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Behavioral Sensing: An Exploratory Study to Assess Self-Regulated Learning and Resource Management Strategy of University Students using Mobile Sensing

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Abstract

Self-regulated learning not only influences students' learning behaviors but is also a significant academic performance factor. Resource management strategy based on self-regulated learning theory is an important indicator for students to demonstrate self-regulatory skills. However, current self-regulated learning and resource management strategy assessments still rely on subjective evaluations and self-assessments, which are time-consuming and laborious. Therefore, we propose a novel method combined with mobile sensing by collecting detailed learning strategy subscales and objective mobile sensing data from N = 211 college students to explore a new approach to assessing self-regulated learning and resource management strategy. To our knowledge, we are the first to propose a mobile sensing approach for assessing self-regulated learning and learning strategies. The method studies the associations between the learning strategy subscales and these daily behavior patterns and presents a set of features for behavior patterns from mobile sensing data. These features represent the self-regulated learning skills of college students. Our study helps to reveal new forms of assessing self-regulated learning and learning strategies and opens the way for personalized interventions in future research.

Keywords: Self-regulated Learning; Resource Management Strategy; Mobile Sensing; Education; Human-computer Interaction

Introduction

Experts in the field of educational psychology have found that some students neither have rich learning resources nor rely on teacher feedback, yet they have higher academic achievement. Through observation, researchers noted that these students are self-motivated and active in the learning process and utilize various learning strategies for effective learning (Zimmerman, B. J. 2013b). In an educational context, Self-Regulated Learning (hereafter SRL) involves students actively controlling their learning. They actively monitor their learning processes and outcomes and can regulate and adjust their behavior to optimize learning outcomes (Pintrich, P. R. 2004). SRL skills are abilities that learners use to manage their learning progress using SRL strategies. Students who apply SRL strategies are more successful in problem-solving and have higher academic achievement, intrinsic motivation, and interest in learning (Zimmerman, B. J., & Schunk, D. H. 2011).

Resource management strategy is one of the three learning strategies identified in SRL by Pintrich and De Groot to reflect the increasing need to manage and control resources (such as time, energy, learning environment, and external assistance) in the learning process (Pintrich, P. R. 2004). Specifically, resource management includes the behavioral and environmental components of SRL strategies, which include time and study environment management (referring to the ability to manage one's own learning time and tasks), effort regulation (referring to an individual's ability to persevere in the face of learning), peer learning (referring collaborating with other students or peers to aid in the learning process), and help-seeking (referring to other people to seek help, such as a teacher or peers, or to consulting outside help and resources) (Pintrich, P. R. 1991). Resource management strategy is an important predictor of SRL skills because it helps students adapt to their environment and changes it to fit their goals and needs (Pintrich, 1999).

Given the importance of SRL and resource management strategy as key indicators of the educational learning process, many studies focus on assessing and designing interventions for them. However, the resource management strategy is the least researched learning strategy. It differs from other learning strategies because it is a social interaction ((Pintrich, 1999; Garcia, Falkner & Vivian, 2018). Although social behavior is likely to influence resource management strategy, most current methods for assessing SRL and resource management strategy rely primarily on self-reports (e.g., questionnaire or survey responses), face-to-face assessments (e.g., interviews), or observational ratings by experts or trained observers (Roth, A., Ogrin, S., & Schmitz, B. 2016). The process of these methods is often laborious, time-consuming, and expensive due to the volume of information, and it may also be limited by space and time. Thus, new methods are needed to assess SRL and the use of resource management strategy consistently and proactively in learning environments.

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This paper is the first to propose using social behavioral features to assess SRL skills and resource management strategy. Considering students' daily lives and learning styles (e.g., class time, studying in common areas of campus, seeking peer support), we developed a mobile application, iSense APP, to collect real-time student data. Specifically, firstly, we collected an SRL questionnaire, a resource management strategy questionnaire, and mobile sensing data from students at a Chinese university. Secondly, we used mobile sensing data from N=211 students over one year to identify behavior patterns. Thirdly, during this period, we also used some widely used instruments, including the " Motivated Strategies for Learning Questionnaire "(MSLQ) (Pintrich et al., 1993), to measure the corresponding SRL skills and learning strategies. Lastly, we calculate behavioral features based on mobile sensing data to explore new methods for evaluating SRL and resource management strategy. The contributions of our work are as follows:

- To our knowledge, we present the first mobile sensing study investigating the association between daily behavior patterns and SRL skills and learning strategies. We collected the data of their SRL & learning strategies measures and real-time mobile sensing data from N = 211 students in China for one consecutive year from March 2022 to March 2023 to explore the association between SRL measures and mobile behavioral patterns.
- Identifying several daily behavior patterns (10 patterns) associated with learning strategies & SRL skills provides the baseline for predicting SRL skills and resource management strategy relatedness using mobile sensing.
- We propose a new method for assessing learning strategies and SRL skills combined with mobile sensing. The method provides the primary conditions for constructing models predicting different SRL skills and resource management strategy. It is an instrumental step for designing timely interventions in student's daily life to enhance SRL skills. In addition, it offers the possibility of generalizing our approach to assessing other psychological variables.

To the best of our knowledge, we are the first to propose a set of behavioral features derived from mobile sensing specifically designed to capture the dynamics of learning behaviors in SRL among college students. We plan to release the dataset for other researchers to study student learning behaviors and lifestyles.

Related Work

SRL provides an important academic learning perspective for current educational psychology research (Schunk &Zimmerman, 2023). Zimmerman et al. (1989, 1990, 1992) discussed the content and structure of SRL theory in detail and conducted many experimental studies. They found that students with high levels of SRL can take the initiative to acquire knowledge and skills without relying on teachers, parents, or other educational institutions. SRL emphasizes students' flexible use of specific SRL strategies to promote learning and achieve learning goals. SRL strategies have been studies for decades in traditional classroom settings. Research in the field of educational psychology and pedagogy has explored methods of assessing SRL and resource management strategy (Fan, Saint, Singh, Jovanovic, & Gaˇsevi´c, 2021; Azevedo & Gaˇsevi´c, 2019), but most of the current research still relies on traditional methods such as self-report, face-to-face, interviews with experts, or manual observation (Han, 2022), which can be both laborious and time-consuming. For these reasons, alternative and innovative methods have emerged to measure changes in SRL strategies, especially in online or blended learning environments. Some examples of new measures include tracking logs, audible reflection verbal protocols, and hyperlink use (Bannert & Mengelkamp, 2008; Greene, Robertson, & Costa, 2011; J¨arvel¨a, Sanna, et al., 2021). These innovations and approaches to SRL are still in the early stages of development (Zimmerman, 2008). Furthermore, research shows that different characteristics and traits of students influence the use of learning strategies (Donche, Vincent, et al.2013), which also highlights the limitations of traditional assessment methods using single modal data.

Many Human-computer Interaction (HCI) studies have attempted to use multiple sensors or learning analytics tools to measure SRL skills or learning strategies during the learning process. Detecting students' emotional states in the classroom by monitoring their operations on computers with cameras provides students feedback that improves their SRL process(Aslan et al., 2019; Delen & Liew, 2016; Perry and Winne, 2006; Davis, Chen, Jivet, Hauff, & Houben, 2016; Siadaty et al., 2016a; J¨arvel¨a & Bannert, 2019). Recognizing students' facial expressions and sitting postures through wearable devices to improve learning strategies that enhance SRL skills (Shih, Chen, Chang, & Kao, 2010; Nussbaumer, Alexander, et al., 2014); Or sensing student's attention during class using camera recording mixed with VR recreation to improve their SRL process (Ahujaet al., 2021). While these sensors such as cameras or wearable devices (e.g., eye-trackers), can use multimedia streams to detect attention allocation and reading behavior, problem-solving in intelligent tutoring systems (Kunhee et al., 2015; Egger, Ley, & Hanke, 2019; Taub & Azevedo, 2019; Holmqvist et al., 2022), but these sensors are cumbersome to install and may even raise privacy concerns when deployed.

In recent years, mobile sensing has shown potential for tracking and modeling user behavior. For example, researchers have investigated and inferred students' diet consumption levels through mobile sensing to understand their physical health issues (Meegahapola et al., 2020); Or analyze the association between students' psychological states (anxiety, depression, decreased general well-being, poor sleep, etc.) and social behavior (Buxton et al., 2015; Mei, Xu, Gao, Ren, & Li, 2018; Demirci, Akgonul, & Akpinar, 2015 Fernandes et al., 2020). Especially after the COVID-19 pandemic has continued to affect students' daily lives over the past few years, researchers have used mobile apps to sense passively students' mental health and behavioral changes in this particular situation (Fonseca et al., 2021). As

Table 1. Compliance in the existing literature

Reference	Target	Recruited participants	Duration
Feng et al.2023	Learning Motivation	58 undergrads students	3 months
Meegahapola,et al.2023	mood inference	678 college students	13 weeks
Wang, et al. 2022	Mental health	180 college students	1 years
Nepal, et al.2022	Mental health	180 undergrads students	1 years
Xu et al.2019	Deprssion	455 college students	106 days
Wang et al.2018(a)	Personailty	646 college students	2 weeks
Wang et al.2018(b)	Deprssion	83 undergrads students	9 weeks
Boukhechba, 2018	Mental health	72 undergrads students	2 weeks
Zhang, 2017	Mood	42 college students	1 month
Farhan, 2016	Deprssion	79 college students	5 months
Huang, 2016	Social anxiety	18 undergrads students	10 days
Sano, 2015	Academic performance, Sleep, Stress, Mental health	66 undergrads students	30 days
Wang, 2014	Mental health, Academic performance	60 college students	10 weeks

shown in Table I, these mental health and medicine studies have demonstrated the feasibility of mobile sensing to assess various psychological variables from a behavioral perspective. However, few HCI studies have ported such approaches to learning environments (Feng, Yu et al., 2023). As far as we are concerned, this allowed us to follow the students in the study and gain insights from their behavior in an unobtrusive, on-site manner.

Methodology

Study Design

In our study, we collected and analyzed data from a long-term study of mobile sensing, primarily using mobile sensing and self-report surveys via questionnaires. The participants were all from a university in China, and 211 students volunteered to participate in the study, which lasted for one year (from March 2022 to March 2023). Specifically, students were recruited and consented at the beginning of the semester (one week before data collection, initially N = 281, on March 6, 2022). After recruitment, during the pre-testing phase (first week of March 2022), participants were given a detailed tutorial to install a mobile sensing application (iSense App) on their phones and asked to keep the app operational until the end (March 15, 2023); We checked the collected data every-day during the study and notified noncompliant participants to recheck the application status. The reason is that a few participants accidentally closed the application during the process.

The year-long study aimed to understand better and investigate the relationship between students' social behavior patterns and SRL. We used mobile sensing on phones to capture behavioral features, along with the combined self-report surveys to assess the use of learning strategies, in order to understand and explain participants' SRL skills comprehensively. Participants were informed of the purpose of the study at the beginning of the experiment. At the same time, participants can also use anonymized subsets of the data set for scientific research.

Data Collection: All participants in the study had the mobile sensing app (Isense APP) installed on their Android phones, which captured data 24 hours a day for a year. We received an average of 22 hours of data per day from all participants. The Isense APP primarily assesses participant behavior by sampling a series of sensors. The relevant data is stored on the phone until the phone is charged and connected to WiFi. When the phone is connected to WiFi, Isense uses SSL encryption and uploads the data to a cloud server. Data is stored in cloud servers and extracted for analysis (cloud storage).

Incentives: To improve compliance and data quality, we conducted self-report surveys by distributing questionnaires (sub-scales of MSLQ) to participants once a week. Participants were paid 20RMB per week for completing the study, and the questionnaires were sent via the Isense App.

Privacy considerations: We do not collect private/personal data like audio or video content. We also anonymized students' actual IDs. This study was approved by the university's Institutional Review Board (March 4, 2022).

Demographics

We initially recruited 281 participants, of whom only 211 ultimately adhered to the study and were assessed weekly on SRL using learning strategies. The reason is that large amounts of missing mobile sensing data resulted in participants being eliminated or voluntarily withdrawing from the study.

Table 2 shows the demographic data of the 211 students used in our analysis. The majority (55.45%, N=117) of participants were male. In terms of faculties, 23.70% (N=50) are from the Faculty of Social Sciences, 14.22% (N=30) are from the Faculty of Engineering, 26.54% (N=56) are from the Faculty of Physical Education, 21.32% (N=45) are from the Faculty of Information Sciences, and 14.22 % (N=30) are departments of medicine. Our participants basically cover the entire university's majors and grades.

Table 2: Demographics of the participants in the study.

Category	Count	Percentage
Sex		
Female	94	44.55%
Male	117	55.45%
Faculty		
Faculty of Social Sciences	50	23.70%
Faculty of Engineering	30	14.22%
Faculty of Information Science	56	26.54%
Faculty of Physical Education	45	21.32%
Medicine	30	14.22%

SRL and Resource Management Strategy Assessment

SRL was measured using the Learning Strategies subscale of the Motivation for Learning Questionnaire (MSLQ), a method validated in Pintrich (1993). These questionnaires are asked randomly once a week. Students also have the option to open the app at any time and answer the survey manually. The MSLQ consists of two subscales: motivation and learning strategies, and the scores of each subscale can be used for research analysis (Ramirez-Echeverry et al., 2016; Tong et al., 2020). In this study, we used scores on learning strategies to measure SRL skills.

Resource management strategy consists of four subscales: (1) time and study environment management, (2) effort regulation, (3) peer learning, and (4) help-seeking. Items for each subscale are measured with a 7-point defined on a Likert-type scale, where 1 represents “not at all true of me,” and 7 represents “very true of me.”. The questionnaire was scored according to the scoring manual of Pintrich et al., 1991. Higher subscale scores indicate a high level of SRL (Pintrich et al., 1991).

Table 3: Statistics of Resource Management Strategy Scale

Sub-Scale (1-7)	Response range	Overall Mean (std)	Within-person range*
Time and study environment management	1-7	3.11(1.94)	2(2-4)
Effort regulation	2-7	4.43(1.56)	4(3-5)
Peer learning	3-7	3.57(1.98)	3(2-5)
Help seeking	2-7	2.76(1.48)	3(1-4)

* Values in median(LQ-UQ) where LQ and UQ means the lower quartile (25%) and upper quartile (75%) respectively.

Table 3 shows the ranges of the subscales, the ranges of study participants' scored responses, the overall mean and standard deviation, and the median, lower, and upper quartiles of within-person ranges of variation across multiple assessments over a year. Many participants experienced various degrees of SRL skills during the study, consistent with other research on SRL (Zimmerman, B. J. 2013; Sutarni, Nani, et al., 2021; Mou, T. Y. 2023). We also observed that participants may score higher on some subscales and lower on others. For example, one participant scored high on time management and effort regulation but low on peer learning and help-seeking.

Behavioral Features

In this study, we integrate mobile sensing data from smartphones, which describe students' daily behavioral patterns during the learning environment, mainly including physical activities, sleep patterns, semantic locations, application usage, and smartphone usage. Please note that due to the diversity of application types and functions, we only divided the detailed usage data collected for 750 different applications into two categories according to the type of interaction behavior, including functions that reflect participants' direct interactions with other people (such as chatting with others using instant messaging applications) and participants indirect interactions with other individuals or groups (such as watching learning videos, etc.). These two new features of interaction have yet to be thoroughly studied. For example, smartphone-based communication functions include the use of voice or video calling applications (such as WeChat, a social media app similar to WhatsApp); Usage time of direct/ indirect applications, such as direct_study (MOOC forums, etc.), indir_study (learning video, etc.), indir_entertainment (music/livestream/shopping, etc.) and direct_entertainment (game, data apps, etc.) were also well investigated, as shown in Table 4.

Table 4: Features extracted from mobile sensing data

Catagory	Details*
physical activities	duration on foot / in vehicle / on bicycle / sedentary, duration of using different genres of apps
sleep changes	Sleep duration, Sleep start, Sleep end
semantic location	Number of locations visited, max distance from the center of campus, duration (dorms, café, library, canteen, shop, gym, study places, social places, class attendance)
phone usage	the name of the app currently running on the device, the duration of using the certain app, number of lock/unlocks & unlocked duration at all places
direct interaction	Instant messenger (call, SMS, WeChat/QQ, etc.), direct_study (MOOC forums, etc.), direct_entertainment (game, dating apps, etc.)
indirect interaction	web_browsering, indir_study(learning-video, etc.), indir_entertainment (music, livestream, shopping, etc.)

Association Analysis

To find out how mobile sensing data is related to SRL skills & resource management strategy, we used principal component analysis (PCA) (Schölkopf, Smola, & Müller, 2005) to extract and interpret participants' behavioral patterns and utilized generalized estimating equations (GEE) (Hardin & Hilbe, 2002; Liang & Zeger, 1986) to explore the association between the extracted behavioral patterns and MSLQ sub-scales' scores. We consider the mobile sensing data within one year prior to MSLQ responses. Next, we will discuss specific association analysis methods in detail.

Extracting and Interpreting Behavioral Features: We first calculated the average individual behavioral features across participants (average daily usage duration of mobile sensing data over a one-year time frame). Secondly, we organize the calculated features in a matrix N. Each column in the matrix N represents a feature, and each row in the matrix N represents a feature associated with one of the 3578 MSLQ responses. We use PCA on the matrix N to find and select the set of principal components (PCs) that explain most of the variance in X. We used PC scores instead of behavioral features in subsequent analyses. The reason is that using PCs scores significantly reduces feature dimensionality than behavioral features, while each PCs can be interpreted as a behavioral pattern and analyzed. For example, if a PCs has a large positive weight in the components for features of "the duration of using the certain app" and "indir_entertainment" features in a learning environment, then we would interpret that PCs as the behavioral pattern of inappropriate time management and have less exposure to face-to-face conversation interaction. Figure 1 shows the cumulative variability of features explained by the top-n PCs. Finally, the 11 PCs in X (explaining 90% of the variance) were selected for analysis.

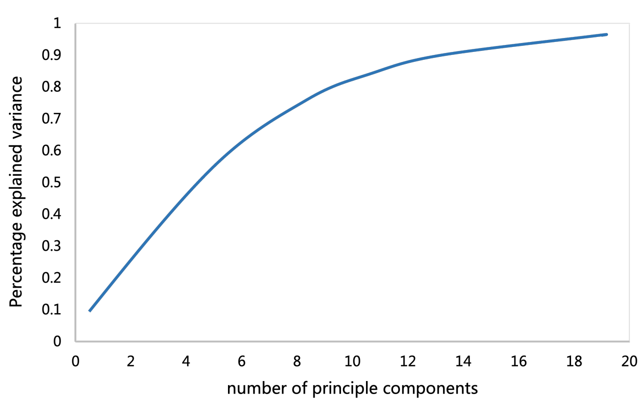

Figure 1: The cumulative variability in the sensed data explained by the top-n principal components.

Association Analysis: Considering the longitudinal nature of our dataset, which may correlate data from the same subjects, we chose the GEE method to determine the association between each selected feature and the 4 MSLQ scores. GEE focuses on estimating the mean response of the population, which is a more robust method for assessing correlations between repeated measurements (Wang, Rui, et al. 2017). Specifically, we first investigate how the selected 11 PCs are related to MSLQ scores by regressing the PC scores to them. Secondly, we adopt Bivariate GEE to a combination of 11 PCs and 4 subscales scores. Finally, we performed the two-stage Benjamini-Hochberg procedure (TSBH) (Benjamini, Krieger, & Yekutieli, 2006) to get the false discovery rate (FDR).

Results

As discussed previously, we used the PCA method to extract behavioral features selected from a set of principal components (PCs) and combined GEE and FDR methods to explore the associations between the selected 11 PCs scores and MSLQ subscale scores. Considering that features in PCs have larger positive or negative weights, we select features with larger absolute weights in PCs to understand the typical behavior that makes up each principal component. Our results showed that 10 of the 11 behavioral patterns (i.e., principal components) were associated with MSLQ subscales.

We detail the 11 behavioral patterns related to the MSLQ subscales in Table 5, which shows the features of each behavioral pattern indexed by PCA. Specifically, Pattern 1 describes students who frequently call during learning time or study places; Pattern 2 describes students who often text or chat during learning time or study places; Pattern 3 describes students who use learning software during learning time or study places; Pattern 4 describes students who spend more time in study places; Pattern 5 describes students who sleep late and often like entertainment apps; Pattern 6 describes students who enjoy participating learning activities; Pattern 7 describes students who prefer to move around in different places, spend less time in their dorm, and use less social media applications; Pattern 8 describes students who spend more time sleeping in their dorm; Pattern 9 describes students who spend more time studying in their spare time; Pattern 10 describes students who spend more time in direct interaction (e.g., WeChat, QQ, Messenger), and use less social networking apps (e.g., Weibo, forum); Pattern 11 describes students who spend more time in indirect interaction(e.g., watching learning videos), and have less exposure to face to face conversation interaction.

We applied association analysis between selected PCs and MSLQ scores to determine which behavioral patterns are highly related to SRL skills and resource management strategy. Table 6 shows behavioral patterns related to the 10 MSLQ subscales. The positive correlation between behavioral patterns and subscales indicates that students with these pattern behaviors are more likely to obtain higher scores in the corresponding subscales and thus have higher SRL skills, *and vice versa.* Next, we describe our findings.

The results show that pattern 3 is positively associated with the MSLQ subscales, and it can be reasonably inferred that students who actively participate in social learning and have the habit of using learning tools have a higher level of SRL.

Table 5: Behavioral patterns and their matching features indexed by n-th component of PCA

Pattern	Features
1.use call apps frequently in the study places	high call-in-and-out numbers during the classroom/study place, high unlock numbers
2. use the phone for text and chat apps in the study places	high SMS-in-and-out numbers during the classroom/study place, high unlock numbers, more time using social networking apps(i.e., WeChat, Blog, etc.)
3. use study apps frequently in the study places	more frequently being in learning areas especially in study places and library, less time at dorm, shorter sleep duration, longer unlock duration, playing less games but often using browser app and music/video apps
4.Spending time in the study places	showing up more frequently in study places, not often playing games/ browser/music apps and indirect interaction apps (Blog, etc.,), however, using social networking apps (e.g., Wechat)
5.using entertainment apps frequently and going to sleep late	using phones often playing games/ browser/music apps, going to sleep late
6.Spending time in the learning activity	going to bed early, call duration during the night period, spend time at dorm, use of direct interaction apps
7.Being physically active outside and spending time in different school places	longer unlock duration, playing less games but often using browser app and music/video apps, more active on walk
8.Spending time for sleep	longer unlock duration, early to bed, early to rise, less active on foot especially during study period, more usage of engagement apps, less frequenting in the study areas
9. Spending time in the study places in the evening or spare time	showing up more frequently especially in study places, less time at dorm, shorter sleep duration, longer lock duration, using learning app or music apps, going to sleep late
10.Spending time in direct interaction	more frequently being in learning areas especially in study places, longer unlock duration, duration of playing call/SMS/QQ/Post/WeChat/dating apps
11.Spending time in indirect interaction	more frequently being in learning areas especially in study places, longer unlock duration, duration of playing games/ browser/music/video apps

Table 6: Patterns associated with resource management strategy

Sub-scale	Associated behavioral pattern
Time and study environment management	pattern 1(-), pattern 2(-), pattern 3(+), pattern 6(+), pattern 9(+)
Effort regulation	pattern 3(+), pattern 4(+), pattern 5(-), **pattern 9(+)**
Peer learning	pattern 3(+), pattern 7(+)，**pattern 10(+)**
Help seeking	pattern 2(+), **pattern 3(+)，pattern 11(+)**

(-) negative association, (+) positive association, all associations with $p < 0.05$. FDR <0.1 in bold

Using learning tools further stimulated their active learning. Another interesting finding is that pattern 2 is negatively associated with time management strategies and positively associated with help-seeking. This may indicate that students who prefer to spend more time on social media applications may be more willing to seek help from others while having relatively lower levels of SRL. The study found that pattern 5 is negatively associated with effort regulation, which may also indicate that students who spend more time on entertainment tend to have lower levels of SRL.

On the contrary, pattern 9 is positively associated with effort regulation and time management, which indicates that students who are willing to study in their spare time actively have higher levels of SRL. It is important to note that pattern 10 and pattern 11 are positively associated with peer learning and help-seeking strategies, respectively. This suggests that students who need to understand course material better rely on methods such as Internet searches and online videos for help. Students can also seek help from other students through direct interactive applications, such as online discussions or instant messaging, to improve their SRL skills.

Discussion

In this paper, we propose an innovative approach blended mobile sensing with self-report surveys as an attempt to assess SRL and resource management strategies. Although our work provides insights for future researchers to investigate the students' SRL behavior and other related psychological states in the learning process, our study still faces several limitations. On the one hand, it mainly focuses on a specific demographic of students within a university in China, which limits the generalizability of our findings. On the other hand, we acknowledge that our data collection measures may not provide a comprehensive analysis. The study did not fully exploit multimodal sensing, as it solely relied on smartphones without integrating other devices with diverse sensor capabilities. Despite these limitations, they serve as a basis for future research opportunities. We believe that our work inspires new directions in future work assessing learning motivation and perceived relevance and paves the way for future research on personalized interventions.

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