Passive Behavioral Sensing: Using Within-Person Variability Features from Mobile Sensing to Assess Self-Regulated Learning

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Abstract

Self-regulated learning (SRL) significantly influences students' learning behaviors and academic performance. However, research has focused on "between-person" differences, neglecting "within-person" variability. Traditional SRL assessments rely on self-reports, which fail to capture fine-grained behavioral changes (such as hourly variations). We propose a novel approach using mobile sensing to assess SRL through within-person variability. We use passive sensing data from the phones of 211 university students to explore this relationship. To assess behavioral variability, we focus on five sensing behaviors—physical activity, social interactions, sleep, location, and app usage data—and calculate four within-person variability features: standard deviation, circadian rhythm, regularity index, and flexible regularity index. Our findings reveal significant associations between these variability features and self-reported SRL skills, particularly in dimensions such as environment structuring, time management, and help seeking. This research provides new insights into assessing SRL and offers a theoretical foundation for future personalized interventions in educational settings.

Keywords: Self-regulated Learning; Within-Person Variability; Mobile Sensing; Education; Human-computer Interaction

Introduction

The university learning environment emphasizes autonomy, which is unfamiliar to many students. In this context, students' academic performance and efficiency rely not only on course content but also their self-regulated learning (SRL) skills (Pintrich, 2004) (Pintrich, 1999). SRL involves self-generated, cyclical thoughts, feelings, and actions to achieve personal goals (Zimmerman, 1990). SRL has been shown to impact academic performance significantly (Zimmerman, 2013) and psychological well-being (Holzer et al., 2021). However, many students struggle with understanding and applying SRL skills (Peverly, Brobst, Graham, & Shaw, 2003), which contribute to burnout and higher dropout rates (Bail, Zhang, & Tachiyama, 2008). Therefore, supporting and enhancing SRL skills is essential.

Although SRL significantly impacts academic achievement, assessing and supporting SRL skills remains challenging. Traditional methods, such as questionnaires and interviews (Roth, Ogrin, & Schmitz, 2016), provide an overview of SRL skills but fail to capture dynamic behavioral changes across various learning contexts (Dinsmore, Alexander, & Loughlin, 2008) (Winne & Perry, 2000). Research shows that SRL skills are not fixed and vary with changing learning environments and task demands (Puustinen & Pulkkinen, 2001). While SRL differences across students are evident, behaviors and strategies fluctuate significantly over time and in different contexts, even within the same student (Saqr, 2023). This "within-person" variability is often overlooked despite its importance for learning interventions and strategy optimization. Most studies focus on "between-person differences", neglecting the behavioral changes exhibited by the same student at different times and in different contexts.

In recent years, mobile sensing technology has provided new opportunities for studying "within-person variability" (W. Wang et al., 2018). Researchers can continuously collect behavioral data through passive sensing systems, enabling more granular analysis of behavioral processes (R. Wang et al., 2014) (Zhang, Li, Chen, & Lu, 2018). However, how to convert this data into an effective means of assessing SRL remains a problem that needs to be addressed. To fill this gap in existing research, this study proposes an innovative approach that uses mobile sensing data to quantify "within-person variability" in student behavior (i.e., behavioral changes of the same student over time and in different environments) and explores its dynamic relationship with SRL. We develop a passive sensing system based on long-term behavioral data from 211 students at a Chinese university. This system collect multimodal behavioral data, including physical activity, social interactions, sleep patterns, location changes, and app usage during students' learning and life activities. By combining data from the self-reported data, we extract four types of variability indicators from students' learning behaviors: standard deviation (STD), circadian rhythm (CR), regularity index (RI), and flexible regularity index (FRI). These indicators aim to capture the dynamic characteristics of student behavior and provide a novel and effective perspective for assessing SRL. Our paper makes the following contributions:

- To the best of our knowledge, we present the first to examine the relationship between within-person behavioral variability and SRL using mobile sensing. We conduct our research with a sample of 211 college students, collecting their SRL data over the course of one year, from March 2022 to March 2023, alongside real-time mobile sensing data.
- We identify several within-person variability features, that are closely associated with SRL, providing fundamental conditions for predicting SRL using mobile sensing.
- We propose a new approach to assess SRL combinedwith mobile sensing. The identified within-person variability features that are highly correlated with the targeted psychological measures provide the fundamental conditions to build models for predicting SRL. It is also an important step to design timely interventions in students' daily lives to enhance SRL. In addition, it provides the possibility to generalize our method to the assessment of other psychological variables.

Related Work

Research in the field of educational psychology and pedagogy has explored methods of assessing SRL (Fan, Saint, Singh, Jovanovic, & Gašević, 2021) (Azevedo & Gašević, 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 (Winne & Jamieson-Noel, 2002), which can be both laborious and time-consuming. For these reasons, alternative and innovative methods have emerged to measure changes in SRL skills. Some examples of new measures include tracking logs, audible reflection verbal protocols, and hyperlink use (Bannert & Mengelkamp, 2008) (Greene, Robertson, & Costa, 2011) (Järvelä, Malmberg, Haataja, Sobocinski, & Kirschner, 2021), although valuable, failing to capture real-time, comprehensive changes in students' behaviors during the learning process (Reimann, 2009).

With the rise of online and blended learning, alternative methods to assess students' SRL skills have emerged. These include monitoring emotional states through camera-based engagement and computer activities to provide feedback for improving SRL (Delen & Liew, 2016) (Davis, Chen, Jivet, Hauff, & Houben, 2016) (Aslan et al., 2019) (Järvelä & Bannert, 2019), using wearable devices to analyze students' facial expressions and postures to enhance SRL (Shih, Chen, Chang, & Kao, 2010) (Nussbaumer et al., 2014), employing eye-tracking for metacognitive monitoring (Taub & Azevedo, 2019), recording students' attention during classes with cameras and VR to improve their SRL (Ahuja et al., 2021), promoting SRL through dashboard visualizations of learner activities (Davis et al., 2016) (Malmberg, Fincham, Pijeira-Díaz, Järvelä, & Gašević, 2021). These methods, while opening new directions, have limited applicability. On one hand, they rely on specialized equipment and specific task contexts, making them difficult to implement in everyday learning. On the other hand, most studies focus on "between-person" differences, neglecting the important "within-person variability"—the dynamic changes in behavior and strategy use by the same student at different times and in different contexts.

Mobile sensing has shown potential for tracking and modeling user behavior in recent years. Smartphones and embedded sensors can passively collect rich behavioral data, such as physical activity, location changes, and app usage. This data reveals behavior patterns in different contexts. For example, researchers have used mobile sensing to infer students' dietary habits and their health (Meegahapola, Ruiz-Correa, & Gatica-Perez, 2020) (Kammoun, Meegahapola, & Gatica-Perez, 2023) or analyze the relationship between mental health states (e.g., anxiety, depression, sleep issues) and social behavior (Buxton et al., 2015) (Mei, Xu, Gao, Ren, & Li, 2018) (Demirci, Akgönül, & Akpinar, 2015) (Mäder, Meegahapola, & Gatica-Perez, 2024) (Nepal et al., 2024) (W. Wang et al., 2022). During the COVID-19 pandemic, mobile apps were used to track students' mental health and behavior changes, demonstrating the applicability of mobile sensing technology (Nepal et al., 2022). Although mobile sensing's potential in mental health and behavioral modeling is proven, its use in education is still in the early stages (Zhao et al., 2023). For our study, this allows us to unobtrusively track students and gain insights from their behavior.

Methodology

Study Design

The iSense study is a 12-month mobile sensing research project conducted at a university in China, examining the relationship between within-person variability in student behavior and SRL. The study takes place on a self-contained campus, where students live on-site, making it ideal for capturing comprehensive learning and daily behaviors. The campus includes dormitories, classrooms, libraries, gyms, cafeterias, and social spaces. The study covers two academic terms (Spring: February to June; Fall: September to December) and the winter and summer vacations, reflecting students' behaviors during different periods.

Demographics

We initially recruited 281 participants, but 211 remained in the study, completing weekly SRL assessments. Many were excluded or withdrew due to missing mobile sensing

Table 1: Statistics analysis of OSLQ Scale

Subscale	Response range	Overall Mean (std)	Within-person range*
Goal setting	1-5	3.49 (1.23)	3 (2-4)
Environment structuring	1-5	4.07 (0.87)	3 (3-4)
Task strategies	1-5	3.79 (0.92)	2 (3-4)
Time management	1-5	3.74 (1.02)	2 (2-4)
Help seeking	1-5	3.78 (0.96)	3 (2-4)
Self evaluation	1-5	3.54 (1.02)	2 (2-4)

* Values are presented as the median (LQ-UQ), where 'LQ' stands for the lower quartile (25th percentile) and 'UQ' for the upper quartile (75th percentile).

data. Of the participants, 55.45% (N=117) were male. Faculty distribution included 23.70% (N=50) from Social Sciences, 14.22% (N=30) from Engineering, 26.54% (N=56) from Physical Education, 21.32% (N=45) from Information Sciences, and 14.22% (N=30) from Medicine. The participants represent a broad range of the university's disciplines and grades.

Data Inclusion Criteria All participants installed the iSense App on their Android phones, which captured data continuously for a year. The data was stored locally until the phone connected to WiFi, at which point it was uploaded to a cloud server using SSL encryption. Data quality was ensured by excluding days with less than 19 hours of sensor data, based on previous studies (R. Wang et al., 2017), to maintain a balance between data quality and quantity.

Incentives To improve compliance and data quality, self-reported surveys were distributed weekly via the iSense App. Upon completion of the study, participants received 50 RMB as compensation. A reward system was also implemented: participants who completed at least 85% of the surveys were eligible for an additional reward, with three participants randomly selected to receive 100 RMB each.

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

Data collection and SRL assessments methods

Self-reported surveys

To rigorously assess SRL, we use the Online Self-Regulated Learning Questionnaire (OSLQ), which is known for its strong validity (Barnard, Lan, To, Paton, & Lai, 2009). SRL is a dynamic process influenced by the learning environment, and the OSLQ's advantage lies in its ability to extend SRL research to various learning contexts. It allows researchers to evaluate SRL skills and their changes across different learning forms, providing valuable insights into both the student and the learning environment (Bruso & Stefaniak, 2016).

The OSLQ consists of six subscales that assess different aspects of SRL: a) Goal setting, b) Environment structuring, c) Task strategies, d) Time management, e) Help seeking, and f) Self-evaluation. Each subscale is rated on a 5-point Likert scale, where 1 represents "strongly disagree" and 5 represents "strongly agree." Higher scores indicate a higher level of SRL. Table 1 shows the mean scores and standard deviations for each subscale, following the scoring methodology by (Ulfatun, Septiyanti, & Lesmana, 2021). Participants exhibited varying levels of SRL throughout the study, consistent with existing research on SRL dynamics (Zimmerman, 2013) (Mou, 2023). Notably, scores differed across subscales, reflecting the varied strengths and challenges students face in managing their learning. For instance, one participant demonstrated high scores in time management and environment structuring but scored low in help seeking.

Table 2: Description of the extracted features.

Type	Extracted Features Description
Physical Activity	Physical activity features are crucial for assessing how students allocate time between active and stationary states, as well as the patterns of behavior changes throughout the semester (Harari et al., 2017). We use the Android Activity Recognition API identify different activity states (Google, 2019): stationary, in-vehicle, on-bicycle, on-foot, running, tilting, walking, unknown, with updates every 30 minutes.
Social interactions	Interpersonal interactions are crucial for students seeking help during their learning process (Zimmerman, 2013). We track call durations and call/SMS frequencies from logs to measure social connections. Social ability-related features inferred from calls and text messages include incoming and outgoing calls, incoming and outgoing SMS, and the duration of communication through voice or video calls via apps.
Sleep	Quality sleep is essential for effective learning (Alshammari et al., 2023). We appliy an existing sleep detection model (R. Wang et al., 2014) to detect participants' sleep duration, start time, and wake-up time.
Location	Students' activity patterns are influenced by the learning environment they are in (Clough, 2009). Combining GPS and WiFi data sources with a semantic understanding of campus locations allows us to identify time spent in specific places, including dorm, classroom, art & entertainment, canteen, study room, parks & outdoors, library, shop, gym, cafe, and not found.
App Usage	The types of applications students use to provide valuable insights into their learning habits and potential distractions (Lin, Liu, Fan, Tuunainen, & Deng, 2021). Given the large number of applications, we do not consider specific apps but categorize them into 26 groups directly derived from the Android market. These categories include: Education, Games, Art, Beauty, Books, Comics, Communications, Dating, Entertainment, Financial Services, Food, Health, Maps, Browsers, Medical, Music, News, Parenting, Customization, Photography, Shopping, Social, Video, Weather, word, not found.

Passive behavioral features

The iSense application efficiently collects a range of behavioral sensing features from raw sensor data, which are crucial for capturing participants' daily behavior patterns. These features include Physical activity, Social interactions, Sleep, App usage, and Location, offering a holistic perspective on factors influencing SRL. Table 2 provides a detailed description of these features, outlining their significance and role.

Within-Person Variability Metrics

In the SRL study, understanding the dynamic changes in student behavior is crucial for analyzing the regularity and flexibility of learning. Within-person variability reflects the fluctuations in student behavior over different periods and reveals its relationship with SRL. To more accurately capture these changes, we design four within-person variability indicators: Standard Deviation (STD), Circadian Rhythm (CR), Regularity Index (RI), and Flexible Regularity Index (FRI). These indicators assess the variation patterns of behavioral features from multiple dimensions, providing rich insights into learning behaviors. First, we divide the daily data into 24 one-hour periods and process sensor data hourly. For example, we calculate the sedentary time for physical activity data for each hour; we count the number of phone unlocking events per hour for phone usage data. Then, we calculate the four intra-individual variability indicators to analyze students' learning behavior patterns.

Standard Deviation (STD) STD quantifies the fluctuation of student behavior characteristics over different periods, reflecting the stability of behavioral changes. It provides the foundation for analyzing student learning patterns during different periods by reflecting the extent of behavioral changes. Specifically: **std_semester_all**: STD over all days during the semester, reflecting behavior fluctuation during normal study periods. **std_holiday_all**: STD over all days during the holidays, reflecting behavior fluctuation during leisure time. **std_day_semester**: STD for the daytime period (8:00-18:00) during the semester, reflecting student behavior fluctuations during study hours. **std_night_semester**: STD for the nighttime period (18:00-08:00) during the semester, reflecting student behavior during both study and rest hours.

Circadian Rhythm (CR) CR measures the stability and regularity of an individual's behavior within the 24-hour biological rhythm (Saeb, Lattie, Schueller, Kording, & Mohr, 2016). In the context of SRL, the stability of behavioral rhythms can significantly impact learning efficiency (Kaplan, Neuber, & Garner, 2019). For example, consistent learning activities, time management, and rest patterns can help improve learning effectiveness and focus.

In this study, we use the Least Squares Spectral Analysis (Lomb-Scargle Periodogram, LSP) (Fu, 2013) to transform behavioral sensor data such as physical activity, phone usage, location data, and app usage from the time domain to the frequency domain. We then calculate the ratio of the energy within a 24 ± 0.5-hour period (corresponding to $\frac{2\pi}{24\pm0.5} = (0.2565, 0.2674)$) to the total spectral energy within a 24 ± 12-hour period (corresponding to $\frac{2\pi}{24\pm12} = (0.1745, 0.5236)$) to define the behavior CR:

$$CR_{\text{behavior}} = \frac{\int_{0.2565}^{0.2674} \text{psd}(x)\,dx}{\int_{0.1745}^{0.5236} \text{psd}(x)\,dx}$$

where $\text{psd}(x)$ represents the power spectral density at frequency bin x. Before performing spectral analysis, we zero-mean align the hourly behavioral signals.

For mobility data, we use semantic location labels obtained from the API. We calculate the CR for each location label and then combine them as follows:

$$CR_{\text{mobility}} = \log(CR_{\text{location}})$$

In terms of specific data: **cr_semester_all**: Calculating the CR during the semester, analyzing students' biological clocks and behavioral patterns during the study period. **cr_holiday_all**: Calculating the CR during the holidays, analyzing behavioral patterns during leisure periods.

Regularity Index (RI) RI quantifies the consistency of student behavior within the same time period on different days, reflecting the repeatability and stability of behavior. There are two types of RI:

Basic RI: Evaluates the similarity of behaviors for continuous variables (e.g., physical activity, phone usage). The formula is:

$$RI_{a,b} = \frac{1}{T}\sum_{t=1}^{T} x_{at} \cdot x_{bt}$$

where T represents the 24 hours of a day, and x_{at} and x_{bt} represent the standardized values of the behavior features at hour t on day a and day b, respectively.

Mobility RI: Evaluates the consistency of students' location data, calculating whether students visit the same semantic locations (e.g., dormitory, classroom) on two different days. The formula is:

$$RI_{\text{mob}} = \frac{1}{T_{\text{traj}}}\sum_{t=1}^{T_{\text{traj}}} c_{at} \cdot c_{bt}$$

where T_{traj} represents the number of overlapping time windows between two days, and c_{at} and c_{bt} represent whether student a and student b visited the same location during time window t on each day, respectively.

For different periods: **ri_semester_avg**: Calculating the average regularity of student behavior during the semester, analyzing consistency during study periods. **ri_holiday_avg**: Calculating the average regularity during holidays, reflecting behavioral consistency during leisure time. **ri_semester_vs__holiday_avg**: Calculating the average hour-by-hour similarity between semester and holidays. **ri_semester_range**: Calculating the range regularity of student behavior during the semester, analyzing consistency during study periods. **ri_holiday_range**: Calculating the range regularity during holidays, reflecting behavioral consistency during leisure time. **ri_semester_vs__holiday_range**: Calculating the range (i.e., the difference of the most similar pair and the most distinguished pair) of hour-by-hour similarity between semester and holidays.

Flexible Regularity Index (FRI) FRI assesses the flexibility of differences in students' SRL behaviors over two days. By calculating the Levenshtein distance (Levenshtein, 1966) (edit distance) between the behavior data, we can quantify the differences in students' learning behaviors over the two days. A lower FRI value indicates higher similarity in students' learning behaviors within the same time period, while a higher FRI value suggests a greater difference in behavior.

For different periods: **fri_semester_avg**: Calculating the average flexibility of student behavior during the

Table 3: SRL subscale in relation to regularity using association analysis.

SRL Subscale	Association	Within-Person Regularity Features
Goal setting	(+)	stationary_std_semester_all, walking_std_semester_all, study room_cr_semester_all, classroom_cr_semester_all, **education_ri_semester_avg**, incoming calls_fri_semester_avg
	(-)	stationary_std_holiday_all, canteen_cr_holiday_all, games_ri_holiday_all, outgoing calls_fri_holiday_avg
Environment structuring	(+)	stationary_std_semester_all, walking_fri_semester_avg, running_ri_semester_avg, sleep_duration_cr_semester_all, dorm_fri_semester_vs_holiday_avg, library_ri_semester_range **education_std_day_semester**, incoming_calls_cr_holiday_all
	(-)	stationary_std_holiday_all, walking_fri_holiday_avg, sleep_duration_cr_holiday_all, **library_fri_semester_vs_holiday_range**, **education_std_holiday_all**
Task strategies	(+)	stationary_std_semester_all, education_fri_semester_avg, sleep_duration_ri_semester_range, call_duration_std_day_semester
	(-)	dorm_ri_semester_vs_holiday_range, **games_fri_semester_range**, incoming_calls_ri_semester_range, **sleep_start_time_ri_semester_vs_holiday_avg**
Time management	(+)	stationary_std_semester_all, education_std_semester_all, health_std_semester_all, sleep_duration_std_semester_all, library_std_semester_all, **library_ri_semester_range**, incoming_calls_ri_semester_avg, education_ri_semester_range
	(-)	walking_std_holiday_all, games_std_holiday_all, sleep_duration_std_holiday_all, social_std_holiday_all, sms_outgoing_ri_holiday_avg, video_ri_semester_range, **entertainment_ri_semester_vs_holiday_range**
Help seeking	(+)	incoming_calls_std_semester_all, incoming_sms_cr_semester_all, study_room_ri_semester_vs_holiday_avg, video_ri_semester_all, library_fri_semester_avg
	(-)	cafe_fri_semester_vs_holiday_range, music_ri_holiday_avg
Self evaluation	(+)	stationary_std_semester_all, library_fri_holiday_avg, sleep_duration_ri_semester_avg,education_ri_semester_range
	(-)	-

All associations with $p < 0.05$. FDR < 0.1 in bold.

semester, reflecting behavioral adjustments during study periods. **fri_holiday_avg**: Calculating the flexibility of student behavior during holidays, reflecting behavioral changes during leisure time. **fri_semester_vs__holiday_avg**: Calculating the average hour-by-hour flexibility between semester and holidays. **fri_semester_range**: Calculating the range flexibility of student behavior during the semester, analyzing consistency during study periods. **fri_holiday_range**: Calculating the range flexibility during holidays, reflecting behavioral consistency during leisure time. **fri_semester_vs__holiday_range**: Calculating the difference in the range of students' flexibility between the semester period and the holiday period. Specifically, it measures the fluctuation in students' ability to adjust their behavior during these two different time periods.

Association Analysis

We use a Linear Mixed Model (LMM) (McCulloch, 2001) to examine the relationship between within-person variability features and SRL subscales. LMM accounts for both fixed and random effects, making it ideal for data with group-level correlations or dependencies (W. Wang et al., 2018). Since our data includes multiple measurements from the same student (e.g., daily sensor data and OLSQ scores), LMM effectively handles individual differences (random effects) and the overall relationship (fixed effects), making it well-suited for analyzing repeated-measures data.

To address the multiple comparison problem, we use the Benjamini-Hochberg procedure (BH) (Benjamini & Hochberg, 1995) (Benjamini & Yekutieli, 2001) to control the false discovery rate (FDR). This method helps manage the risk of false positives, ensuring the reliability of our results.

Result

We present the results of the association analysis using passive sensing data, reporting only significant associations with p-values below 0.05 and further distinguishing results with FDR values under 0.1, as shown in Table 3.

Goal setting reflects a student's skill to plan learning objectives, linked to their behavior and environment. Six within-person variability features were positively correlated with goal setting. These results suggest that individuals with more consistent and organized behaviors tend to set more explicit learning goals. These students exhibit stable routines throughout the semester and are more capable of adapting their behaviors to reach their learning objectives. Additionally, their activities in study rooms and classrooms show strong circadian rhythms, reflecting their ability to adjust their learning environment to support task completion effectively. Furthermore, four features were negatively correlated with goal setting. These findings suggest that students with more flexible and irregular behaviors during holidays tend to struggle with goal setting. They may lack effective self-regulation during rest periods, which hinders their ability to maintain consistent learning goals. The variability in their social and app usage patterns, especially during the holidays, likely contributes to this challenge.

Environment structuring reflects a student's skill to optimize their learning environment. We found eight within-person variability features positively correlated with environment structuring. These results suggest that individuals who exhibit more consistent and organized behaviors, such as regular walking and structured sleep patterns, are better at structuring their environment to support their learning. They tend to organize their time and physical surroundings to enhance their academic focus, making their learning environment more conducive to goal achievement. Additionally, five features were negatively correlated, suggesting that students with more variable behaviors during holidays struggle with structuring their learning environment. This inconsistency may hinder their ability to maintain a productive study space, especially during breaks.

Task strategies relate to how students approach and complete tasks. Four within-person variability features were positively correlated, indicating that students with more behavioral flexibility, such as varied stationary activities or call durations, tend to develop adaptive task strategies. These students can adjust their approaches based on task demands. Conversely, four features were negatively correlated, suggesting that students with higher variability in dormitory activities, gaming, or incoming calls struggle to develop effective task strategies. The lack of regularity in their behaviors may hinder their ability to plan and execute tasks efficiently.

Time management reflects how well students allocate and manage their time. Eight within-person variability features were positively correlated, indicating that individuals with higher variability and regularity in their activities, particularly in areas such as studying, sleep, health, and phone usage, tend to exhibit better time management skills. These students may be more adept at balancing and allocating time for various tasks, suggesting that flexibility in their behavior patterns contributes to effective time management. However, seven features were negatively correlated, showing that students who exhibit greater variability in their behaviors, especially during holidays, in areas such as physical activity, gaming, social interactions, and entertainment, tend to have poorer time management. The lack of regularity and consistency in their actions may hinder their skill to allocate their time effectively for academic or personal tasks, leading to less optimal time management skill.

Help seeking reflects students' behaviors in seeking support. We found five within-person variability features positively correlated with help seeking. These findings suggest that students who exhibit more variability in activities like incoming calls, messaging, study-related behaviors, and regularity in their video and library usage patterns are more likely to seek help. The flexibility and regularity in their activities reflect a more proactive approach to accessing resources, such as reaching out for assistance when needed. Conversely, we found two within-person variability features negatively correlated with help seeking. These results indicate that students with less variability or less regularity in their activities related to social or leisure settings, such as cafe visits or music listening, tend to seek less help. This may suggest a preference for independent study or a lower need for external support in academic endeavors.

Self evaluation reflects a student's skill to assess their performance. We found four within-person variability features positively correlated with self-evaluation. These results suggest that students with more significant variability in behaviors, such as stationary activities and regularity in their sleep and study patterns, tend to engage in better self evaluation practices. These individuals may be more aware of their learning progress and adjust their strategies.

Conclusion

This study implemented mobile sensing to capture individual differences in college students' daily behaviors, app usage, location, and social interactions, demonstrating how within-person variability patterns from smartphone sensors correlate with self-reported SRL skills. Our findings show that students' behavioral regularity, flexible routines, and activity patterns are strongly linked to SRL dimensions such as goal setting, time management, and help seeking. This large-scale study is the first to explore how within-person variability can assess SRL, offering a new tool for evaluating large participant groups with minimal burden.

Despite the findings, limitations persist. Sensor data captures behavior but does not fully reflect psychological states, particularly in complex tasks like self evaluation skill. Future research should integrate physiological signals and emotion monitoring for a more comprehensive SRL assessment. Additionally, the study sample was limited to one university, so expanding to diverse regions and disciplines is necessary. This research offers valuable insights into SRL by combining passive sensor and self-report data. Future work can improve data collection, expand samples, and explore varied modeling techniques to support personalized learning better. Our system can be easily deployed for behavior tracking in personalized SRL projects and is especially useful for passive SRL assessment in blended learning environments and human-centered applications. Mobile sensors also hold promise beyond SRL, including in mental health, psychological state prediction, and workplace performance.

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