iSense: Passive Inference of Student Self-Regulated Learning and Emotional Regulation Using Smartphone

Tongyu Zhao[1,2] (id9269@alunos.uminho.pt), Jiaying Gao[3] (jiayingg20@mails.jlu.edu.cn), Yatong Zu[4] (zuyatong@jlu.edu.cn), Adriano Tavares[2] (atavares@dei.uminho.pt), Hao Xu[1,*] (xuhao@jlu.edu.cn)
[1]College of Computer Science and Technology, Jilin University, Changchun, China
[2]School of Engineering, University of Minho, Guimarães, Portugal
[3]Changchun University of Science and Technology, changchun, China
[4]College of Physical Education, Jilin University, Changchun, China
[*]Corresponding author

Abstract

Early detection of self-regulation challenges in university students is critical for academic success, yet conventional assessment methods struggle to capture these behavioral processes' multidimensional and dynamic nature. To address this, we develop iSense - a smartphone-based system that enables privacy-aware, passive monitoring of self-regulated learning (SRL) and academic emotional regulation (AER) through multi-modal behavioral sensing (social interactions, mobility, app usage, and sleep). In our 12-month longitudinal study involving 211 college students, the system successfully identified significant behavioral correlates of SRL/AER states. Our hybrid population-personalized prediction model achieved mean absolute errors of 7.9% (SRL) and 9.3% (AER), representing a 22% improvement over conventional baselines. Importantly, the results demonstrate how knowledge transfer from student populations can facilitate the development of accurate, personalized models that require minimal individual-specific data for rapid adaptation to new students. This scalable solution overcomes limitations of traditional self-report methods for diverse educational settings.

Keywords: Self-regulated learning; Academic Emotional Regulation; Smartphones Sensing; Education

Introduction

University learning involves substantial cognitive and emotional demands. In highly autonomous learning environments, students must employ self-regulated learning (SRL) strategies to plan and manage academic tasks while simultaneously using academic emotion regulation (AER) strategies to cope with stress and uncertainty (Lourenço & Paiva, 2024; Restrepo et al., 2023). SRL and AER are critical for academic success and mental well-being (Sverdlik et al., 2022). However, key questions remain unresolved: why some students consistently demonstrate effective self-regulation while others struggle under similar conditions, how AER strategies are deployed during periods of academic pressure, and how observable behavioral patterns—such as physical activity, social interaction, and sleep—relate to these processes.

To address these questions, we conduct our study in an enclosed residential campus at a Chinese university. This setting offers three advantages. First, academic and daily activities occur within a unified physical space, enabling comprehensive behavioral observation. Second, the university's structured academic calendar (spring: February–June; fall: September–December) produces predictable stress cycles, allowing examination of regulation strategies under varying pressure levels. Third, although the large student population (N = 211) challenges traditional assessment methods (Derakhshan et al., 2023; Parsons et al., 2019), it provides an ideal testbed for scalable mobile sensing approaches.

These contextual characteristics highlight the limitations of conventional assessments in capturing the dynamic and multidimensional nature of student behavior (Derakhshan et al., 2023; Parsons et al., 2019). To overcome these limitations, we develop iSense, a smartphone-based sensing system for continuous and unobtrusive assessment of SRL and AER in naturalistic settings. Through a year-long longitudinal deployment, we collect high-resolution behavioral data—including physical activity, mobility, app usage, social interaction, and sleep—from 211 participants. The primary contributions of this study are as follows:

1. We demonstrate that SRL and AER states can be reliably inferred from smartphone sensor data alone. A year-long longitudinal study reveals strong associations between passive behavioral features and standardized self-report measures, validating this scalable approach to learning analytics.
2. We develop a comprehensive behavioral profiling framework using physical, social, sleep, and app usage features. Our machine learning pipeline identifies key behavioral markers and achieves mean absolute errors of 7.9% (SRL) and 9.3% (AER), without relying on intrusive physiological or facial data.
3. We implement and deploy the iSense system. By integrating population-level patterns with personalized modeling, iSense enables accurate SRL and AER prediction even with limited personal data, supporting rapid adaptation for new students.

Related work

Effects of SRL and AER on learning: A growing body of research underscores the roles of AER and SRL in supporting students' academic development. AER—managing academic emotions—has influenced performance, well-being, and adaptability across educational stages. For example, (Camacho-Morles et al., 2021) found that although ER and academic emotions are correlated, each uniquely contributes

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to academic outcomes beyond cognitive factors. Similarly, AER in adolescents has been linked to higher reading and math achievement, teacher-rated academic behavior, competence, and GPA (Adynski et al., 2024; Pedrini et al., 2022). (Chakraborty & Chechi, 2019) introduced the Academic Emotion Regulation Questionnaire (AERQ), which identifies the emotion regulation strategies students use in academic settings and emphasizes the role of academic emotions in shaping learning behaviors. In parallel, SRL has been consistently recognized as a powerful predictor of academic success (Xu et al., 2023). Students who can effectively set goals, plan, monitor, and adapt their learning strategies tend to achieve better learning outcomes. For example, goal setting and planning are strong predictors of goal attainment (Saks, 2024), while time management, consistent effort, and self-monitoring are foundational to learning success (Fu et al., 2025). These skills are vital in higher education, where students must navigate increasing autonomy and cognitive demands (Ma & She, 2024). These findings highlight the intertwined nature of emotional and cognitive regulation: students who regulate how they feel and learn are better equipped to manage academic challenges and sustain achievement.

Mcogscieasurement methods of SRL and AER: Given the critical role of SRL and AER in learning processes, extensive research has investigated various assessment methodologies. Traditional approaches, particularly self-report surveys, remain predominant in the field (Roth et al., 2016). Derived methods such as experience sampling (Liao et al., 2023) have gained wider adoption for their temporal granularity. Phenomenological approaches, including interviews and teacher ratings (Zheng et al., 2023) provide qualitative assessments of SRL and AER, yet share similar limitations with self-reports due to their reliance on subjective expert judgments (Rovers et al., 2019). More labor-intensive techniques like participant observation logs, case studies, and retrospective interviews (Lee et al., 2017; Liebendörfer et al., 2023) face comparable challenges regarding implementation feasibility and measurement discontinuity. Recent methodological advances have incorporated neuroscientific techniques to examine the neural correlates of regulatory processes during learning. Brain imaging, eye-tracking, and EEG (Raković et al., 2024; Taub & Azevedo, 2019) demonstrate strong face validity and content specificity, though concerns persist regarding their reliability across diverse learning contexts. Behavioral assessment methods offer alternative measurement paradigms, including expert observation, trained-coder video analysis (Assi & Cohen, 2023), and dashboard visualizations of learner activities (Zheng et al., 2021). Compared with methods requiring specific spaces, instruments, or sensors, there is growing interest in passive sensing for assessing psychological variables or states among human-computer interaction researchers.

Modeling student behavior based on mobile sensing: 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 et al., 2020) (Kammoun et al., 2023) or analyze the relationship between mental health states (e.g., anxiety, depression, sleep issues) and social behavior (Mäder et al., 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, 2025). For our study, this allows us to track students and gain insights from their behavior unobtrusively.

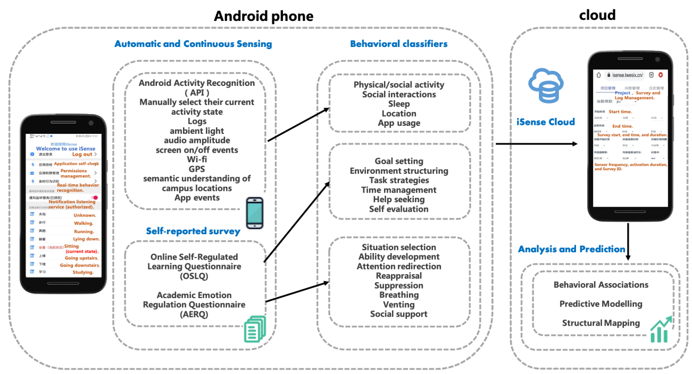

Figure 1: iSense app, sensing and analytics system architecture.

System design and data collection

System framework

We propose the system framework in Figure 1 for analyzing students' SRL and AER via smartphone sensing. A continuously running Android app collects multi-dimensional behavioral data—including social interactions, sleep patterns, app usage, and physical activity—and allows students to periodically report their SRL and AER states as ground truth. From these data, we extract behavioral features and apply feature selection to identify the most representative subset. Association models between behavioral features and SRL/AER states are then established using statistical and machine learning approaches, and the system's performance is validated against self-reported data. Detailed implementation is described in subsequent sections.

Implementation of iSense

We develop the iSense Android app to collect sensor data and self-reports for analyzing SRL and AER behaviors. Figure 2 illustrates its four core functions: behavior state switching, questionnaire uploading, report history browsing, and sensor data visualization. Weekly survey notifications prompt students to report learning states, either via the notification or

Figure 2: Screenshots of iSense.

by launching the app. Upon first use, participants provide consent and receive a unique anonymized student ID, which serves as the control center for self-checks, permission management, real-time behavior recognition, activity switching, and notification settings.

The app collects multiple data streams—including GPS (with authorization), screen on/off, nearby WiFi (anonymized IDs), and 15-second samples from the microphone, light sensor, accelerometer, compass, and gyroscope. Application usage, call/SMS metadata (timestamps only), and social activity patterns are also recorded. To optimize battery life, data are logged locally every 5 minutes and transmitted daily via WiFi. Privacy is preserved through anonymization, optional GPS disabling, and exclusion of sensitive content. The cloud platform processes these data to generate personalized reports summarizing questionnaire responses, sensor logs, and compliance metrics (daily/weekly/monthly), as shown in Figure 2.

The study was approved by the university IRB (March 4, 2022). This integrated system enables comprehensive behavioral monitoring while maintaining rigorous privacy protections.

Data collection

We recruit 211 students for a year-long study (March 2022–March 2023) across multiple departments: Social Sciences (23.7%, N=50), Engineering (14.2%, N=30), Sports (26.5%, N=56), Information Science (21.3%, N=45), and Medicine (14.2%, N=30), providing a diverse sample. All participants installed the iSense app on their Android phones, which continuously collected data for one year. Participants received 50 RMB for completing surveys, with an additional incentive: those completing at least 85% of surveys were entered into a random draw for a 100 RMB reward.

Feature extraction

Data Preprocessing

The dataset underwent rigorous preprocessing to ensure quality. Incomplete submissions lacking sensor data or self-reports were removed, and sensor data without corresponding reports were excluded. Partial gaps (e.g., disabled GPS) were set to null values, which had minimal impact on model performance due to feature selection.

Following prior work (R. Wang et al., 2017), a 19-hour daily sensor threshold was applied, resulting in 113–287 days of valid data per participant (*mean* = 225.9 days). Most participants contributed over 150 days. Self-report data were similarly robust, with an average of 78.8 valid questionnaires per participant; 31% (N = 65) completed more than 100, some extending submissions two months beyond the study period. These high-compliance records formed the basis for model development.

Feature extraction

The iSense app continuously collects behavioral data to characterize students' daily routines and learning behaviors. Key features include:

Mobile phone data

1. **Physical activity.** Using the Android Activity Recognition API (≈95% accuracy (Google, 2019)), we track eight activity states, focusing on stationary and walking periods as indicators of study sessions. Users can also manually report their current activity to complement automated tracking, enabling finer-grained behavior analysis (Figure 2).
2. **Social interactions.** Call duration and call/SMS frequency are logged to capture students' social engagement, reflecting help-seeking and collaborative learning behaviors (Zhao et al., 2023).
3. **Sleep.** Sleep-wake cycles are inferred from light sensors, audio amplitude, and screen on/off events using a validated detection model (R. Wang et al., 2014), achieving ±32 minutes accuracy compared to ground truth (Alshammari et al., 2023).
4. **Location.** Primary campus locations are identified via GPS, with WiFi fingerprinting enhancing precision in GPS-limited areas. Semantic mapping allows interpretation of movement patterns relevant to learning behaviors (Clough, 2009).
5. **App usage.** Apps are categorized into 26 types based on Android Market classifications, preserving privacy while revealing meaningful patterns of educational and leisure device use (Lin et al., 2021).

These features are derived from system APIs and custom iSense components, ensuring both technical robustness and educational relevance.

Self-reported assessments To balance data richness with participant burden, surveys were administered at three time points: pre-study and two mid-study periods. The current analysis focuses on SRL skills and emotion regulation strategies assessed via validated instruments.

1. **Pre-study diversity questionnaire.** Collected baseline demographic (gender, age, grade) and psychosocial traits to contextualize subsequent behavioral patterns.

Table 1: Statistics analysis of SRL and AER questionnaire scales

Subscale	Response range	Overall Mean (std)	Within-person range*
Situation selection	1-5	3.85 (0.91)	3 (3-4)
Ability development	1-5	3.92 (0.89)	3 (3-4)
Attention redirection	1-5	3.78 (0.95)	2 (3-4)
Reappraisal	1-5	3.82 (0.88)	3 (3-4)
Suppression	1-5	3.58 (0.98)	2 (2-4)
Breathing	1-5	3.65 (1.02)	2 (2-4)
Venting	1-5	3.43 (1.12)	2 (2-4)
Social support	1-5	3.80 (0.90)	3 (2-4)
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).

2. **Mid-study questionnaires I & II.** The Academic Emotion Regulation Questionnaire (AERQ) (Chakraborty & Chechi, 2019) assesses academic emotion regulation through 37 items on a 5-point Likert scale across eight subscales (e.g., situation selection, reappraisal, social support), with higher scores indicating more effective strategies. SRL is measured via the Online Self-Regulated Learning Questionnaire (OSLQ) (Barnard et al., 2009), covering six components: Goal Setting, Environment Structuring, Task Strategies, Time Management, Help Seeking, and Self-Evaluation. Table 1 summarizes subscale statistics, including response ranges, means, standard deviations, and within-person variability, providing a comprehensive view of participants' self-regulation profiles.

Analysis and result

Methods overview

We first perform bivariate regression to examine relationships between SRL and AER scores and passively collected behavioral features (see Section Bivariate Regression Analysis). Next, gradient-boosted regression trees (GBRT) are used to predict overall SRL and AER scores (Prediction Analysis). Personalized models are then constructed to capture smoothed trajectories, reflecting long-term behavioral patterns.

Multi-source spatio-temporal data matching and feature space visualization

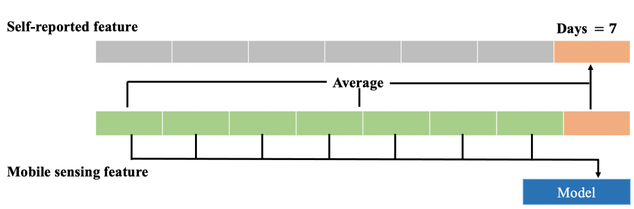

Figure 3: Time Window Aggregation Strategy.

Time window aggregation strategy We use a systematic weekly aggregation strategy to align sensor-derived features with self-reported psychological states. For questionnaires administered at 7-day intervals, sensor features are averaged over the preceding week to generate predictive inputs (Figure 3). For example, a self-report on Day 7 uses the mean of each feature from Days 1–7, Day 14 uses Days 8–14, and so on. Formally, this is expressed as:

$$\bar{x}_t = \frac{1}{W} \sum_{i=t-W}^{t} x_i \tag{1}$$

where x_i is the raw daily feature on day i, W is the time window size (7 days), and $\bar{x}_t$ is the aggregated feature for predicting the self-report at day t.

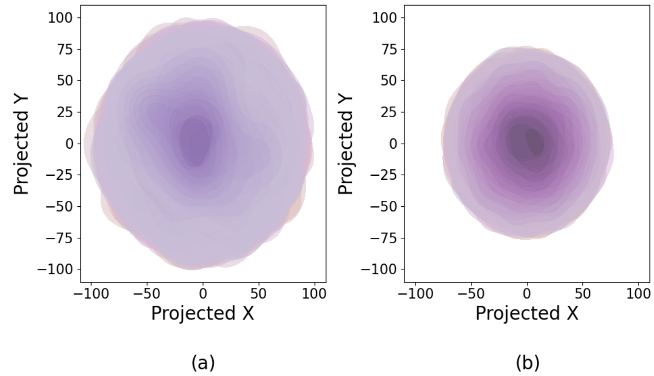

Figure 4: t-SNE visualization of behavioral features. (a) Data points color-coded by Student ID show distinct individual clusters. (b) Data points color-coded by SRL/AER sum scores form local clusters, though with more blending.

Feature space visualization To explore the structure of our high-dimensional behavioral features, we use t-distributed Stochastic Neighbor Embedding (t-SNE) (Hinton & Van Der Maaten, 2008) to project the data into a two-dimensional space while preserving local neighborhood relationships.

Figure 4(a) shows that behavioral features cluster primarily by student, indicating strong inter-individual differences. Figure 4(b), color-coded by SRL/AER scores, shows local grouping of similar scores but with lower purity, suggesting that overall behavior patterns are influenced by both SRL/AER levels and individual-specific factors. These observations highlight the importance of personalized modeling to improve predictive performance.

Bivariate regression analysis

Our longitudinal design involves repeated measurements per participant, which violate independence assumptions of standard methods like correlation or ordinary regression. To account for within-subject correlations when examining relationships between behavioral features and SRL/AER, we employ Generalized Estimating Equations (GEE), a robust marginal modeling approach that estimates regression parameters while handling correlated responses through specified working correlation structures.

The GEE framework models the marginal expectation of SRL/AER scores Y_{it} for participant i at time t as

$$E(Y_{it}) = \mu_{it}, \tag{2}$$

Table 2: Bivariate regression results.

Dimension	Associated Behavior
Self-Regulated Learning (SRL)	
Goal Setting	Higher duration in "studying" activity state (+) Longer time connected to top education-related SSIDs (+) Higher usage of education category apps (+) Higher screen-on ratio during late-night periods (-) Frequent visits to entertainment-related places (-)
Environment Structuring	Longer stay in study room or classroom locations (+) More consistent SSID connection to study-related APs (+) Regular device charging pattern (+) Lower variance in activity states (+) Irregular changes in screen usage (-)
Task Strategies	Scheduled and repeated use of education apps (+) Regular sleep onset and wake-up times (+) Longer periods of stationary or "studying" states (+) Frequent use of entertainment or social apps during study hours (-) High variance in screen-on duration (-)
Time Management	Stable sleep duration (+) Early morning walking or on-foot activity (+) App usage transitions aligned with class schedule (+) Frequent screen-on during sleep intervals (-) High variability in call or SMS times (-)
Help Seeking	Higher frequency of outgoing calls to Top 5 contacts (+) Frequent SMS with Top 5 contacts (+) Longer duration in library or social locations (+) Increased communication app usage (+) Fewer calls/SMS to known contacts (-)
Self-Evaluation	Consistent studying activity state during the day (+) Less night-time app usage (-)
Academic Emotion Regulation (AER)	
Situation Selection	Frequent visits to quiet study areas (e.g., library) (+) Less time spent at canteen or entertainment areas (+) Lower use of entertainment/social apps during academic hours (+) Higher noise/light levels in dorm during sleep (-)
Ability Development	Repeated use of education apps (+) Increased time in academic locations (+) Fewer screen-on events during sleep intervals (+) High entertainment app usage during productive hours (-)
Attention Redirection	Short screen-on bursts followed by "studying" activity (+) Less frequent interruptions by calls/SMS (+) Periodic on-foot activity between sessions (+) Frequent multi-app switching or usage of unrelated apps (-)
Reappraisal	Moderate music app use during breaks (+) Presence in parks or outdoors during stress periods (+) Stable sleep duration (+) Irregular light/noise patterns during sleep (-)
Suppression	Less social app use during high academic demand (+) Longer stationary time blocks (+) Low variance in screen usage at night (+) Frequent social app switching or late-night activity (-)
Breathing	*Not measurable from current sensor features*
Venting	Increased SMS or call frequency during stressful times (-) Unusual increases in noise or movement at night (-) Rapid transitions between locations and app categories (-)
Social Support	Frequent use of communication apps (+) High frequency of calls with Top 5 contacts (+) More time spent in group or social locations (+) Longer durations in dorm alone (-)

linked to the feature vector X_{it} via

$$g(\mu_{it}) = \beta_0 + X_{it}\beta, \tag{3}$$

where g is the link function. Based on distributional tests, we use a Poisson distribution with log link. Coefficients β quantify the direction and magnitude of each feature's association, with β_0 as the intercept; significance is assessed via p-values testing $\beta = 0$.

We examine all 1,526 associations between 109 behavioral features and 14 SRL/AER dimensions, applying the Benjamini-Hochberg procedure to control the False Discovery Rate at 5% (Benjamini & Yekutieli, 2001). Table 2 shows the positive coefficients indicate features associated with better SRL/AER outcomes, while negative coefficients indicate detrimental associations.

SRL dimension: Subcomponents exhibited distinct behavioral signatures. Goal Setting and Environment Structuring corresponded with consistent learning spaces (frequent classroom/library visits, stable academic WiFi connections, regular device charging). Task Strategies and Time Management were reflected in aligned temporal rhythms, including scheduled educational app use, regular sleep-wake patterns, and app-switching matching class timetables. Help Seeking manifested via frequent communication with core contacts and active use of learning/social spaces, while Self-Evaluation was associated with sustained daytime study and limited nighttime app activity.

AER dimension: Situation Selection involved preference for quiet environments and minimal use of entertainment locations/apps. Attention Redirection and Ability Development appeared in short, focused study sessions, repeated educational app usage, and limited nighttime screen activity. Strong Reappraisal and Suppression corresponded to stress-relieving activities (outdoor time, music) and lower variability in nighttime digital behavior. Social Support was reflected by stable interactions with close contacts and moderate social space use, whereas Venting involved increased communication, higher nighttime ambient noise, and frequent location changes under stress. Breathing could not be measured due to sensor limitations.

Additionally, risk-related behaviors—excessive nighttime screen use, frequent entertainment app switching during study, and irregular communications—were linked to lower SRL and may signal suboptimal learning states. Moderate social interactions supported AER, but excessive social app use during study hours impaired focus and learning efficiency.

Prediction analysis

We evaluate two supervised learning approaches for predicting aggregated SRL and AER scores. The first examines the amount of personal data needed for accurate predictions by training models with varying proportions of target-individual data combined with population data, then testing on that individual. The second focuses on fully personalized models, comparing performance on smoothed versus raw scores and assessing how temporal distance between training and testing affects prediction accuracy.

Personalized SRL/AER predictions We implement Gradient-Boosted Regression Trees (GBRT) for SRL/AER score prediction, using the additive ensemble $F(x) = \sum_{m=1}^{M} \gamma_m h_m(x)$, where each base learner $h_m(x)$ is sequentially optimized to minimize the Huber loss. This approach suits the observed heterogeneity in behavioral patterns and motivates a three-tiered personalization framework.

Table 3: Performance comparison of the three-tier personalization framework (MAE as percentage of score range). "Pos" refers to positive correlation, where behaviors are linked to better outcomes, while "Neg" indicates a negative correlation, with behaviors associated with poorer outcomes. "Total" combines performance across both positive and negative behaviors.

	Model	**SRL-Pos**		**SRL-Neg**		**SRL-Total**		**AER-Pos**		**AER-Neg**		**AER-Total**	
		MAE%	r	MAE%	r	MAE%	r	MAE%	r	MAE%	r	MAE%	r
Demographic Baselines	Ridge Regression	18.9	0.20	19.6	0.19	33.6	0.29	19.5	0.19	21.4	0.17	38.9	0.30
	Gradient Boosting	16.9	0.21	19.6	0.20	33.5	0.30	19.5	0.20	21.4	0.18	38.9	0.32
	Multi-Layer Perceptron	18.8	0.20	20.9	0.19	35.9	0.29	20.3	0.19	22.1	0.17	39.4	0.31
Sensor Baselines	LOSO	15.5	0.33	18.3	0.30	30.8	0.43	18.2	0.31	19.9	0.29	36.8	0.40
Hybrid	20% Personal	10.3	0.61	11.9	0.62	22.2	0.65	12.3	0.58	13.4	0.54	26.4	0.61
	40% Personal	8.9	0.68	10.4	0.68	19.2	0.72	10.7	0.65	11.6	0.61	22.3	0.68
	60% Personal	7.2	0.75	8.6	0.73	15.8	0.76	8.8	0.71	9.7	0.68	18.6	0.75
	80% Personal	**6.1**	0.81	**7.1**	0.78	**13.2**	0.81	**7.3**	0.77	**8.0**	0.74	**15.4**	0.79
Individual	Full Personal	5.7	0.84	6.5	0.83	11.7	0.84	6.7	0.80	7.3	0.79	13.5	0.83

We first establish demographic-only baselines: (1) Ridge Regression with basic demographics, (2) Gradient Boosting with demographics plus weekly behavioral summaries, and (3) Multi-Layer Perceptron with demographics and coarse behavioral embeddings. These serve as reference points for assessing the contribution of multimodal sensor data.

Our sensor-enhanced framework begins with a Leave-One-Student-Out (LOSO) population model, trained on all other students' data, simulating new student deployment. We then build hybrid models by progressively adding 20%, 40%, 60%, and 80% of individual data, evaluating the incremental value of personalization. Full-personalization models establish upper bounds on achievable accuracy.

Evaluation uses a 10-fold block cross-validation with $h = 6$ block temporal separation ($\approx$ two weeks), preserving temporal structure and ensuring independence between training and test blocks. Individual models train on one block ($n \approx 1$) and test on remaining blocks, with 5–13 test observations per student (median = 9). Hybrid models follow the same protocol, incorporating complete group data plus varying individual data in forward-chaining folds, e.g., 20% personal data trains on blocks 1–2 plus group data and tests on blocks 3–10, iteratively shifting the training window while maintaining temporal separation.

Prediction performances Table 3 shows the Mean Absolute Error (MAE) and Pearson correlation coefficient r for all models used to predict the positive, negative, and total SRL/AER scores. For the best-performing hybrid model on positive scores, the prediction performance achieved an MAE of 6.1%, with a strong correlation to the ground truth values ($r = 0.81$). In contrast, the leave-one-student-out (LOSO) model exhibited poorer prediction performance with an MAE of 15.5%, although the predicted scores were still significantly correlated with the true values ($r = 0.33$).

As the training set incorporates more data from the target student, the model's prediction performance improves. When 20% of a student's data is combined with the population-level data for training, the hybrid model achieves an MAE of 10.3%, showing a substantial improvement over the LOSO model. The correlation between predictions and actual scores at this stage is $r = 0.61$. With additional student-specific data incorporated into training, the MAE further decreases and the predictive correlation improves. When 80% of the student data is used, the model attains an MAE of 6.1%, indicating a significant performance gain.

For negative and total scores, similar trends are observed (Table 3). The LOSO model performs poorly, but the hybrid model with 20% student data achieves MAEs of 11.9% (SRL-Neg) and 7.3% (AER-Pos) with $r = 0.62$ and $r = 0.77$, respectively. Performance improves as more individual data is added, with the fully personalized model reaching an MAE of 6.5% ($r = 0.83$) for negative scores.

The total SRL/AER score spans a broader range; the individual model achieves an MAE of 5.7%, slightly better than positive (6.1%) and negative (6.5%) scores, indicating it better captures overall SRL/AER state. These results highlight the importance of personalized modeling: even a small portion of student-specific data (e.g., 20%) combined with population data yields reliable, significantly correlated predictions. Prediction accuracy further improves as more individual data becomes available.

Conclusion and future work

This study presents *iSense*, a smartphone-based system for passive monitoring of SRL and AER in university students. Over a year, the system collected behavioral data—social interactions, sleep, app usage, and mobility—alongside self-reported SRL and AER scores. iSense demonstrates that sensor data can effectively predict SRL and AER states with MAEs of 7.9% and 9.3%, respectively. Findings highlight significant associations between digital behaviors and psychological states, the value of minimal personalized data combined with population patterns.

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References

Adynski, H., Propper, C., Beeber, L., Gilmore, J. H., Zou, B., & Santos Jr, H. P. (2024). The role of emotional regulation on early child school adjustment outcomes. *Archives of Psychiatric Nursing*, *51*, 201–211.

Alshammari, T. K., Rogowska, A. M., Basharahil, R. F., Alomar, S. F., Alseraye, S. S., Al Juffali, L. A., Alrasheed, N. M., & Alshammari, M. A. (2023). Examining bedtime procrastination, study engagement, and studyholism in undergraduate students, and their association with insomnia. *Frontiers in Psychology*, *13*, 1111038.

Assi, A., & Cohen, A. (2023). Video-based srl program for teachers and students. *Proceedings of the 15th International Conference on Education Technology and Computers*, 175–182.

Barnard, L., Lan, W. Y., To, Y. M., Paton, V. O., & Lai, S.-L. (2009). Measuring self-regulation in online and blended learning environments. *The internet and higher education*, *12*(1), 1–6.

Benjamini, Y., & Yekutieli, D. (2001). The control of the false discovery rate in multiple testing under dependency. *Annals of statistics*, 1165–1188.

Camacho-Morles, J., Slemp, G. R., Pekrun, R., Loderer, K., Hou, H., & Oades, L. G. (2021). Activity achievement emotions and academic performance: A meta-analysis. *Educational Psychology Review*, *33*(3), 1051–1095.

Chakraborty, R., & Chechi, V. K. (2019). Validation of revised academic emotion regulation questionnaire (aerq) in the indian context. *International Journal of Scientific & Technology Research*, *8*(12), 1203–1209.

Clough, G. (2009). Geolearners: Location-based informal learning with mobile and social technologies. *IEEE Transactions on learning technologies*, *3*(1), 33–44.

Derakhshan, A., Wang, Y., Wang, Y., Ortega Martín, J. L., et al. (2023). Towards innovative research approaches to investigating the role of emotional variables in promoting language teachers' and learners' mental health.

Fu, Y., Wang, Q., Wang, X., Zhong, H., Chen, J., Fei, H., Yao, Y., Xiao, Y., Li, W., & Li, N. (2025). Unlocking academic success: The impact of time management on college students' study engagement. *BMC psychology*, *13*(1), 323.

Google. (2019). *Google activity recognition api* [Accessed: 2024-12-03]. https://developers.google.com/android/reference/com/google/android/gms/location/ActivityRecognitionClient

Hinton, G., & Van Der Maaten, L. (2008). Visualizing data using t-sne journal of machine learning research. *Journal of Machine Learning Research*, *9*(2579-2605), 4.

Kammoun, N., Meegahapola, L., & Gatica-Perez, D. (2023). Understanding the social context of eating with multimodal smartphone sensing: The role of country diversity. *Proceedings of the 25th International Conference on Multimodal Interaction*, 604–612.

Lee, D. J., Weathers, F. W., Sloan, D. M., Davis, M. T., & Domino, J. L. (2017). Development and initial psychometric evaluation of the semi-structured emotion regulation interview. *Journal of personality assessment*, *99*(1), 56–66.

Liao, H., Zhang, Q., Yang, L., & Fei, Y. (2023). Investigating relationships among regulated learning, teaching presence and student engagement in blended learning: An experience sampling analysis. *Education and Information Technologies*, *28*(10), 12997–13025.

Liebendörfer, M., Kempen, L., & Schukajlow, S. (2023). First-year university students' self-regulated learning during the covid-19 pandemic: A qualitative longitudinal study. *ZDM–Mathematics Education*, *55*(1), 119–131.

Lin, Y., Liu, Y., Fan, W., Tuunainen, V. K., & Deng, S. (2021). Revisiting the relationship between smartphone use and academic performance: A large-scale study. *Computers in Human Behavior*, *122*, 106835.

Lourenço, A. A., & Paiva, M. O. (2024). Academic performance of excellence: The impact of self-regulated learning and academic time management planning. *Knowledge*, *4*(2), 289–301.

Ma, L., & She, L. (2024). Self-regulated learning and academic success in online college learning. *The Asia-Pacific Education Researcher*, *33*(3), 519–533.

Mäder, A. R., Meegahapola, L., & Gatica-Perez, D. (2024). Learning about social context from smartphone data: Generalization across countries and daily life moments. *Proceedings of the CHI Conference on Human Factors in Computing Systems*, 1–18.

Meegahapola, L., Ruiz-Correa, S., & Gatica-Perez, D. (2020). Alone or with others? understanding eating episodes of college students with mobile sensing. *Proceedings of the 19th International Conference on Mobile and Ubiquitous Multimedia*, 162–166.

Nepal, S., Liu, W., Pillai, A., Wang, W., Vojdanovski, V., Huckins, J. F., Rogers, C., Meyer, M. L., & Campbell, A. T. (2024). Capturing the college experience: A four-year mobile sensing study of mental health, resilience and behavior of college students during the pandemic. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, *8*(1), 1–37.

Nepal, S., Wang, W., Vojdanovski, V., Huckins, J. F., Dasilva, A., Meyer, M., & Campbell, A. (2022). Covid student study: A year in the life of college students during the covid-19 pandemic through the lens of mobile phone sensing. *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems*, 1–19.

Parsons, S., Kruijt, A.-W., & Fox, E. (2019). Psychological science needs a standard practice of reporting the reliability of cognitive-behavioral measurements. *Advances in Methods and Practices in Psychological Science*, *2*(4), 378–395.

Pedrini, L., Meloni, S., Lanfredi, M., & Rossi, R. (2022). School-based interventions to improve emotional regulation skills in adolescent students: A systematic review. *Journal of Adolescence*, *94*(8), 1051–1067.

Raković, M., Li, Y., Foumani, N. M., Salehi, M., Kuhlmann, L., Mackellar, G., Martinez-Maldonado, R., Haffari, G., Swiecki, Z., Li, X., et al. (2024). Measuring affective and motivational states as conditions for cognitive and metacognitive processing in self-regulated learning. *Proceedings of the 14th Learning Analytics and Knowledge Conference*, 701–712.

Restrepo, J. E., Cardona, E. Y. B., Montoya, G. P. C., Bardales, M. d. l. M. C., Alemán, Y. P. V., et al. (2023). Academic stress and adaptation to university life: Mediation of cognitive-emotional regulation and social support. *Anales de Psicología/Annals of Psychology*, *39*(1), 62–71.

Roth, A., Ogrin, S., & Schmitz, B. (2016). Assessing self-regulated learning in higher education: A systematic literature review of self-report instruments. *Educational assessment, evaluation and accountability*, *28*, 225–250.

Rovers, S. F., Clarebout, G., Savelberg, H. H., De Bruin, A. B., & van Merriënboer, J. J. (2019). Granularity matters: Comparing different ways of measuring self-regulated learning. *Metacognition and Learning*, *14*, 1–19.

Saks, K. (2024). The effect of self-efficacy and self-set grade goals on academic outcomes. *Frontiers in psychology*, *15*, 1324007.

Sverdlik, A., Rahimi, S., & Vallerand, R. J. (2022). Examining the role of passion in university students' academic emotions, self-regulated learning and well-being. *Journal of Adult and Continuing Education*, *28*(2), 426–448.

Taub, M., & Azevedo, R. (2019). How does prior knowledge influence eye fixations and sequences of cognitive and metacognitive srl processes during learning with an intelligent tutoring system? *International Journal of Artificial Intelligence in Education*, *29*, 1–28.

Wang, R., Chen, F., Chen, Z., Li, T., Harari, G., Tignor, S., Zhou, X., Ben-Zeev, D., & Campbell, A. T. (2014). Studentlife: Assessing mental health, academic performance and behavioral trends of college students using smartphones. *Proceedings of the 2014 ACM international joint conference on pervasive and ubiquitous computing*, 3–14.

Wang, R., Wang, W., Aung, M. S., Ben-Zeev, D., Brian, R., Campbell, A. T., Choudhury, T., Hauser, M., Kane, J., Scherer, E. A., et al. (2017). Predicting symptom trajectories of schizophrenia using mobile sensing. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, *1*(3), 1–24.

Wang, W., Nepal, S., Huckins, J. F., Hernandez, L., Vojdanovski, V., Mack, D., Plomp, J., Pillai, A., Obuchi, M., Dasilva, A., et al. (2022). First-gen lens: Assessing mental health of first-generation students across their first year at college using mobile sensing. *Proceedings of the ACM on interactive, mobile, wearable and ubiquitous technologies*, *6*(2), 1–32.

Xu, Z., Zhao, Y., Liew, J., Zhou, X., & Kogut, A. (2023). Synthesizing research evidence on self-regulated learning and academic achievement in online and blended learning environments: A scoping review. *Educational Research Review*, *39*, 100510.

Zhao, T., Gao, J., Feng, Y., Zu, Y., Tavares, A., Gomes, T., Pinto, S., & Xu, H. (2025). Passive behavioral sensing: Using within-person variability features from mobile sensing to assess self-regulated learning. *Proceedings of the Annual Meeting of the Cognitive Science Society*, *47*.

Zhao, T., Gao, J., Feng, Y., Zu, Y., Tavares, A., Gomes, T., & Xu, H. (2023). Behavioral sensing: An exploratory study to assess self-regulated learning and resource management strategy of university students using mobile sensing. *Proceedings of the Annual Meeting of the Cognitive Science Society*, *46*.

Zheng, J., Huang, L., Li, S., Lajoie, S. P., Chen, Y., & Hmelo-Silver, C. E. (2021). Self-regulation and emotion matter: A case study of instructor interactions with a learning analytics dashboard. *Computers & Education*, *161*, 104061.

Zheng, J., Lajoie, S., & Li, S. (2023). Emotions in self-regulated learning: A critical literature review and meta-analysis. *Frontiers in psychology*, *14*, 1137010.