to different degrees and in different ways, which can obviously have a significant impact on the resulting student satisfaction with the course and (perhaps most importantly) on student behavior in each course in the online learning environment. While we accounted for this important part of the variability (i.e., course-level variability) in the analyses we conducted by using multilevel modelling, we did not use any additional second-level variables within the individual models that might reveal the influence of course-level differences on the relationships examined between the student-level variables. Future research could enrich the models we present with relevant course-level variables to test whether these variables moderate the relationships examined in this study.

Another limitation of the study is that we only focused on three indicators of learning behavior, which should be understood as proxy indicators that obviously cannot fully capture student learning behavior in an online learning environment. Future research could focus both on a wider range of proxy indicators of student learning behavior and on the development and use of more sophisticated methods of investigating and measuring student online learning behavior.

Last but not least, the study sample can be considered as a limitation of the study. Although we were able to collect a sample of 882 students studying in 76 different courses, the sample we obtained has some limitations. For example, only those students who were willing to complete our questionnaire were included in the sample. This means that we only have data from a subset of students from each course, which may introduce some bias into the analyzed data. The same applies to the courses in our sample, as only those courses whose instructors were willing to cooperate with our research and provide us with access to their courses were included in our sample.

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