Social Behavioral Sensing: An Exploratory Study to Assess Learning Motivation and Perceived Relatedness of University Students using Mobile Sensing

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Abstract

Learning motivation plays a crucial role in student's daily study life since it greatly affects academic performance and engagement. Perceived relatedness, based on self-determined theory, is an important predictor of learning motivation. Today, assessment for both of them still relies on subjective evaluations and self-reports, which is time-consuming and onerous. Hence, we propose a novel approach blended with mobile sensing by simultaneously collecting psychological measurements and objective mobile sensing data from N=58 undergraduates to explore new methods of assessing learning motivation and perceived relatedness. We identify a variety of social behavioral patterns from mobile sensing data, and investigate associations between psychological measures and these patterns. Our study helps enlighten what the new forms of assessing learning motivation and perceived relatedness in education could be, and paves the way for personalizing intervention in future research.

Keywords: Learning Motivation, Perceived Relatedness, Mobile Sensing, Social Sensing, Education

Introduction

Motivation in the learning process has been widely researched in pedagogy and psychology since it could power students with academic activities (Furió et al., 2015; Di Serio, Ibáñez, & Kloos, 2013; Dermitzaki et al., 2013) and has a profound impact on their academic engagement and performance. Based on self-determination theory (SDT), learning motivation could be described as intrinsic or extrinsic forces that lead students to take action in order to fulfill or achieve the learning goal or expectation. In this case, learning motivation is categorized as intrinsic motivation, extrinsic motivation and amotivation (Mitchell et al., 2012; Ryan & Deci, 2000). Among them, the intrinsic motivation depicts one's natural tendency and inherent features in the learning process, it drives an individual to take part in academic activities for experiencing pleasure, challenging and uniqueness rather than expecting extrinsic rewards or under certain pressure (Deci & Ryan,2016; Legault, 2020). Besides, the motivation categorized as extrinsic at the initial stage could be transformed into intrinsic as the learning process proceeds (Tohidi & Jabbari, 2012). Relatedness, one of the three basic psychological needs which are also identified by Deci & Ryan in SDT, describes the will to be with or connected to others (Mellin, 2008). It is an important predictor of learning motivation since satisfying such need could encourage one's intrinsic motivation (Ryan & Deci, 2000). And perceived relatedness is used to measure the relatedness satisfaction. Given the importance of learning motivation and perceived relatedness as the key indicators in the learning process in education, there are a number of studies focusing on assessing them and designing the interventions for them. However, most of the methods currently adopted to assess learning motivation and perceived relatedness primarily rely on self-reports (e.g., questionnaires or survey responses), face-to-face evaluation (e.g., interviews) or observations scoring by experts or trained observers. Through informative, the process of these approaches is often laborious, time-consuming and costly, which could also be restricted spatially and timely. Hence, new approaches for continuously and passively assessing learning motivation and perceived relatedness in the daily life context are needed.

In this paper, inspired by the above need and current emerging studies, we seek to investigate and develop a new approach for assessing the learning motivation and perceived relatedness in a daily context. The study is driven by the following exploratory research question: What social behavioral patterns are associated with learning motivation and perceived relatedness in student's daily life? With this question, we aim to investigate and identify the social behavioral patterns of students from mobile sensing data collected from their smartphones, meanwhile collect the learning motivation and perceived relatedness measures through self-report responses, then investigate the associations between the social behavioral pattern and targeted psychological variables to identify the particular patterns that are highly associated.

To answer the above question, we collected a dataset of learning motivation & perceived relatedness measures and mobile sensing data from undergraduate students who attending a selective university in China. We developed a mobile application iSense app to collect real-time data from students. Then we used the mobile sensed data from smartphones of N=58 undergraduate students for three months (one academic semester in their university) to identify the social behavioral patterns. In addition, we used sub-scales of academic self-regulation questionnaire (SRQ-A) and Basic Psychological Need Satisfaction Scale (BPNSFS) (Chen et al., 2015) to measure the learning motivation and perceived relatedness correspondingly by delivering the questionnaires to the students weekly within the three months alongside the mobile sensing. Finally, we conducted the association analysis on the identified social behavioral patterns and targeted psychological measures to select highly associated behavioral patterns, also compare the behavioral changes in terms of identified behavioral patterns among students with different levels of targeted psychological measures. Please be aware that the data we collect are from a group of undergraduate students with a specific demographic from a selected university in China, hence we would suggest our readers to be cautious while interpreting our results, we are not certain how well these results could be generalized across populations in different territories. In this paper, we focus on understanding the daily social behavioral patterns from the mobile sensing data and assessing the learning motivation & perceived relatedness of students to explore the relationship between them. The contributions of our work are as follows:

- To the best of our knowledge, we present the first mobile sensing study that investigates relationships of the objective social behavioral patterns with learning motivation and perceived relatedness. We consider the N=58 undergraduate students and collect the data of their learning motivation & perceived relatedness measures and real-time mobile sensing data for three consecutive months from March 2022 to June 2022 in China to investigate relationships of the targeted psychological measures and social mobile behavioral patterns.
- Identify a number of social behavioral patterns (5 patterns) that are associated with learning motivation and perceived relatedness levels, provide fundamental conditions for predicting learning motivation and perceived relatedness using mobile sensing
- We propose a new approach for assessing learning motivation and perceived relatedness combined with mobile sensing. The identified social behavioral patterns which are selected to be highly associated with the targeted psychological measures provide the fundamental conditions to build models for predicting learning motivation and perceived relatedness. It is also an instrumental step for designing timely interventions in student's daily life to enhance learning motivation. Additionally, it provides the possibility to generalize our approach for other psychological variable assessment.

All the students who participated in the study are clear of the risks associated with collecting sensitive and private data during mobile sensing. Concerned with the ethics and privacy in this study, in order to prevent causing serious privacy issues, we have made sure before the study started that all the participants knowingly consent to give up few of privacy during the study. The relevant risks were explicitly stated in the consent forms and discussed in detail while recruiting participants. Moreover, we have taken our best effort to protect the participants' privacy. The data we collected by the mobile app was unidentifiable. The data we sensed is stored in our private server which is non-public.

The paper is organized as follows. We start by discussing the related work on current methods for assessment of learning motivation and perceived relatedness and the use of mobile sensing for psychological measures in relevant areas in Section 2. Then, we describe our methodology in Section 3 by detailing our study design, describing the dataset of the mobile sensing and the assessment of learning motivation & perceived relatedness, explaining the behavioral features and association analysis. Following this, we report the results by answering the research question in Section 4. Next, we discuss our findings and implications in Section 5. Then, limitations of our work are elaborated in Section 6. Finally, the concluding remarks are presented in Section 7.

Related Work

Studies in the field of educational psychology and pedagogy have investigated the assessment methods for learning motivation and perceived relatedness (William, 2011), however, most of the current research still rely on the conventional methods like self-report surveys, face- to-face interviews or manual observations by experts, which are laborious and time-consuming. Besides, research shows that students' various characteristics and traits will influence their perceived relatedness differently (Reyes et al., 2012), which also highlights the limits of using single modal data for assessment by applying the traditional methods. Revealing, a number of HCI studies have made attempts to measure the psychological variables in the learning process with multiple sensors or learning analytic tools (Holstein, McLaren, & Aleven, 2019; Wang et al., 2014; Mavrikis, Gutierrez-Santos, & Poulovassilis, 2016; Tissenbaum et al., 2016; VanLehn et al., 2021). Detecting student's emotional states in class by monitoring their behavioral engagement with cameras and their operations on computers (Aslan et al., 2019); Recognizing student's facial expressions with wearable devices to determine their emotion and psychological states in learning (Berque & Newman, 2015; Holstein, McLaren, & Aleven, 2018; Zarraonandia et al., 2013); Or sensing student's attention during class using camera recording mixed with VR recreation (Ahuja et al., 2021). However, some sensors like cameras or wearable devices (e.g., smart glasses) need to be previously set up and some sensors are even cumbersome to equip, or causing the privacy concerns while deploying.

In recent years, mobile sensing or passive sensing are widely studied for measuring the psychosocial variables or states, specifically in the medical and mental health areas (Canzian & Musolesi, 2015; Aung et al., 2016; Wang et al., 2014; Saeb et al., 2015). Researchers investigated and inferred the food consumption level of students via mobile sensing for their daily health concerns (Meegahapola et al., 2021); Investigating the relationships of mobile social media usage via mobile sensing and student's academic performance (Giunchiglia et al., 2018); Or analyzing the associations of student's mental states (depression, stress, loneliness and flouring) with passive sensing behaviors. Particularly after the COVID-19 pandemic continuously affects the daily life of students for the last few years, researchers used mobile app to passively sense students' mental well-being and their behavioral changes under such special condition (Nepal et al., 2022). Plenty of studies in mental health and medical field have proven the feasibility of mobile sensing for assessing various psychological variables from the behavioral perspective. However, a limited amount of HCI studies migrate such methods in the learning context.

Methodology

In what follows, we discuss the design of our study, demographic information of the participated students, the dataset of the mobile sensing data and the assessment for learning motivation & perceived relatedness, behavioral features and association analysis.

Study Design

In this paper, we collected and analyzed data from a continuing mobile sensing study which is following N = 58 university undergraduates from one university in China using smartphone sensing and self-report surveys via questionnaires, the whole study lasts for three months (12 weeks for data collection) from March 2022 to June 2022 (beginning of second week in March to the end of first week in June). Students were recruited and consented at the beginning of their spring academic semester (initially N = 65 on March 6, 2022), one week before the data collection. After recruitment, in the pretesting phase (the first week in March 2022), we gave the participants a detailed tutorial on installing the mobile sensing app (iSense App) on their mobile phones and asked them to keep the app installed and running until the end of our study (on June 5, 2022); the end date is also the end of their spring academic semester in 2022, this includes the semester time and few short breaks from the university; we started collecting and analyzing the data since March 13, 2022; During the process of the study , we checked the daily collection of the sensed data and would inform the noncompliant participants (e.g., there were few participants who accidentally shut down the app in this process) to recheck the app status and get the back in the study. Our study is approved by the selected University's Institutional Review Board (on March 4, 2022). We conducted the self-report survey by delivering the questionnaires (sub scales of SRQ-A and BPNSFS) once every week to the participants, and the participants were compensated 20 RMB per week for completing the surveys, the questionnaires were sent to their smartphones via the mobile sensing app. The goal of our study is to understand and investigate the relationships of the students' social behavioral patterns associated with learning motivation and perceived relatedness. We use the mobiles sensing on smartphones to capture behavioral features, along with the combination of conducting self-report surveys to measure the targeted psychological variables, in order to get a holistic view of participants' behaviors for analysis.

Demographics

We initially recruited 65 participants, in the end the study, 58 participants who were complying with the study and weekly assessment of learning motivation and perceived relatedness are involved for the analysis. 2 participants withdrew from the study in the second week and 5 other participants are eliminated due to a large amount of missing data in mobile sensing. Table 1 shows the demographics of the 58 students used in the analysis. All the participants are Chinese undergraduate students who are at their second year of attending the university. The majority (67.24%, N=39) of our participants are male. Interns of their majors, 87.93% (N=51) are majored in Sports Training, 5.17% (N= 3) are majored in Rhythmic gymnastics, 3.45% (N=2) are majored in Tennis and 3.45% (N=2) are majored in Swimming. We mainly made our recruitment in the school of Physical Education; hence the participants' majors are basically physical education relevant.

Table 1: Demographics of the participants in the study. The table below shows the demographic information of the students in our study

Category	Count	Percentage
Sex		
Female	19	32.67%
Male	39	67.24%
Major		
Sports Training	51	87.93%
Gymnastics	3	5.17%
Tennis	2	3.45%
Swimming	2	3.45%

Mobile Sensing Data

The iSense App is designed and developed for the mobile sensing data collection from multiple sensors on smartphones simultaneously. The app captures the phones activities including the number of calls (in/out calls), application usage (only the name of the application which is running on the device without any exact content) and number of text messages. The app captures the phones activities every 10 mins and stores locally on the device if offline, the stored data will be uploaded to our private server once the device get connected to WIFI. We compute the behavioral features from the sensed data on a daily basis (e.g., duration of a certain application using time in a day) to capture and record participants' behaviors.

Learning Motivation and Perceived Relatedness Assessment

A The learning motivation is measured using the sub-scale of Academic Self-Regulation Questionnaire (SRQ-A) survey, validation of the scale is presented in Ryan and Connell (1989). The SRQ-A consists of 4 sub-scales including external regulation, introjected regulation, identified regulation and intrinsic motivation, and each individual sub scale score could be used in research analysis, in this study, we use the scores of intrinsic motivation to measure the learning motivation. For the perceived relatedness, we use the sub-scale of the Basic Psychological Need Satisfaction and Frustration (BPNSFS) scale (Chen et al., 2015), it consists of six sub-scales including autonomy satisfaction, relatedness satisfaction, competence satisfaction and autonomy frustration, relatedness frustration, competence frustration. Evidence of reliability and validity has been provided by previous research for the scale (Liga et al., 2020). We use the scores of sub-scale relatedness satisfaction to measure the perceived relatedness in this study. Table 2 shows the range of the scored responses from the participants on measuring their learning motivation and perceived relatedness.

Table 2: Statistics of Sub-Scales for Learning Motivation and Perceived Relatedness

Sub-Scale	Response range	Overall mean(std)
Learning motivation (Intrinsic Motivation)	1-5	3.00(1.48)
Perceived relatedness (Relatedness Satisfaction)	1-5	2.00(1.81)

Behavioral Features

In this study we intend to explore the daily behavioral patterns of the students in the learning process with a primary focus on interactive behaviors, we incorporate features that represent and describe from their smartphone mobile sensing data, more specifically, mostly the mobile usage data. We label and compute 27 features from the sensed data encompassing detailed usage data (e.g., the name of the app currently running on the device, the duration of using the certain app, etc.) of 450 different applications. Then we categorize these features into three categories based on the social interactive type of the application, the categories including non-social, indirect social and direct-social are listed in Table 3. We decide the categories according to the degree of the social interactivity while using that particular app. Direct-Social category includes the features reflecting that the participants have direct interactions with other individuals, like the use of instant messenger apps to chat. Similarly, Indirect-Social encompasses the features which indicate that the participants have interactions with other individual or groups indirectly, not restricted by getting instant feedbacks, such as web browsing or news reading. In turn, Non-Social category describes the features of having no interactions with external people or surroundings directly or indirectly, for instance, taking a selfie independently using the camera of the smartphone(camera). Few new features we consider in our work have not been thoroughly studied before, more specifically, we classify the behaviors that are relevant to social interactions into explicit features. For example, social_study includes the usage of social medias or applications that are study oriented (apps for MOOC or to find tandems for language learning, etc.); social_business describes the usage of the applications which involves the trading among different people (apps for second-hand trading ,etc.); social_date are the applications used for dating (Tinder, etc.); social_blog includes the usage of the integrated social media platforms (Weibo, a social media app similar to Twitter in China, etc.) and social_bbs are the usage of various forums (Douban, etc.).

Table 3: Features extracted and computed from the mobile sensing data

Category	Details
Non-Social	camera, health, game_single, navigation, system, weather, tool_other, tool_study, finance, others
Indirect-Social	info_entertainment, web_browsering, shopping, music, video, social_bbs, radio/podcast, livestream, info_study
Direct-Social	social_business, IM (instant messenger), call, SMS, social_study, game_multiple, social_blog, social_date

Learning Motivation and Perceived Relatedness Assessment

Aiming to find out how the mobile sensed data is associated with learning motivation and perceived relatedness, we apply the principal component analysis (PCA) (Schölkopf, Smola, & Müller, 2005) to extract and interpret the behavioral patterns of participants and use generalized estimation equations (GEE) (Hardin & Hilbe, 2002; Liang & Zeger, 1986) to explore the associations between the extracted behavioral patterns (repressed by the principal components of behavioral features computed from sensed data) and the SRQ-A & BPNSFS sub-scales' scores. We consider the sensed data within 12 weeks prior to SRQ-A&BPNSFS responses. In the following, we will elaborate our method of association analysis comprehensively.

For principal component analysis, we calculate the mean for each feature on a daily basis per participant (mean of daily usage duration of a specific app in a 7-day time frame), then we organize the features in a matrix X, a column in X represents one of 27 features, and a row in X represents the features that are associated with one of the 696 SRQ-A&BPNSFS responses. Next, we use PCA on X to find and select a group of principal components (PCs) which explain most of the variance in X. After that, we use PC scores instead of behavioral features in our following analysis. We first select a group of PCs which reduce the dimensionality of features significantly. Secondly, we interpret each PC as a behavioral pattern for analysis. For example, if a PC has large positive weight in the component for features of game_multi and livestream, then we would interpret this PC as the behavioral pattern of playing online games frequently and often watch game stream. Figure 1 shows the cumulative variability in the features explained by the top-n PCs. Finally, 11 PCs in X (explaining 90% of the variance) are selected for analysis.

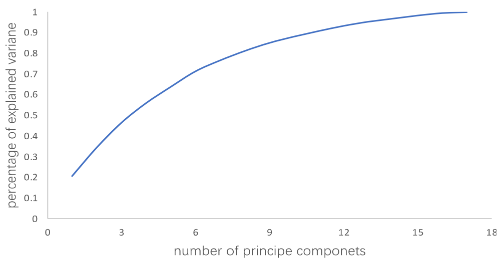

Figure 1: The cumulative variability in the sensed data explained by the top-n principal components.

For the association analysis, we adopt Bivariate GEE to investigate how the selected 11 PCs are related to SRQ-A&BPNSFS scores by regressing the PC scores to them. The SRQ-A&BPNSFS data is longitudinal since we collected multiple responses from one participant at different time within 12 weeks during our study. And the responses from the same subject are dependent. Then we combined data of the 11 PCs and 2 sub-scales' scores and applied GEE to this combination. Lastly, we conduct the two-stage Benjamini-Hochberg procedure (TSBH) (Benjamini, Krieger, & Yekutieli, 2006) to get the false discovery rate (FDR).

Results

We interpret the selected 11 PCs into the behavioral patterns listed in Table 4. Considering the large positive or negative weights of the features in PCs, we make rational inferences and interpretations to extract and summarize the corresponding behavioral patterns. Among them, pattern 8 describes the people who use smartphones to get information for entrainment, such as reading comics and sports news, we interpret the details based on the apps used in the info_entertainment feature, since the majority of the apps in this feature group are apps for online comics or sports news related apps. In terms of learning behaviors, pattern 2 suggests that students who like to study with others together meanwhile using study tools (e.g., dictionary in particular domain of expertise, etc.) in their learning process; pattern 4 suggest students who like to study whilst listening to music.

Table 4: Behavioral patterns and their matching features indexed by n-th component of PCA

Pattern	Features
1.Use social apps to date and like listening to podcast/radio	social_date, system, radio/podcast, tool_others
2.Use study tool apps frequently, and use more social study apps to learn meanwhile like browsing bbs	tool_study, social_study, social_bbs
3.Use smartphones to play online games with others and like watching livestream/videos (games related)	video, game_multi, livestream
4. Like to listen music on smartphones and read/search learning related resources	music, info_study
5.Use smartphones to chat with others a lot	IM
6.Use social networking platforms frequently, like to post or tweet	social_blog, camera
7.Use shopping apps frequently	shopping
8.Use smartphone read/search contents for entertainments, like reading comics or sports news	info_entertainment
9.Play single-player game with smartphones a lot	game_single
10.Use browser for web browsing a lot	browser_web
11.Use second hand trading platform a lot	social_business, finance

We applied the association analysis between selected PCs and the SRQ-A&BPNSFS scores to find out which behavioral patterns are highly associated with learning motivation and perceived relatedness. we listed the findings in Table 5 below. Positive associations between behavioral patterns and sub-scales suggest that students who behave in these patterns are more likely to gain higher scores in the corresponding sub-scales; in contrast, negative associations suggest that students who have the matching behaviors are more likely to have lower scores in the corresponding sub-scales. Table 5 shows the patterns associated with 2 sub-scales measuring learning motivation and perceived relatedness.

Learning motivation is measured using the sub-scale intrinsic motivation of SRQ-A, for extrinsic motivation could also be internalized into intrinsic motivation. Thus, we use the intrinsic motivation to measure the motivation level in the learning process in our study. And the sub-scale relatedness satisfaction of BPNSFS is used for measuring perceived relatedness.

Table 5: Patterns associated with learning motivation and perceived relatedness

Sub-scale	associated behavioral pattern
Learning motivation (Intrinsic Motivation)	**pattern 2(+),** pattern 3(-), pattern 9(-)
Perceived relatedness (Relatedness satisfaction)	pattern 1(+), pattern 2(+), pattern 3(+), pattern 5(+)

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

The results show that Pattern 2 is positively associated with both learning motivation and perceived relatedness, it is reasonable to infer that students who are active in social studying and have a habit of using learning tools are more like to feel emotionally supported and socially connected from their social study experience furthermore get motivated in their learning process. Another interesting finding is that Pattern 3 is negatively associated with learning motivation whereas positively associated with perceived relatedness. This may indicate that students who enjoy playing online games or mostly engage themselves in games would be likely to have a high level of perceived emotional support (could be from other online players) whilst having a relatively low level of learning motivation. Pattern 9 is found to be negatively associated with learning motivation, which could also indicate that students who like playing games are apt to be less motivated in learning. Also shown by the results, Pattern 1 is positively associated with perceived relatedness, which indicates that students who are used to playing with dating apps may perceive a higher level of emotional support. Pattern 5 suggests students who like chatting online with instant messaging apps would have the tendency of getting a higher level of perceived relatedness.

Discussion

We use the approach blended with mobile sensing and computational interaction to better capture and understand students' social behavioral patterns associated with learning motivation & perceived relatedness. We identify a group of behavioral patterns that are positively or negatively associated with targeted psychological measures. To the best of our knowledge, our work is the first one to use mobile sensing in a real world setting to study learning motivation and perceived relatedness. Pertinently, the approach we proposed for assessing learning motivation & perceived relatedness in this paper could also be applicable to other psychological measures in education or relevant areas. Our work provides an innovative perspective for developing the new methods of assessment and paves the way for timely personalized intervention.

Implications for predicting learning motivation and perceived relatedness through mobile social behavioral sensing in education. Our approach accentuates the advantages of using mobile sensing data in assessing targeted psychological variables by continuously capturing various components of learning motivation & perceived relatedness associated behaviors multi-modally. Also, our approach illustrates the process of using classical PCA techniques to categorize and interpret behavioral patterns associated with psychological measures, which could also be a fundamental step as the precondition for training or developing models with machine learning/deep learning techniques to predict targeted psychological variables in education. It inspires researchers with the possible future integration of mobile sensing into subsequent design or development of predictive models and intervention systems.

Implications for sensing students in need. mobile sensing devices like smartphones enable us to better understand students' behavioral patterns associated with their psychological states. Specifically, the continuous and real-time assessment provides the ability to sense the students in need in various situations, for teachers or instructors are not capable of noticing and observing every student all the time.

Limitations

We recognize that our work has several limitations, a conspicuous one is that the sample size in our study is small and we only investigated the students with specific demographics (similar majors that are all PE related) in one particular university in China. Hence, it should be particularly cautious to make any generalizations based on our results. With limited demographic representation in our sample, further studies are needed to validate whether we can obtain similar findings on other different populations. Also, we did not take the various characteristics (e.g., personalities) or other personal features into consideration in the study. Besides, we didn't utilize all the sensors in smartphones, instead, we mainly focused on the mobile application usage; for that reason, the coverage of students' behaviors from the sensed data is not diverse enough. Therefore, the behavioral patterns we extracted are relatively limited.

Conclusion

In this paper, we propose an innovative approach blended mobile sensing with self-report surveys as an attempt to assess learning motivation and perceived relatedness. We present a study which demonstrates the process of extracting and interpreting behaviour patterns from the mobile sense data collected via smartphones. Then we identify a number of behavioural patterns associated with learning motivation and perceived relatedness, which provides the insights for future researchers to investigate the student's behaviours and motivation as well as other relevant psychological states in learning process. We believe that our work inspires the new directions of assessing learning motivation and perceived relatedness in future work and paves the way for future research on personalizing intervention.

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References

Ahuja, K., Shah, D., Pareddy, S., Xhakaj, F., Ogan, A., Agarwal, Y., & Harrison, C. (2021, May). Classroom digital twins with instrumentation-free gaze tracking. *In Proceedings of the 2021 chi conference on human factors in computing systems* (pp. 1-9).

Aslan, S., Alyuz, N., Tanriover, C., Mete, S. E., Okur, E., D'Mello, S. K., & Arslan Esme, A. (2019, May). Investigating the impact of a real-time, multimodal student engagement analytics technology in authentic classrooms. *In Proceedings of the 2019 chi conference on human factors in computing systems* (pp. 1-12).

Aung, M. S. H., Alquaddoomi, F., Hsieh, C. K., Rabbi, M., Yang, L., Pollak, J. P., ... & Choudhury, T. (2016). Leveraging multi-modal sensing for mobile health: a case review in chronic pain. *IEEE journal of selected topics in signal processing*, 10(5), 962-974.

Benjamini, Y., Krieger, A. M., & Yekutieli, D. (2006). Adaptive linear step-up procedures that control the false discovery rate. *Biometrika*, 93(3), 491-507.

Ben-Zeev, D., Wang, R., Abdullah, S., Brian, R., Scherer, E. A., Mistler, L. A., ... & Choudhury, T. (2016). Mobile behavioral sensing for outpatients and inpatients with schizophrenia. *Psychiatric services*, 67(5), 558-561.

Berque, D. A., & Newman, J. T. (2015). GlassClass: exploring the design, implementation, and acceptance of google glass in the classroom. *In Virtual, Augmented and Mixed Reality: 7th International Conference, VAMR 2015, Held as Part of HCI International 2015, Los Angeles, CA, USA, August 2-7, 2015, Proceedings 7* (pp. 243-250). Springer International Publishing.

Canzian, L., & Musolesi, M. (2015, September). Trajectories of depression: unobtrusive monitoring of depressive states by means of smartphone mobility traces analysis. *In Proceedings of the 2015 ACM international joint conference on pervasive and ubiquitous computing* (pp. 1293-1304).

Chen, B., Vansteenkiste, M., Beyers, W., Boone, L., Deci, E. L., Van der Kaap-Deeder, J., ... & Verstuyf, J. (2015). Basic psychological need satisfaction, need frustration, and need strength across four cultures. *Motivation and emotion*, 39, 216-236.

Deci, E. L., & Ryan, R. M. (2016). Optimizing students' motivation in the era of testing and pressure: A self-determination theory perspective. *Building autonomous learners: Perspectives from research and practice using self-determination theory*

Dermitzaki, I., Stavroussi, P., Vavougios, D., & Kotsis, K. T. (2013). Adaptation of the Students' Motivation towards Science Learning (SMTSL) questionnaire in the Greek language. *European journal of psychology of education*, 28, 747-766.

Di Serio, Á., Ibáñez, M. B., & Kloos, C. D. (2013). Impact of an augmented reality system on students' motivation for a visual art course. *Computers & Education*, 68, 586-596.

Furió, D., Juan, M. C., Seguí, I., & Vivó, R. (2015). Mobile learning vs. traditional classroom lessons: a comparative study. *Journal of Computer Assisted Learning*, 31(3), 189-201.

Giunchiglia, F., Zeni, M., Gobbi, E., Bignotti, E., & Bison, I. (2018). Mobile social media usage and academic performance. *Computers in Human Behavior,* 82, 177-185.

Hardin, J. W., & Hilbe, J. M. (2002). *Generalized estimating equations.* chapman and hall/CRC.

Holstein, K., McLaren, B. M., & Aleven, V. (2018). Student learning benefits of a mixed-reality teacher awareness tool in AI-enhanced classrooms. I*n Artificial Intelligence in Education: 19th International Conference, AIED 2018, London, UK, June 27–30, 2018, Proceedings, Part I 19* (pp. 154-168). Springer International Publishing.

Holstein, K., McLaren, B. M., & Aleven, V. (2019). Co-designing a real-time classroom orchestration tool to support teacher-AI complementarity. Grantee Submission.

Legault, L. (2020). *Intrinsic and extrinsic motivation.* Encyclopedia of personality and individual differences, 2416-2419.

Liang, K. Y., & Zeger, S. L. (1986). Longitudinal data analysis using generalized linear models. *Biometrika*, 73(1), 13-22.

Liga, F., Ingoglia, S., Cuzzocrea, F., Inguglia, C., Costa, S., Lo Coco, A., & Larcan, R. (2020). The basic psychological need satisfaction and frustration scale: Construct and predictive validity in the Italian context. *Journal of Personality Assessment,* 102(1), 102-112.

Martinez-Maldonado, R., Pardo, A., Mirriahi, N., Yacef, K., Kay, J., & Clayphan, A. (2015, March). The LATUX workflow: designing and deploying awareness tools in technology-enabled learning settings. *In Proceedings of the fifth international conference on learning analytics and knowledge* (pp. 1-10).

Mavrikis, M., Gutierrez-Santos, S., & Poulovassilis, A. (2016, April). Design and evaluation of teacher assistance tools for exploratory learning environments. *In Proceedings of the Sixth International Conference on Learning Analytics & Knowledge* (pp. 168-172).

Meegahapola, L., Ruiz-Correa, S., Robledo-Valero, V. D. C., Hernandez-Huerfano, E. E., Alvarez-Rivera, L., Chenu-Abente, R., & Gatica-Perez, D. (2021). One more bite? Inferring food consumption level of college students using smartphone sensing and self-reports. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, 5(1), 1-28.

Mellin, E. A. (2008). Rejection sensitivity and college student depression: Findings and implications for counseling. *Journal of College Counseling,* 11(1), 32-41.

Mitchell, J. I., Gagné, M., Beaudry, A., & Dyer, L. (2012). The role of perceived organizational support, distributive justice and motivation in reactions to new information technology. *Computers in Human Behavior*, 28(2), 729-738.

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

Reyes, M. R., Brackett, M. A., Rivers, S. E., White, M., & Salovey, P. (2012). Classroom emotional climate, student engagement, and academic achievement. *Journal of educational psychology*, 104(3), 700.

Ryan, R. M., & Connell, J. P. (1989). Perceived locus of causality and internalization: examining reasons for acting in two domains. *Journal of personality and social psychology*, 57(5), 749.

Ryan, R. M., & Deci, E. L. (2000). Intrinsic and extrinsic motivations: Classic definitions and new directions. *Contemporary educational psychology*, 25(1), 54-67.

Ryan, R. M., & Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American psychologist*, 55(1), 68.

Ryan, R. M., & Deci, E. L. (2017). *Self-determination theory: Basic psychological needs in motivation, development, and wellness.* Guilford Publications.

Saeb, S., Zhang, M., Karr, C. J., Schueller, S. M., Corden, M. E., Kording, K. P., & Mohr, D. C. (2015). Mobile phone sensor correlates of depressive symptom severity in daily-life behavior: an exploratory study. J*ournal of medical Internet research*, 17(7), e4273.

Schölkopf, B., Smola, A., & Müller, K. R. (2005, June). Kernel principal component analysis. *In Artificial Neural Networks—ICANN'97: 7th International Conference Lausanne, Switzerland, October 8–10, 1997 Proceeedings* (pp. 583-588). Berlin, Heidelberg: Springer Berlin Heidelberg.

Tissenbaum, M., Matuk, C., Berland, M., Lyons, L., Cocco, F., Linn, M., ... & Dillenbourg, P. (2016). Real-time visualization of student activities to support classroom orchestration. Singapore: International Society of the Learning Sciences.

Tohidi, H., & Jabbari, M. M. (2012). The effects of motivation in education. *Procedia-Social and Behavioral Sciences*, 31, 820-824.

VanLehn, K., Burkhardt, H., Cheema, S., Kang, S., Pead, D., Schoenfeld, A., & Wetzel, J. (2021). Can an orchestration system increase collaborative, productive struggle in teaching-by-eliciting classrooms? *Interactive Learning Environments*, 29(6), 987-1005.

Wang, R., Chen, F., Chen, Z., Li, T., Harari, G., Tignor, S., ... & Campbell, A. T. (2014, September). StudentLife: assessing mental health, academic performance and behavioral trends of college students using smartphones. I*n Proceedings of the 2014 ACM international joint conference on pervasive and ubiquitous computing* (pp. 3-14).

Wiliam, D. (2011). What is assessment for learning? *Studies in educational evaluation*, 37(1), 3-14.

Zarraonandia, T., Aedo, I., Díaz, P., & Montero, A. (2013). An augmented lecture feedback system to support learner and teacher communication. *British Journal of Educational Technology,* 44(4), 616-628.