Education and Information Technologies
https://doi.org/10.1007/s10639-024-12995-3

# The influence of SDL on learning satisfaction in online learning and group differences between undergraduates and graduates

Meina Zhu[1] · Min Young Doo[2] · Sara Masoud[3] · Yaoxian Huang[4]

Received: 19 May 2024 / Accepted: 12 August 2024


## Abstract
This study examines the influences of learners' motivation, self-monitoring, and self-management on learning satisfaction in online learning environments. The participants were 185 undergraduates and 99 graduate students majoring in computer science and engineering. The participants' motivation, self-monitoring, self-management, and learning satisfaction were measured using a questionnaire. Results indicated that motivation, self-monitoring, and self-management significantly influenced learning satisfaction and the three factors together accounted for approximately 60% of the variance in learning satisfaction. Motivation was the most influential factor on learning engagement. Group differences emerged between undergraduates and graduate students in the influences of motivation, self-monitoring, and self-management on learning satisfaction. Compared to undergraduate students, graduate students had statistically higher scores in motivation, self-monitoring, and self-management, but not in learning satisfaction. The three factors also influenced undergraduate and graduate students differently in the regression analysis results. Motivation and self-monitoring, but not self-management influenced undergraduates' learning satisfaction, whereas motivation and self-management, but not self-monitoring influenced graduates' learning satisfaction. Further studies are needed to investigate the reasons for the group differences. The implications are that instructors need to utilize SDL strategies extensively to enhance learning satisfaction in online learning. In addition, designers, instructors, and institutions should tailor the learning strategies more effectively for their target audience given the differences in the influence of SDL on learning satisfaction between undergraduates and graduates.

**Keywords** Self-directed learning · Motivation · Self-monitoring · Self-management · Learning satisfaction · Online learning · Higher education

Extended author information available on the last page of the article

Published online: 28 August 2024

## 1 Introduction

The number of learners who enrolled in online courses rapidly increased during the COVID-19 pandemic, which accelerated universities' shift from traditional in-person settings to online environments (Gardner, 2020; Kelly, 2020). Through the unprecedented online learning experiences during the pandemic, researchers and educators identified pivotal factors that led to successful online learning. Several researchers found that self-directed learning (SDL) leads to active participation, high learning motivation and engagement, and preparedness of learners (Kim, 2024; Li et al., 2023; Sun et al., 2023). Notably, the flexible structure of online courses gives learners the opportunity to exercise control over their own learning (e.g., learning autonomy), including when and how they engage in the learning process (Milligan & Littlejohn, 2014). Research has consistently found that SDL skills have a positive impact on online learning outcomes (Broadbent & Poon, 2015; Broadbent, 2017; Richardson et al., 2012; Wang et al., 2013). Learners possessing higher levels of SDL skills tend to derive greater benefits from online learning resources (Geng et al., 2019) as they adeptly manage their time and learning resources and participate in course activities (Chu & Tsai, 2009; Hung et al., 2010). Consequently, SDL has been extensively highlighted as a crucial factor in the successful acquisition of knowledge and a predictor of learners' readiness for online learning (Durnali, 2020; Karatas & Arpaci, 2021; Wei & Chou, 2020). Due to the importance of SDL, Garrison (1997) stated that SDL may be the most researched topic in adult education.

Learning satisfaction is another extensively researched topic in education. Hence, it has gained considerable attention from instructors and educational researchers because learning satisfaction reflects learners' perceptions of their learning experience and the outcomes they achieve (Alqurashi, 2019; Artino, 2009; Kuo et al., 2014; Littlejohn et al., 2016). Since learning satisfaction is a key indicator of successful learning, it has been treated as an important learning result related to affective aspects of learning. Learning satisfaction also applies to online learning. Extensive research has demonstrated a positive correlation between learners' satisfaction, student success (Chang & Smith, 2008), and retention rates in online education (Lee & Choi, 2013; Park & Choi, 2009). Jiang and colleagues (2021), Bollinger and Halupa (2012), and Stokes (2001) emphasized the importance of learning satisfaction in online learning indicating that high learning satisfaction leads to a lower attrition rate and increased learning engagement and learning achievement. Thus, learning satisfaction could lead to learners' future intention to enroll in online learning.

Due to the importance of learning satisfaction in online learning, numerous recent studies have investigated influential factors related to learners' satisfaction (Davis et al., 2018; Kuo et al., 2014; Liu et al., 2022; Rabin et al., 2020). The effects of SDL on learning outcomes have been investigated in various learning domains, including cognitive, meta-cognitive, affective, and behavioral learning domains (Doo et al., 2023; Doo & Zhu, 2024). However, little research has focused on the influence of SDL on learning satisfaction. Previous SDL studies have mostly focused on the influences of SDL on learning achievement (e.g., Broadbent & Poon, 2015; Broadbent, 2017; Hsu & Shiue, 2005; Kim, 2024; Long, 1990; Wang et al., 2013). For example, Broadbent and Poon (2015) found that learning achievement was measured with exam scores, assignment scores, final grades, or GPA in their systematic review of the effects of self-regulated learning strategies on learning achievement in online learning in higher education.

Given the importance of learning satisfaction in online learning, this study aims to investigate the impact of SDL on learning satisfaction in online learning environments. Among the various learning domains, we chose science, technology, engineering, and mathematics (STEM) fields as the context of this study. The U.S. Bureau of Labor Statistics in 2021 reported substantial growth in Computer Science and Engineering (CSE) occupations, spurred by the flourishing digital economy. The U.S. Bureau of Labor Statistics in 2022 estimated that approximately 667,600 new computer science jobs will be created, highlighting the increasing demand for qualified workers in CSE. Given the accelerated growth in STEM fields, particularly in CSE fueled by the continuous emergence of new technologies, it is crucial to provide effective CSE education. In addition, there has been a rise in the availability of fully online Computer Science and Engineering (CSE) degrees and courses (Payne, 2022). This trend requires that we understand how students learn online in STEM fields from a self-directed learning perspective. Computer science and engineering also require hands-on learning activities, which are typically challenging for online learning (Zhu et al., 2024). Therefore, it is crucial to conduct a deeper investigation into how motivation, self-monitoring, and self-management influence learning satisfaction in CSE online learning. This study also compares the influence of SDL on learning satisfaction between undergraduates and graduates based on their different perspectives of SDL. The differences between undergraduates and graduates in their academic maturity, responsibilities, and learning approaches could lead to differences in motivation, self-monitoring, and self-management. A thorough understanding of these differences is critical to tailor online learning programs to meet the unique needs of these groups and to improve learning satisfaction.

## 2 Theoretical framework

### 2.1 Self-directed learning

Researchers have viewed SDL from two perspectives: (1) SDL as the personal attributes of learners or personality characteristics (Guglielmino, 1978; Lounsbury et al., 2009; Long, 1990) and (2) SDL as the learning process or instructional method (Brockett & Hiemstra, 1991; Knowles, 1975). The first perspective views SDL as inherent learner traits or characteristics, encompassing skills and attributes such as motivation, self-monitoring, self-management, and self-control. Long (1990) explained that essential attributes for self-directed learners include independence, self-efficacy, intrinsic motivation, metacognition, deep learning, and prioritization. Other attributes of SDL include learner autonomy, responsibility, and control over the learning process (Sze-Yeng & Hussian, 2010). This perspective focuses on individual differences in SDL. For example, Lounsbury and colleagues (2009) examined the relationship between SDL and personality traits as well as career-related traits. They found a significant correlation between SDL and openness, (low) anxiety, optimism, work drive, optimism, career decidedness, and self-actualization. Based on their results, they described self-directed learners as individuals who are more engaged in self-directed learning are more likely to have a firm sense of identity; experience higher levels of life satisfaction; have higher levels of vocational interests for investigative, artistic, enterprising, and conventional occupations; and they are more likely to be conscientious, well-adjusted, optimistic, self-actualized, intuitive, hard-working, and open to new experiences. (p. 417)

The second perspective views SDL as a learning process in which learners take charge of planning, implementing, and evaluating their own learning (Knowles, 1975; Merriam & Bierema, 2014; Song & Hill, 2007). Knowles (1975) defined SDL as "a process in which individuals take the initiative, with or without the help of others, in diagnosing their learning needs, formulating learning goals, identifying human and material resources for learning, choosing and implementing appropriate learning strategies, and evaluating learning outcomes" (p. 18). Brookfield (1986) also characterized SDL as a process empowering learner to set learning goals, make plans for learning, make learning progress, and evaluate learning outcomes. This viewpoint has practical implications for instructors and university administrators as they can strengthen learners' self-directed learning by helping them set learning goals and make plans. Good examples of this perspective include Centers for Teaching and Learning providing workshops or seminars to teach SDL skills.

Garrison (1997) criticized previous SDL research as overly focused on external management of learning. Garrison specifically highlighted the lack of attention given to the learning process in SDL such as the motivation and cognitive aspects of learners. Garrison defined SDL as "an approach where learners are motivated to assume personal responsibility and collaborative control of the cognitive (self-monitoring) and contextual (self-management) processes in constructing and confirming meaningful and worthwhile learning outcomes" (p.18). As a combination of the two primary perspectives on SDL and to integrate the external management of learning, learning motivation, and cognitive responsibilities (i.e., SRL), Garrison developed a three-dimensional model of SDL consisting of motivation, self-monitoring, and self-management (see Fig. 1). This model is still relevant today.

Regarding motivation, Garrison (1997) started with motivation in his SDL model and emphasized its importance as a "pivotal issue in SDL" (p. 26). Since motivation is a significant predictor of learning behaviors and performance, the importance of motivation in learning cannot be overemphasized (Williams & Deci, 1996; Williams et al., 1997). Artino (2008) also emphasized the importance of motivation because

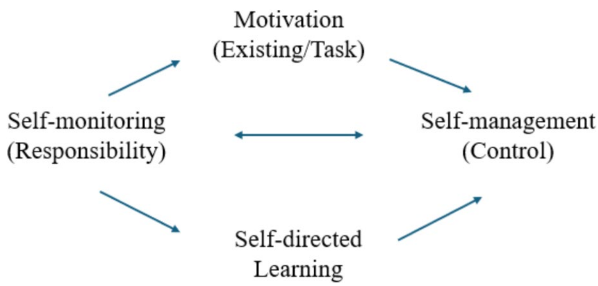


**Fig. 1** Garrison's self-directed learning. *Note* Adapted from Garrison's Dimensions of Self-Directed Learning (1997, p. 22)

motivation (e.g., task value beliefs) is a strong predictor of the utilization of metacognition and cognitive strategies (e.g., learning strategies), learning achievement, and learning satisfaction. Motivation in this model encompasses entering motivation and task motivation. The difference between the two types of motivation is that entering motivation signifies the initial drive for learning with rational intentions to pursue learning goals, whereas task motivation relates to the motivation to sustain learners' engagement throughout the learning process. Garrison (1997) explained that task motivation is more associated with self-management including task control.

Self-monitoring involves learners taking responsibility for cognitive and metacognitive processes in learning (Garrison, 1997). There is no universal distinction between self-regulated learning and self-directed learning, so the two terms are often used interchangeably (Linkous, 2021; Saks & Leijen, 2014). Self-monitoring in this model indicates self-regulated learning focusing on cognitive and meta-cognitive aspects of constructing meaning. Cognitive responsibilities include activities, such as monitoring their own learning process, applying appropriate learning strategies for successful learning outcomes, and evaluating learning achievement. The metacognitive process involves reflective and critical thinking of learning process. Examples of self-monitoring include self-regulation, self-monitoring, self-regulated learning strategies, self-control, and cognitive and meta-cognitive learning strategies (Li et al., 2023; Zhu et al., 2024).

Self-management, such as task management and external control, has traditionally been emphasized in SDL research. Self-management refers to the behavioral aspects of learners considering the external factors and task control activities that influence the learning process (Garrison, 1997). Better learner control in self-management is expected to help learners take more responsibility for their own learning process in terms of self-monitoring and motivation. Examples of self-management include time management, effort regulation, and learning resource management (Garrison, 1997). The relationship between motivation, self-monitoring, and self-management is intricately interconnected. Garrison called them the "three overlapping dimensions" of SDL.

### 2.2 SDL in online learning

The importance of SDL is even more important in online learning environments, and SDL skills are considered key dimensions of online learning readiness (Chu & Tsai, 2009; Hung et al., 2010; Hsu & Shiue, 2005). Since the interaction between learners and instructors is restricted due to the spatial and/or temporal separation in online learning environments, learners are expected to possess SDL skills to appropriately exercise increased learning autonomy in online learning (e.g., defining their learning objectives or making progress in learning at their own pace) (Cıgdem & Ozturk, 2016; Lin & Hsieh, 2001; Song & Hill, 2007; Torun, 2020).

Numerous studies have highlighted the influences of SDL skills on learners' academic performance (Broadbent & Poon, 2015; Broadbent, 2017; Richardson et al., 2012; Wang et al., 2013; Zheng et al., 2018). Doo and Zhu (2024) also examined the effects of SDL based on Garrison's model on learning achievement in online learning using a meta-analysis. The overall effect size of SDL on learning achievement was a medium effect size ($g=0.508$). The results indicated that the effect size of motivation ($g=0.658$) was the largest followed by self-monitoring ($g=0.519$), and self-management ($g=0.279$). The effect size of self-management was statistically smaller than motivation and self-monitoring. The influence of SDL on learning outcomes varied in learning domains: affective domain ($g=0.625$), cognitive domain ($g=0.401$), behavioral/participation domain ($g=0.403$), and meta-cognitive domain ($g=1.043$). Lee and colleagues (2019) reported the systematic review results that examined the influences of SDL strategies on learning in massive open online courses (MOOCs). Using a systematic review, they identified MOOC learners' motivational strategies, such as self-efficacy, task value, and goal setting. In their analysis, self-management strategies (i.e., behavioral aspects) included help-seeking, time management, and effort regulation.

### 2.3 SDL and learning satisfaction

SDL has the potential to influence learners' inclination towards online learning (or intention for further study) and could increase learning satisfaction and learning achievement. Topala and Tomozii (2014) discussed the lack of consensus on the meaning of learning satisfaction. It generally indicates learners' general satisfaction with the learning environment or context, or the joy or pleasure they experience during the learning process. Given that learning satisfaction is an important indicator of learning success, it has been adopted as a dependent variable in many educational studies. However, few studies have examined the relationship between SDL and learning satisfaction in online learning environments. Thus, we expanded our literature search to include affective learning outcomes, such as a sense of academic achievement and learners' preferences for online learning.

Here we present a summary of the relevant empirical studies about the relationship between SDL/SRL and affective learning outcomes. Lee and colleagues (2019) conducted a systematic review and reported that SDL strategies enhanced a sense of academic achievement (i.e. affective domain) in addition to improving learning achievement in MOOCs. Chu and Tsai (2009) examined influential factors for adult learners' preferences for online learning. The participants were 541 students who were enrolled in computer classes at community colleges and adult learning centers in Taiwan. They found that SDL readiness is a critical factor to predict learners' preferences for online learning and the explanatory power is greater than other variables (e.g., general self-efficacy or Internet-usage). Other studies, which were not conducted in STEM fields (e.g., Hsu & Shiue, 2005, Meyer & colleagues, 2019), also indicated that learners with strong SDL skills are willing to take on challenging tasks and take ownership of their own learning, including taking responsibility for initiating and managing learning processes. Artino (2008) examined the influences of self-efficacy, task values, and perceived instructional quality on learning satisfaction in online learning using regression analysis. The results indicated that task value in motivation (e.g., task motivation in Garrison's model) is a significant predictor of learning satisfaction ($B=0.31$, $p<.001$) such as self-efficacy and instructional quality. These previous research findings have identified the influences of SDL on affective aspects of learning outcomes.

Artino and Stephens (2009) examined differences between undergraduates and graduates in online learning in terms of academic motivation and self-regulation (or self-monitoring). They hypothesized that graduates are superior to undergraduates in self-monitoring in online learning because of the developmental nature of self-regulation and graduates' longer exposure to higher education (or longer learning experiences). Research has also indicated that graduates outperform undergraduates in self-monitoring (e.g., critical thinking and elaboration). However, Artino and Stephens (2009) reported mixed findings related to motivation: undergraduates demonstrated higher task value and future intention to enroll in online learning than graduates. However, compared to graduates, undergraduates had lower self-efficacy and higher procrastination tendencies. Based on their research findings, Artino and Stephens (2009) emphasized the need to provide customized learning support for undergraduates and graduates in online learning because their needs (e.g., academic motivation and self-regulation) are different. Heo and Han (2018) examined the relationship between SDL readiness and motivation, academic stress, and age of online learners. They found that motivation and academic stress (reversely) predicted SDL readiness, but the relationship between age and SDL readiness was not significant. These conflicting findings on the relationship between SDL and age by Artino and Stephens (2009) and Heo and Han (2018) indicate that further examination is needed. Hence, it is necessary to examine the group differences between undergraduates and graduates in the influence of SDL on learning satisfaction The research questions that guided this study are as follows:

1. To what extent do motivation, self-monitoring, and self-management influence learning satisfaction in online learning within the STEM field in higher education institutions?
2. Which aspect of SDL is the most influential to learning satisfaction?
3. Are there differences between undergraduates and graduates in terms of the influence of motivation, self-monitoring, and self-management on learning satisfaction?

# 3 Methods

## 3.1 Contexts and participants

The participants of this study were students who were currently enrolled in online courses at the time of data collection or had previously taken online courses in the College of Computer Science and Engineering at Wayne State University, a large university in the Midwest in the US. The study received approval from the Institutional Review Board (IRB) at Wayne State University. The data for this study were collected in Spring 2021 using an electronic survey. The questionnaire was sent to all students in the College of Computer Science and Engineering via the college email listserv. Participation in this study was voluntary (i.e., no credit given for survey participation) and a $25 gift card was offered to randomly selected individuals who completed the questionnaire to encourage participation in the study. The initial number of participants was 370 individuals, and 284 participants completed the whole questionnaire (76.8%), excluding missing or incomplete responses. Among the 284 participants, more than two-thirds of the participants were undergraduates ($N$=185, 65.1%) and the remaining 34.9% were graduate students ($N$=99). While most students (75%) had previously enrolled in more than three online courses, the number of online courses taken by the participants varied: 1–3 courses (15%), 4–6 courses (25%), 7–9 courses (22%), 10–12 courses (25%), and more than 12 courses (13%). Although all participants in this study were enrolled in the College of Computer Science and Engineering, their majors or concentrations varied: computer science ($N$=76, 26.8%), electrical/electronic engineering ($N$=34, 12.0%), biomedical engineering ($N$=29, 10.2%), civil engineering ($N$=18, 6.3%), industrial engineering ($N$=17, 6.0%), chemical engineering ($N$=14, 4.9%), other engineering majors ($N$=39, 13.7%), and not reported ($N$=57, 20.1%).

### 3.2 Measurement instruments

The questionnaire included three sections: demographic questions, SDL measurement, and learning satisfaction measurement. Demographic questions included majors, class years, and online learning experiences of the participants. The SDL measurement was adopted from Zhu et al., (2020) and Zhu and Doo, (2022), which was developed for measuring MOOC learners' SDL by adopting SDL scales of Fisher and King, (2010) and Williamson (2007) with modification. The initial Cronbach's alphas for the self-management, self-monitoring, and motivation items were 0.71, 0.76, and 0.65, respectively (Zhu & Bonk, 2019). To make the measurement scale more suitable for the context of the current study, we changed the term MOOCs to online learning. The SDL measurement included 27 items in three sub-categories: motivation (9 items), self-monitoring (9 items), and self-management (9 items) (see Appendix). Learning satisfaction was measured with six questions on overall learning satisfaction, satisfaction about educational and professional development, satisfaction about interaction with peers and instructors, and future intention to enroll in an online learning course. The Cronbach's alphas for motivation, self-monitoring, and self-management and learning satisfaction measurement exceeded 0.80, indicating an acceptable score, as shown in Table 1.

Examples from the SDL measurements for motivation, self-monitoring, and self-managing are as follows: "I enjoy learning new information while taking online courses" and "I would like to know the deep reasons behind the facts while taking online courses" (motivation); "I am in control of my learning while taking online courses" and "I evaluate my own performance while taking online courses" (self-monitoring); "I am able to keep my learning routine in online courses separate from

**Table 1** Research instruments and correlations

| Variables | Number of items | Cronbach's alpha |
|---|---|---|
| Motivation | 9 | 0.87 |
| Self-monitoring | 9 | 0.83 |
| Self-management | 9 | 0.85 |
| Satisfaction | 6 | 0.92 |

my other commitments" and "I can apply a variety of learning strategies while taking online courses" (self-management). Statements to measure learning satisfaction included: "Overall, I am satisfied with online courses" and "In the future, I would be willing to take an online course again." The participants were asked to rate their self-directed learning on a 5-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree).

### 3.3 Data analysis

We conducted descriptive analysis of the major variables (i.e., motivation, self-monitoring, self-management, and learning engagement) including the means, standard deviations, kurtosis and skewness to check the assumption of normality. To answer the research questions, the influence of the three factors of SDL on learning satisfaction were investigated using multiple regression analysis. Finally, we compared the self-directed learning of undergraduates ($N=185$) and graduates ($N=94$) in descriptive statistics and inferential statistics. The data were analyzed using SPSS (version 28.0).

## 4 Results

### 4.1 Descriptive data

As Table 2 shows, the average score of the four variables ranged from 3.31 to 3.84 on a 5-point Likert scale: motivation (M=3.59, SD=0.78), self-monitoring (M=3.84, SD=0.64), self-management (M=3.62, SD=0.75), and learning satisfaction (M=3.59, SD=0.78). Since the range of skewness and kurtosis of the four variables was between −1 and 1, the normality assumptions were satisfied (Kline, 2011). We also checked the possibility of multicollinearity among the independent variables. Hair Jr. and colleagues (2010) warned that it is necessary to be careful about the existence of multicollinearity when the correlation among independent variables is higher than 0.9 or when the variance inflation factor (VIF) is higher than 10. The correlations among the four variables of this study ranged from 0.65 to 0.76 at $p<.001$.

**Table 2** Descriptive data ($N=284$)

| Variables | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| Motivation | 1 | 0.75** | 0.72** | 0.76** |
| Self-monitoring | | 1 | 0.68** | 0.65** |
| Self-management | | | 1 | 0.65** |
| Learning satisfaction | | | | 1 |
| Mean | 3.59 | 3.84 | 3.62 | 3.31 |
| SD | 0.78 | 0.64 | 0.75 | 1.11 |
| Skewness | −0.363 | −0.269 | −0.231 | −0.242 |
| Kurtosis | −0.308 | 0.265 | −0.432 | −0.886 |

*Note* ** $p<.001$, * $p<.05$

**Table 3** Comparisons between undergraduates and graduates

| | Undergraduates ($N$=185) | | Graduates ($N$=99) | | df | t-values | $p$-values |
|---|---|---|---|---|---|---|---|
| | M | SD | M | SD | | | |
| Motivation | 3.48 | 0.83 | 3.79 | 0.65 | 282 | 3.24** | 0.001 |
| Self-monitoring | 3.78 | 0.70 | 3.94 | 0.50 | 282 | 2.08* | 0.039 |
| Self-management | 3.55 | 0.75 | 3.77 | 0.71 | 282 | 2.41* | 0.017 |
| Learning satisfaction | 3.22 | 1.17 | 3.47 | 0.97 | 282 | 1.83 | 0.068 |

*Note* ** $p<.001$, * $p<.05$

**Table 4** Results of multiple regression analysis

| | Unstandardized Coefficients | | Standardized Coefficients | t-values | $p$-values |
|---|---|---|---|---|---|
| | B | SE | β | | |
| Motivation | 0.738 | 0.090 | 0.421 | 8.22** | 0.001 |
| Self-monitoring | 0.253 | 0.104 | 0.145 | 2.44* | 0.015 |
| Self-management | 0.258 | 0.085 | 0.174 | 3.04* | 0.003 |

*Note* Constant = -1.247, $F(3, 280) = 140.69^{**}$. $p<.001$, $R^2=0.60$

We found that the VIF among the variables was between 2 and 3. Hence, we concluded that the VIF is not a concern in this study.

The motivation, self-monitoring, self-management, and learning satisfaction of undergraduates ($N$=185) and graduates ($N$=99) were compared (see Table 3). The average scores of graduate students in motivation (M=3.79, SD=0.65) were higher than undergraduates (M=3.48, SD=0.83) and the group difference in motivation was statistically significant ($t$=3.24, $p<.001$). The graduates also significantly performed better in self-monitoring (M=3.94, SD=0.50) than undergraduates (M=3.78, SD=0.70) ($t$=2.08, $p<.05$). The graduate participants outperformed in self-management (M=3.77, SD=0.71) compared to undergraduate participants (M=3.55, SD=0.75) and the differences between the two groups were statistically significant ($t$=2.41, $p<.05$). However, there were no statistical differences between undergraduates (M=3.22, SD=1.17) and graduates in learning satisfaction (M=3.47, SD=0.97) ($t$=1.83, *ns*).

### 4.2 Influence of SDL elements on learning satisfaction

To estimate the influence of each SDL element (i.e., motivation, self-monitoring, and self-management) on learning satisfaction, we conducted multiple regression analysis. As Table 4 shows, three elements of SDL account for 60.1% of the variance in learning satisfaction: $F$ (3, 280)=140.69, $p<.001$. Motivation, self-monitoring, and self-management were all statistically significant factors in learning satisfaction. Motivation was the most influential factor on learning satisfaction (B=0.738, $p<.001$), followed by self-management (B=0.258, $p<.05$) and self-monitoring (B=0.253, $p<.05$).

**Table 5** Group differences in multiple regression results

| | | Unstandardized Coefficients | | Standardized Coefficients | *t*-values | *p*-values |
|---|---|---|---|---|---|---|
| | | B | SE | β | | |
| Undergraduates ($N$=185) | Motivation | 0.754 | 0.110 | 0.533 | 6.86** | 0.001 |
| | Self-monitoring | 0.316 | 0.124 | 0.188 | 2.56* | 0.011 |
| | Self-management | 0.183 | 0.109 | 0.118 | 1.68 | 0.095 |
| Graduates ($N$=99) | Motivation | 0.749 | 0.163 | 0.503 | 4.59** | 0.001 |
| | Self-monitoring | 0.029 | 0.201 | 0.015 | 0.143 | 0.886 |
| | Self-management | 0.428 | 0.135 | 0.313 | 3.18* | 0.002 |

*Note* Undergraduates: Constant = -1.247, $F(3, 181)=91.69^{**}p<.001$, $R^2=0.603$, Graduates: Constant= -1.096, $F(3, 95)=46.57^{**}$. $p<.001$, $R^2=0.595$

### 4.3 Group differences in influences of SDL on learning satisfaction

To examine the group differences between undergraduates ($N=185$) and graduates ($N=99$) in the influences of motivation, self-monitoring, and self-management on learning satisfaction, we analyzed the data using regression analysis (see Table 5). In the undergraduate student group ($N=185$), the influence of motivation (B=0.754, $p<.001$) and self-monitoring (B=0.188, $p<.05$) were statistically significant, but not self-management (B=0.118, *ns*). Motivation and self-monitoring account for 60.3% of the variance in undergraduates' learning satisfaction: $F(3, 181)=91.69^{**}$. $p<.001$. In the graduate student group ($N=99$), the influence of motivation (B=0.749, $p<.001$) and self-management (B=0.428, $p<.05$) were statistically significant, but not self-monitoring (B=0.029, *ns*). Motivation and self-management account for 59.5% of the variance in graduates' learning satisfaction: $F(3, 95)=46.57^{**}$. $p<.001$.

## 5 Discussion

The purpose of this study is to investigate the influence of motivation, self-monitoring, and self-management on learning satisfaction in online learning using Garrison's SDL model. The group differences between undergraduates and graduates in the influence of motivation, self-monitoring, and self-management on learning satisfaction were also examined.

The results showed that the influence of motivation, self-monitoring, and self-management significantly influenced learning satisfaction in online learning. Motivation, self-monitoring, and self-management together accounted for approximately 60% of learning satisfaction. The findings suggest that SDL is a crucial factor for learning satisfaction in online learning and indicate the strong explanatory power of Garrison's SDL model on learning satisfaction in online learning environments. These research findings support the Doo and Zhu's, (2024) meta-analysis results showing the medium effect size of SDL on learning achievement in affective domain (g=0.625).

The research findings also support Sun et al.'s (2023) previous study. They found that students' SDL attitude and approach positively predicted learning engagement mediated by perceived value of knowing learning goals (PVKLG). The results indicated that it is necessary to enhance PVKLG so the effects of SDL are more effective for learning engagement.

Motivation was the most influential factor on learning satisfaction ($B = 0.738$, $p < .001$) among Garrison's SDL models in this study. This finding confirmed the meta-analysis results by Doo and Zhu, (2024) reporting the larger effect size of motivation ($g = 0.658$) than self-monitoring ($g = 0.519$) and self-management ($g = 0.279$). It also supports Lee and colleagues' (2019) claims that SDL strategies enhance a sense of academic achievement (e.g., learning satisfaction) and is consistent with Artino's (2008) regression results that motivation (i.e., task values) is a strong predictor of learning satisfaction ($B = 0.31$, $p < .001$).

This study also found that there are group differences between undergraduates and graduates in the influence of motivation, self-monitoring, and self-management on learning satisfaction. The results of the descriptive analysis indicated that graduate students had higher scores than undergraduates in all variables (i.e., motivation, self-monitoring, self-management, and learning satisfaction). The group differences were statistically significant in motivation, self-monitoring, and self-management. This result supports Artino and Stephens' (2009) hypotheses and research findings that graduates outperformed undergraduates in self-monitoring. They explained the reason that graduates perform better in self-monitoring due to the developmental nature of self-regulation and longer higher education experiences of graduates. Our research results support the perspective of SDL as a learning process (Brockett & Hiemstra, 1991; Knowles, 1975).

We also found group differences in the influences of motivation, self-monitoring, and self-management on learning satisfaction between undergraduates and graduates. The results of the regression analysis for each group indicated that motivation was the most influential element of learning satisfaction regardless of the education level (i.e., undergraduates vs. graduates). However, self-monitoring and self-management influenced the learning satisfaction of undergraduates and graduates differently: motivation and self-monitoring, but not self-management, were statistically significant to undergraduates' learning satisfaction. In addition, motivation and self-management, but not self-monitoring, were statistically significant to predict graduates' learning satisfaction. Further studies are needed to investigate the reasons for the group differences between undergraduates and graduates in the influences of self-monitoring and self-management on learning satisfaction (e.g., different course structures for undergraduates and graduates, different class requirements for each group).

Implications for academics are that SDL should be fostered in class and on campus as a learning process. Given that SDL is a learning process (Brockett & Hiemstra, 1991; Knowles, 1975), Morris and Rohs (2023) asserted that students' SDL competence should be promoted in school. Instructors and university administrators can also take advantage of digital technologies (e.g. online learning) to facilitate students' SDL skills. In addition, our findings on different influences of SDL on learning satisfaction between undergraduates and graduates indicate that each group has unique needs for SDL and it is necessary to customize instructional strategies to make online learning programs more suitable for each group. Specifically, for undergraduates, self-monitoring was more influential than self-management. Thus, instructors who teach undergraduates in online learning may consider adopting self-regulation, self-monitoring, self-regulated learning strategies, self-control, and cognitive and meta-cognitive learning strategies extensively to improve students' satisfaction and learning outcomes. The current study encourages instructors who teach graduate students virtually to apply self-management strategies, including time management, learning resource management, and effort regulation to enhance graduates' learning satisfaction. We recommend the following references to those who are interested in learning SRL strategies and self-management strategies in depth: Pintrich et al. (1991), Zimmerman (2002), Broadbent (2017), Yen et al. (2018), Zhu and Bonk, (2022), and Zhu et al., (2024).

Despite the meaningful findings, this study has several limitations. First, the sample size of this study was small (i.e., 284 participants including 185 undergraduates and 99 graduates), and participants were homogenous because the data were collected in one university (i.e., students who majored in computer science and engineering in the same university). Future researchers can extend this study by inviting more participants with diverse social and cultural backgrounds to enhance the external validity of the research findings. Second, the scope of this study was limited to examine the influence of SDL on learning satisfaction. To more thoroughly understand the effects of SDL on learning achievement, future researchers could expand the scope of this research to investigate the influences of SDL and the various types of learning outcomes (e.g., cognitive and behavioral learning outcomes) as well as learning satisfaction. Third, the data source of this study was a self-reported questionnaire. We suggest that future researchers collect various types of data using a combination of methods, such as semi-structured interviews, grades, or course evaluations, for more powerful research insights. Cronin-Golomb and Bauer (2023) claimed that SDL is a multifaceted and complex process across the lifespan from a lifelong learning perspective. They criticized that most SDL research was conducted as experimental research or examined in intentionally controlled environments to investigate predefined research questions using self-reported data or observation. Given that SDL occurs across the lifespan, we recommend that researchers extend the current study by adopting more naturalistic approaches.

## 6 Conclusion

The current study found that the influence of motivation, self-monitoring, and self-management significantly influenced learning satisfaction in online learning. Our findings confirm that SDL is a good predictor of learning satisfaction. As learning environments expand their boundaries beyond traditional classrooms to online learning, the importance of SDL has become an essential influential factor. Online learning is a learner-centered environment by nature and provides learners with augmented learning autonomy. Thus, learners need to be equipped with learning motivation, self-monitoring and self-management competencies to successfully complete their online learning courses. This study extends our understanding of the influence of SDL on learning outcomes and focuses on learning satisfaction.

This study identified differences in the influence of SDL on learning satisfaction between undergraduates and graduates. Given that SDL is a learning process across the lifespan (Cronin-Golomb & Bauer, 2023), different age groups have different SDL levels, which highlights the need to tailor online learning programs to satisfy diverse groups of students. As Garrison (1997) asserted, becoming self-directed learners is the prerequisite to obtain meaningful learning outcomes. Thus, researchers need to expand and extend the scope of SDL factors to help learners succeed in the ever-changing learning environments.

## Appendix: Measurement

1. Self-directed Learning (27 items)

- Self-management

1. I prefer to schedule my own learning plan while taking online courses.
2. I am self-disciplined about completing the required work while taking online courses.
3. I have good management skills (e.g., time, learning resources, etc.) while taking online courses.
4. I set specific times to study while taking online courses (e.g., 9:00 am or 10:00 am in the morning).
5. I set strict time frames for learning while taking online courses (e.g., 1 h, 2 h, etc.).
6. I am able to keep my learning routine in online courses separate from my other commitments.
7. I can apply a variety of learning strategies while taking online courses.
8. I am disorganized while taking online courses. ®
9. I am confident in my ability to search for information related to learning content in online courses.

- Motivation

10. I want to learn new information through online courses pertaining to my major.
11. I enjoy learning new information while taking online courses.
12. I enjoy the challenges that may occur while taking online courses (e.g., analysis/application of concepts).
13. I do not enjoy studying for online courses ®.
14. I critically evaluate information that I received while taking online courses.
15. I would like to know the deep reasons behind the facts while taking online courses.
16. I learn from the feedback provided by my peers while taking online courses.
17. I learn from the feedback provided by my instructor while taking online courses.
18. When presented with a problem I cannot resolve, I ask for assistance through different means while taking online courses.

- Self-monitoring

19. I am responsible for my own learning while taking online courses.
20. I am in control of my learning while taking online courses.
21. I have high learning standards while taking online courses.
22. I prefer to set my own learning goals while taking online courses.
23. I evaluate my own performance while taking online courses.
24. I have high beliefs in my learning abilities while taking online courses.
25. I can find information related to learning content for myself while taking online courses.
26. I am able to focus on answering or solving a problem while taking online courses.
27. I am aware of my own limitations while taking online courses.

2. Learning satisfaction (6 items)

1. Overall, I am satisfied with online courses.
2. The online courses contributed to my educational development.
3. The online courses contributed to my professional development.
4. I am satisfied with the level of interaction among students in online courses.
5. I am satisfied with the level of interaction between my instructor and students in online courses.
6. In the future, I would be willing to take an online course again.

**Author contributions** Meina Zhu: Conceptualization, investigation (instrument development and data collection), data curation, project administration, initial data analysis, writing-review and editing. Min Young Doo: Conceptualization (supporting); formal analysis; visualization; writing – original draft preparation; writing – review and editing. Sara Masoud: Investigation (instrument development and data collection). Yaoxian Huang: Investigation (instrument development and data collection).

**Funding** The authors declare that we have no funding source for this research.

**Data availability** The data used and/or analyzed in the current study are available from the corresponding author upon reasonable request.

## Declarations

**Consent to participate** Verbal informed consent was obtained prior to the survey.

**Conflict of interest** There were no conflicts of interest in this research.

## References

Alqurashi, E. (2019). Predicting student satisfaction and perceived learning within online learning environments. *Distance Education*, *40*(1), 133–148. https://doi.org/10.1080/01587919.2018.1553562

Artino, A. R. (2008). Motivational beliefs and perceptions of instructional quality: Predicting satisfaction with online training. *Journal of Computer Assisted Learning*, *24*(3), 260–270. https://doi.org/10.1111/j.1365-2729.2007.00258.x

Artino, A. R., & Stephens, J. M. (2009). Academic motivation and self-regulation: A comparative analysis of undergraduate and graduate students learning online. *Internet & Higher Education*, *12*(3), 146–151. https://doi.org/10.1016/j.iheduc.2009.02.001

Bollinger, D. U., & Halupa, C. (2012). Student perceptions of satisfaction and anxiety in an online Doctoral Program. *Distance Education*, *33*, 81–98. https://doi.org/10.1080/01587919.2012.667961

Broadbent, J. (2017). Comparing online and blended learner's self-regulated learning strategies and academic performance. *The Internet and Higher Education*, *33*, 24–32. https://doi.org/10.1016/j.ihe-duc.2017.01.004

Broadbent, J., & Poon, W. L. (2015). Self-regulated learning strategies & academic achievement in online higher education learning environments: A systematic review. *The Internet and Higher Education*, *27*, 1–13. https://doi.org/10.1016/j.iheduc.2015.04.007

Brockett, R. G., & Hiemstra, R. (1991). *Self-direction in adult learning: Perspectives on theory, research, and practice*. Routledge.

Brookfield, S. (1986). *Understanding and facilitating adult learning: A comprehensive analysis of principles and effective practices*. Open University.

Chang, S., & Smith, R. (2008). Effectiveness of personal interaction in a learner-centered paradigm distance education class based on student satisfaction. *Journal of Research on Technology in Education*, *40*(4), 407–426. https://doi.org/10.1080/15391523.2008.10782514

Chu, R., & Tsai, C. C. (2009). Self-directed learning readiness, internet self-efficacy and preferences towards constructivist internet-based learning environments among higher-aged adults. *Journal of Computer Assisted Learning*, *25*(5), 489–501. https://doi.org/10.1111/j.1365-2729.2009.00324.x

Cıgdem, H., & Ozturk, M. (2016). Critical components of online learning readiness and their relationship with learner achievement. *Turkish Online Journal of Distance Education*, *17*(2), 98–109. https://doi.org/10.17718/tojde.09105

Cronin-Golomb, L. M., & Bauer, P. J. (2023). Self-motivated and directed learning across the lifespan. *Acta Psychologica232*, 103816. https://doi.org/10.1016/j.actpsy.2022.103816.

Davis, D., Chen, G., Hauff, C., & Houben, G. J. (2018). Activating learning at scale: A review of innovations in online learning strategies. *Computers & Education*, *125*, 327–344. https://doi.org/10.1016/j.compedu.2018.05.019

Doo, M. Y., & Zhu, M. (2024) A meta-analysis of effects of self-directed learning in online learning environments Abstract Lay Description. *Journal of Computer Assisted Learning*, *40*(1), 1–20 https://doi.org/10.1111/jcal.12865

Doo, M. Y., Zhu, M., & Bonk, C. J. (2023). Influences of self-directed learning on learning outcomes in MOOCs: Meta-analysis. *Distance Education*, *44*(1), 86–105. https://doi.org/10.1080/01587919.2022.2155618

Durnali, M. (2020). The effect of self-directed learning on the relationship between self-leadership and online learning among university students in Turkey. *Tuning Journal for Higher Education*, *8*(1), 129–165. https://doi.org/10.18543/tjhe-8(1)-2020pp129-165

Fisher, M. J., & King, J. (2010). The self-directed learning readiness scale for nursing education revisited: A confirmatory factor analysis. *Nurse Education Today*, *30*(1), 44–48. https://doi.org/10.1016/j.nedt.2009.05.020

Gardner, L. (2020, March 20). Covid-19 has forced higher education to pivot to online learning. Here are 7 take aways so far. *The Chronicle of Higher Education*, https://www.chronicle.com/article/covid-19-has-forced-higher-ed-to-pivot-to-online-learning-here-are-7-takeaways-so-far/

Garrison, D. R. (1997). Self-directed learning: Toward a comprehensive model. *Adult Education Quarterly*, *48*(1), 18–33. https://doi.org/10.1177/074171369704800103

Geng, S., Law, K. M. Y., & Niu, B. (2019). Investigating self-directed learning and technology readiness in blending learning environment. *International Journal of Educational Technology in Higher Education*, *16*(1), 1–22. https://doi.org/10.1186/s41239-019-0147-0

Guglielmino, L. M. (1978). *Development of the self-directed learning readiness scale*. [Unpublished doctoral dissertation]. University of Georgia.

Heo, J., & Han, S. (2018). Effects of motivation, academic stress and age in predicting self-directed learning readiness (SDLR): Focused on online college students. *Education and Information Technologies*, *23*(2), 61–71. https://doi.org/10.1007/s10639-017-9585-2

Hsu, Y. C., & Shiue, Y. M. (2005). The effect of self-directed learning readiness on achievement comparing face-to-face and two-way distance learning instruction. *International Journal of Instructional Media*, *32*(2), 143–156.

Hung, M., Chou, C., Chen, C., & Own, Z. (2010). Learner readiness for online learning: Scale development and student perceptions. *Computers & Education*, *55*(3), 1080–1090. https://doi.org/10.1016/j.compedu.2010.05.004

Jiang, H., Islam, A. Y. M. A., Gu, X., & Spector, J. M. (2021). Online learning satisfaction in higher education during the COVID-19 pandemic: A regional comparison between Eastern and Western Chinese universities. *Education and Information Technologies*, *26*(6), 6747–6769. https://doi.org/10.1007/s10639-021-10519-x

Karatas, K., & Arpaci, I. (2021). The role of self-directed learning, metacognition, and 21st century skills predicting the readiness for online learning. *Contemporary Educational Technology*, *13*(3), ep300. https://doi.org/10.30935/cedtech/10786

Kelly, R. (2020, April 16). 4,000-Plus U.S. higher ed institutions impacted by COVID-19; more than 25 million students affected. *Campus Technology*https://campustechnology.com/articles/2020/04/16/4000-plus-us-higher-ed-institutions-impacted-by-covid19-more-than-25-million-students-affected.aspx

Kim, S. (2024). The effect of metacognition and self-directed learning readiness on learning performance of nursing students in online practice classes during the COVID-19 pandemic period. *Nursing Open*, *11*(1), e2093. https://doi.org/10.1002/nop2.2093

Knowles, M. S. (1975). *Self-directed learning: A guide for learners and teachers*. Association.

Kuo, Y. C., Walker, A. E., Schroder, K. E. E., & Belland, B. R. (2014). Interaction, internet self-efficacy, and self-regulated learning as predictors of student satisfaction in online education courses. *The Internet and Higher Education*, *20*, 35–50. https://doi.org/10.1016/j.iheduc.2013.10.001

Lee, Y., & Choi, J. (2013). A structural equation model of predictors of online learning retention. *The Internet and Higher Education*, *16*, 36–42. https://doi.org/10.1016/J.IHEDUC.2012.01.005

Lee, D., Watson, S. L., & Watson, W. R. (2019). Systematic literature review on self-regulated learning in massive open online courses. *Australasian Journal of Educational Technology*, *35*(1), 28–41. https://doi.org/10.14742/ajet.3749

Li, H., Zhu, S., Wu, D., Yang, H. H., & Guo, Q. (2023). Impact of information literacy, self-directed learning skills, and academic emotions on high school students' online learning engagement: A structural equation modeling analysis. *Education and Information Technologies*, *28*, 13485–13504. https://doi.org/10.1007/s10639-023-11760-2

Li, Z., Zhu, M., Kadirova, D., Bonk, C. J. (2023). Towards self-directed learning: How do Nepali adolescents learn with MOOCs? *Distance Education*, *44*(4), 655–674. https://doi.org/10.1080/01587919.2023.2267460

Linkous, H. M. (2021). Self-directed learning and self-regulated learning: What's the difference? A literature analysis. *American Association for Adult and Continuing Education*. ED611648.

Littlejohn, A., Hood, N., Milligan, C., & Mustain, P. (2016). Learning in MOOCs: Motivations and self- regulated learning in MOOCs. *The Internet and Higher Education*, *29*, 40–48. https://doi.org/10.1016/j.iheduc.2015.12.003

Lin, B., & Hsieh, C. T. (2001). Web-based teaching and learner control: A research review. *Computers & Education*, *37*(3), 377–386.

Liu, Z., Yu, P., Liu, J., Pi, Z., & Cui, W. (2022). How do students' self-regulation skills affect learning satisfaction and continuous intention within desktop-based virtual reality? A structural equation modelling approach. *British Journal of Educational Technology*, *54*(3), 667–685. https://doi.org/10.1111/bjet.13278

Long, H. B. (1990). College students' self-directed learning readiness and educational achievement. In H. B. Long, & Associates (Eds.), *Self-Directed Learning: Consensus and Conflict (pp. 107–122)* Oklahoma Research Centre for Continuing Professional and Higher Education.

Lounsbury, J. W., Levy, J. J., Park, S., Gibson, L. W., & Smith, R. (2009). An investigation of the construct validity of the personality trait of self-directed learning. *Learning and Individual Differences*, *19*(4), 411–418. https://doi.org/10.1016/j.lindif.2009.03.001

Merriam, S. B., & Bierema, L. L. (2014). *Adult learning. Linking theory and practice*. Jossey-Bass.

Meyer, O. A., Omdahl, M. K., & Makransky, G. (2019). Investigating the effect of pre-training when learning through immersive virtual reality and video: A media and methods experiment. *Computers & Education*, *140*, 103603. https://doi.org/10.1016/j.compedu.2019.103603

Milligan, C., & Littlejohn, A. (2014). Supporting professional learning in a massive open online course. *International Review of Research in Open and Distance Learning*, *15*(5), 197–213. https://doi.org/10.19173/irrodl.v15i5.1855

Morris, T. H., & Rohs, M. (2023). The potential for digital technology to support self-directed learning in formal education of children: A scoping review. *Interactive Learning Environments*, *31*(4), 1974–1987. https://doi.org/10.1080/10494820.2020.1870501

Park, J., & Choi, H. J. (2009). Factors influencing adult learners' decision to drop out or persist in online learning. *Educational Technology & Society*, *12*(4), 207–217. https://doi.org/10.2307/jeductechsoci.12.4.207. https://www.jstor.org/stable/

Pintrich, P., Smith, D., Garcia, T., & McKeachie, W. (1991). *A manual for the use of the motivated strategies for learning questionnaire*. MSLQ). University of Michigan.

Rabin, E., Henderikx, M., Yoram, M. K., & Kalz, M. (2020). What are the barriers to learners' satisfaction in MOOCs and what predicts them? The role of age, intention, self-regulation, self-efficacy and motivation. *Australasian Journal of Educational Technology*, *36*(3), 119–131. https://doi.org/10.14742/ajet.5919

Richardson, M., Abraham, C., & Bond, R. (2012). Psychological correlates of university students' academic performance: A systematic review and meta-analysis. *Psychological Bulletin*, *138*(2), 353–387. https://doi.org/10.1037/a0026838

Saks, K., & Leijen, Ä. (2014). Distinguishing self-directed and self-regulated learning and measuring them in the E-learning context. *Procedia - Social and Behavioral Sciences*, *112*, 190–198. https://doi.org/10.1016/j.sbspro.2014.01.1155

Song, L., & Hill, J. R. (2007). A conceptual model for understanding selfdirected learning in online environments. *Journal of Interactive Online Learning*, *6*(1), 27–42.

Stokes, S. P. (2001). Satisfaction of college students with the digital learning environment: Do learners' temperaments make a difference? *Internet and Higher Education*, *4*(1), 31–44. https://doi.org/10.1016/S1096-7516(01)00046-X

Sun, W., Hong, J. C., Dong, Y., Huang, Y., & Fu, Q. (2023). Self-directed learning predicts online learning engagement in higher education mediated by perceived value of knowing learning goals. *The Asia-Pacific Education Researcher*, *32*(3), 307–316. https://doi.org/10.1007/s40299-022-00653-6

Sze-Yeng, F., & Hussain, R. M. R. (2010). Self-directed learning in a socio-constructivist learning environment. *Procedia-Social and Behavioral Sciences*, *9*, 1913–1917. https://doi.org/10.1016/j.sbspro.2010.12.423

Topal, I., & Tomozii, S. (2014). Learning satisfaction: Validity and reliability testing for SLSQ (students' learning satisfaction questionnaire). *Procedia-Social and Behavioral Sciences*, *128*, 380–386. https://doi.org/10.1016/j.sbspro.2014.03.175

Torun, E. D. (2020). Online distance learning in higher education: E-learning readiness as a predictor of academic achievement. *Open Praxis*, *12*(2), 191–208. https://doi.org/10.5944/openpraxis.12.2.1092

Wang, C. H., Shannon, D., & Ross, M. (2013). Students' characteristics, self-regulated learning, technology self-efficacy, and course outcomes in online learning. *Distance Education*, *34*(3), 302–323. https://doi.org/10.1080/01587919.2013.835779

Wei, H., & Chou, C. (2020). Online learning performance and satisfaction: Do perceptions and readiness matter? *Distance Education*, *41*(1), 48–69. https://doi.org/10.1080/01587919.2020.1724768

Williams, G. C., & Deci, E. L. (1996). Internalization of biopsychosocial values by medical students: A test of self-determination theory. *Journal of Personality and Social Psychology*, *70*, 767–779. https://doi.org/10.1037/0022-3514.70.4.767

Williams, G. C., Saizow, R., Ross, L., & Deci, E. L. (1997). Motivation underlying career choice for internal medicine and surgery. *Social Science and Medicine*, *45*, 1705–1713. https://doi.org/10.1016/S0277-9536(97)00103-2

Williamson, S. N. (2007). Development of a self-rating scale of self-directed learning. *Nurse Researcher*, *14*(2), 66–83. https://doi.org/10.7748/nr200701. 14.2. 66. c6022.

Yen, M. H., Chen, S., Wang, C. Y., Chen, H. L., Hsu, Y. S., & Liu, T. C. (2018). A framework for self-regulated digital learning (SRDL). *Journal of Computer Assisted Learning*, *34*(5), 580–589. https://doi.org/10.1111/jcal.12264

Zheng, L., Li, X., & Chen, F. (2018). Effects of a mobile self-regulated learning approach on students' learning achievements and self-regulated learning skills. *Innovations in Education and Teaching International*, *55*(6), 616–624. https://doi.org/10.1080/14703297.2016.1259080

Zhu, M., & Bonk, C. J. (2019). Designing MOOCs to facilitate participant self-monitoring for self-directed learning. *Online Learning*, *23*(4), 106–134. https://doi.org/10.24059/olj.v23i4.2037

Zhu, M., Bonk, C. J., & Doo, M.-Y. (2020). Self-directed learning in MOOCs: Exploring the relationships among motivation, self-monitoring, and self-management. *Educational Technology Research and Development*, *68*(5), 2073–2093. https://doi.org/10.1080/01587919.2023.2267460

Zhu, M., & Bonk, C. J. (2022). Guidelines and strategies for fostering and enhancing self-directed online learning. *Open Learning: The Journal of Open, Distance and e-Learning*, 1–17. https://doi.org/10.1080/02680513.2022.2141105

Zhu, M. & Doo, M. Y. (2022). The relationship among motivation, self-monitoring, self-management, and learning strategies of MOOC learners. *Journal of Journal of Computing in Higher Education*, *34*(2), 321–342. https://doi.org/10.1007/s11423-020-09747-8

Zhu, M., Berri, S., Huang, Y., & Masoud, S. (2024). Enhancing computer science and engineering students' self-directed learning and satisfaction with online learning. *Computers and Education Open*. https://doi.org/10.1016/j.caeo.2024.100168

Zimmerman, B. J. (2002). Becoming a self-regulated learner: An overview. *Theory into Practice*, *41*, 64–70. https://doi.org/10.1207/s15430421tip4102_2



## Authors and Affiliations

**Meina Zhu[1] · Min Young Doo[2] · Sara Masoud[3] · Yaoxian Huang[4]**

✉ Min Young Doo
mydoo@Kangwon.ac.kr

1 Learning Design and Technology, Wayne State University, Detroit, MI, USA

2 Department of Education, Kangwon National University, 1 Gangwondaehakgil, Chuncheon-si 24341, Kangwon-do, Korea

3 Industrial and Systems Engineering, Wayne State University, Detroit, MI, USA

4 Civil and Environmental Engineering, Wayne State University, Detroit, MI, USA