Innovative Attempt at Enhancing Psychological Assessment: A Preliminary Investigative Study of Measuring College Students' Learning Motivation Levels through the Lens of Passive Sensing via Smartphones

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Abstract

Assessing the levels of motivation in the learning process are pivotal in the daily life of college students, for the learning motivation profoundly impacts their overall academic performance. Yet, the prevailing methods to measure learning motivation levels still predominantly depend on expert evaluation and self-report, advancements in passive smartphone sensing have not been fully utilized in measuring motivation levels in learning process. In this study, we investigate and analyze behaviors and behavioral changes associated with their levels of learning motivation of N=118 undergraduate college students integrating passive smartphone sensing with self-report survey. We collect a dataset regarding the students' daily behaviors and self-report responses using a mobile application and questionnaire. Subsequently, we identify a variety of behaviors based on behavioral features captured from passive sensing data, followed by an exploration of the correlations between levels of learning motivation and the identified behaviors. Moreover, we analyze differences in behavioral changes among groups characterized by varying levels of learning motivation. Our study contributes to enhancing psychological assessment approaches by introducing a novel integrated method for more quantified and multidimensional measurement of learning motivation, providing valuable perspectives for assessing and intervening learning motivation in future research endeavors.

Keywords: learning motivation; passive sensing; human computer interaction; education; psychology

Introduction

Learning motivation, as an appealing topic in pedagogy and psychology (Ball, 1982; Young, 1950), has garnered substantial research attention since it empowers students with academic activities and shapes students' academic engagement and performance profoundly (Furió et al., 2015; Di et al., 2013; Dermitzaki et al., 2013). It can be characterized as intrinsic or extrinsic elements propelling students toward action to attain their learning objectives or meet their expectations within the framework of self-determination theory (SDT). Specifically, learning motivation is delineated into intrinsic motivation, extrinsic motivation, and amotivation (Mitchell et al., 2012; Ryan & Deci, 2000), among which the Intrinsic motivation signifies an individual's inherent inclinations and innate characteristics during the learning process and the extrinsic motivation has the potential to transition into intrinsic motivation as the learning process unfolds (Tohidi & Jabbari, 2012). In this study, we explore and define the level of learning motivation by focusing on the broader intrinsic learning motivation within the framework of the SDT theory. Considering the crucial roles of learning motivation levels as primary indicators during the learning process, measurement of learning motivation has attracted lots of research interest among scholars. A large number of studies have been conducted on learning motivation measurement methods varying from the commonly adopted self-reports (e.g., questionnaires) to the phenomenological methods like expert evaluation (e.g., interviews) or observations by professionals (Fulmer & Frijters, 2009). Through these approaches provide detailed and descriptive information in measuring learning motivation level, the generalizability of them is restricted timely and spatially. Besides, such conventional methods, being both demanding in terms of effort and time, hinge on participants' willingness to adhere to them (Fredricks & McColskey, 2012) and are constrained by an excessive reliance on subjective interpretation.

In light of the identified necessity and the ongoing advancements in research, this paper aims to delve into innovative methods of psychological measurement that offer a more quantitative and continuous approach, specifically targeting at the measurement of learning motivation levels within the daily lives of students. Our focus revolves around the exploration and quantification of learning motivation levels through a behavioral perspective, achieved by seamlessly integrating passive mobile sensing. Simultaneously, we periodically collect self-report responses from students and seek to investigate the correlations between the behaviors identified through passive sensing data and the self-reported responses. As such, our study is driven by the following research questions (RQ):

- RQ1**:** How do college students' daily behaviors relate to their learning motivation levels?

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- RQ2: What are the behavioral changes of the students with different learning motivation levels?

To answer the above questions, we conduct a preliminary study by collecting a dataset consisting of tracked learning motivation level via passive smartphone sensing and self-report survey from a group of undergraduate students from one selected college in China. We designed and developed a mobile application to passively collect real-time daily behavioral data from students. Then we utilized the collected data from smartphones of N=118 undergraduate students over a span of 14 consecutive weeks to identify the students' behaviors and used sub-scales of academic self-regulation questionnaire (SRQ-A) (Ryan & Deci, 2000) to measure learning motivation level. The questionnaires were randomly administered once a week to students, aligning with the passive sensing data collection throughout the entire study. Then, we conducted the association analysis on the identified behaviors and learning motivation level to investigate their relationships. Lastly, we compared the behavioral changes among students with different levels of learning motivation at the behavioral feature level.

Please note that the data we have gathered were collected from a specific demographic of undergraduate students at a college in China. Hence, we advise our readers to exercise caution when interpreting our findings, as the generalizability of our results across populations are uncertain with limitations. In this paper, we focus on advancing the current methods for measuring learning motivation level from a passive sensing perspective by conducting a preliminary study investigating relationships between daily behaviors and learning motivation levels. The contributions of our work are outlined below:

- We present a comprehensive preliminary study using passive smartphone sensing integrating self-report survey, our study also provides a preliminary functional framework for the development of future novel integrated approach to the measurement of learning motivation and lays the foundation for research on motivation intervention.
- Our study demonstrates a method paradigm for behavior identification and analysis, we identify 9 behaviors by clustering and encompass exploratory analysis of the associations between behaviors and learning motivation levels. Moreover, we compare the behavioral changes of students with different learning motivation levels and discover differences in sleep habits and mobile phone usage.
- We propose an integrated multimodal approach for measuring learning motivation level by leveraging passive smartphone sensing, which enhances the conventional psychological assessment methodologically and provides the insights to generalize our approach for other psychological variable assessment and measurement.

Our study is approved by the Institutional Review Board of the conducting institution. All participants in the study were duly informed about the potential risks associated with the collection of sensitive and private data through passive smartphone sensing. Addressing ethical and privacy concerns, we ensured that participants provided explicit consent to share specific aspects of their privacy in the study. Comprehensive information about potential risks was clearly outlined in the consent form, thoroughly explained, and discussed during the recruitment phase. Additionally, stringent measures were implemented to safeguard participants' privacy. All data collected through the mobile application was anonymized and securely stored on our private server, with a commitment to using the data exclusively for the purposes of this study.

The paper is structured as follows. We commence with a review of existing methodologies measuring learning motivation level in psychology and pedagogy in Section 2. Moving to Section 3, we provide an in-depth description of the study methodology, encompassing the study design, demographics of participants, data collection, behavioral features, behavior identification and association analysis. Subsequently, Section 4 and 5 are dedicated to presenting and describing the obtained results corresponding to the two research questions. Then in Section 6, we summarize the study's findings and their implications, followed by a discussion of the study's limitations in Section 7. Finally, we present the conclusion in Section 8.

Related Work

Research in educational psychology and pedagogy has explored various methods for psychologically measuring learning motivation (Weiner, 1990; William, 2021), however, rather conventional methods such as self-report survey is still predominant. The methods derived from this, such as experiential sampling, are also widely utilized (Larson & Csikszentmihalyi, 1983). In addition, compared to traditional questionnaires, phenomenological methods which provide descriptive and qualitative measurements, such as interviews (Shedivy, 2004; Perry et al., 2023; Yeung, 2004) or teacher ratings (Wigfi eld et al., 2008), are also applied widely. However, these approaches share limitations similar to self-report methods, as they highly rely on the subjective interpretation of experts or evaluators (Spinelli, 2005). Other methods, including running records of participant observation, case studies, and semi-structured retrospective interviews, also share the same limitations and are relatively labor-intensive. Additionally, the utilization of these methods for measuring learning motivation may result in discontinuity. Recently, neuropsychological methods like brain imaging, functional magnetic resonance imaging (fMRI) scans (Arana et al., 2003; Elliott et al., 2003; Taylor et al., 2004; Mizuno et al., 2008) and electroencephalographs (EEG) (Dubrovinskaya & Machinskaya, 2002) are also commonly used to measure motivational states at the neuronal activity with strong face validity and content specificity (Elbaum & Vaughn, 2003). However, showcasing psychometric reliability and replicability across various situations can pose challenges for these methods. Besides, behavioral methods, such as behavior observation by experts or encoding behavior videos by trained viewers, are also used for measuring learning motivation, especially the intrinsic motivation (Henderlong & Paris, 1996; Reeve & Nix, 1997).

In contrast to the methods mentioned above that require specific spaces, precision instruments or specialized sensors, there has been a rising research interest in passive sensing methods for assessing psychological variables or states for human computer interactive (HCI) researchers. Revealingly, quite a few studies have tried applied multiple sensors (e.g., wearable devices) to measure the psychological variables or states in the learning context (Holstein et al., 2019; Wang et al., 2014; Mavrikis et al., 2016; Tissenbaum et al., 2016). For instance, using smartphones to investigate the relationship between mobile social media usage and academic performance (Giunchiglia et al., 2018). However, there is a shortage of HCI studies that have extended these methodologies into the domain of learning contexts targeted at motivation tracking.

Methodology

In the following section, we discuss the methodological design of our study, demographic information of the participants, data collection of learning motivation level measures and passive sensing data, behavioral features, identification for behaviors and association analysis.

Study Design

The data we collected and analyzed in this paper originates from a continuing passive mobile sensing study tracking a cohort of 118 undergraduates at a college in China throughout their consecutive 14 weeks of daily study life using passive sensing and self-report surveys. We recruited students starting from the second week of February 2023, a period of two weeks was allocated for recruitment on campus through the university's student forum. Then we spent one week guiding the students to complete the mobile application installation and conducting pretests for data collection. From March 6 to June 12, we continuously collected the data via passive sensing and participants' self-report survey responses. There were 118 undergraduate students consented and participated in our study, all participants are required to keep the mobile sensing application installed and running on their smartphones during the consecutive 14 weeks of data collection period, all holidays and short breaks from the college are also included. Concurrently, we collect the self-reported data on participants' learning motivation level with a simplified version of experience sampling method by administering the questionnaire once a week at random time. Participants are asked to answer the self-report survey and are compensated 50 RMB per week for completing the questionnaire as required. This is study is approved by the selected college's institutional review board.

Demographics

Initially, 130 participants were recruited as the study started, 118 participants who completed the study by adhering to the study requirements and finishing the weekly assessment of learning motivation are included in the analysis. 7 participants were excluded from the study due to substantial data loss in passive sensing and 3 participants were excluded because of missing data in weekly self-report responses. Additionally, 2 participants opted to withdraw from the study in the first week citing academic commitments. All participants are Chinese undergraduate students, and the majority of the participants are males, comprising 60.2%(N=71) of the total. Regarding the distribution of their fields of study, Clinical Medicine accounts for 25.4%(N=30), Medical Imaging for 19.5%(N=23), Pharmacy for 16.1%(N=19), Biochemistry for 10.2%(N=12), Vehicle Engineering for 9.3%(N=11), Electronic Automation for 6.8%(N=8), Software Engineering for 5.1%(N=6), Economics for 3.4%(N=4), English Literature for 2.5 %(N=3) and Philosophy for 1.7%(N=2).

Data Collection

Passive Sensing Data: Mobile Application We developed a native Android app for passive data collection from participants' smartphones, aiming to minimize interference and capture authentic daily life information. The data is first stored on the mobile device itself. Once the phone establishes an internet connection, it proceeds to upload the data to our private servers before removing the data from the device. To be more precise, the application captures details such as physical activities (walking, running, bicycling, etc.), counts of calls and text messages, ambient environment info (ambient sound and light), battery and screen events (screen unlock/lock), location and application usage (the uploaded data only includes the name label of the application running on the smartphone's system at that moment).The app logged the smartphone activities mentioned above by utilizing the available sensors at intervals of 5 minutes. Then from the acquired data we derive behavioral features (e.g., duration of unlock) on a daily basis to document and profile participants' behaviors.

Self-report Measures: Learning Motivation Level We measure the level of learning motivation using the Academic Self-Regulation Questionnaire (SRQ-A) sub-scale, with its validation detailed in Ryan and Connell (1989). Comprising four sub-scales, namely external regulation, introjected regulation, identified regulation, and intrinsic motivation, the SRQ-A allows individual sub-scale scores for research analysis. In this investigation, we utilized the scores related to intrinsic motivation. Participants completed the questionnaire once a week at random times, providing self-report survey responses regarding their learning motivation levels. We obtain results of scored responses ranging from 1 to 5, yielding an overall mean of 2.95 with a standard deviation of 1.48.

Behavioral Features

In this study, our goal is to investigate and enhance psychological assessing method for learning motivation level by integrating the smartphone sensor data and self-report survey data. we aim to collect the behavioral data via passive sensing in attempt to capture and profile the participants' daily behaviors as faithfully as possible. The mobile application runs in the background on the participants' smartphones to collect the data unobtrusively. Next, we integrate features that delineate the following aspects of daily behaviors from smartphone passive sensing data. These features are computed on a daily basis.

Mobility. Taking into both phone energy conservation and data quality, the mobile application retrieves GPS data every 5 minutes. We use the collected data to derive the locations that participants visited and the distance they travelled.

Physical activity. We discern the participant's ongoing activities through the utilization of the activity recognition API, we use this information to decide the participants' physical status and the duration of different physical activities (e.g., the duration of walking).

Semantic locations. Since all the participants live in the student residence hall (on campus) and the vast majority of their campus life takes place on campus. We collect the raw GPS coordinates with our mobile application then label the locations with semantics using a third-party API together with the university campus map (which provides the detailed labels for various zones and buildings within the campus).

Sleep patterns and environment context. We extract sleep data from the smartphones and derive the sleep duration and sleep start and end time (Wang et al., 2014; Chen et al., 2013) with a margin of error of around 40 minutes. We derive the ambient environmental data from the smartphones including ambient sound level and ambient light level.

Smartphone usage. We use the mobile application to capture a variety of phone usage including the screen events (e.g., duration of the unlock), battery events (e.g., the number of charging cycles), communications (e.g., the number of calls) and the detailed participants' daily use of different mobile apps. Data on specific app usage are collected once every 5 mins, then we categorize the 779 mobile apps from the collected data into 42 genres (e.g., education, entertainment, music/audio, etc.) and compute the duration of using different apps.

Behavior Identification and Association Analysis

Clustering For Behavior Identification In order to understand and profile the participants form a behavioral perspective, we employ the clustering method for behavior identification and furthermore generate concrete descriptions and interpretations of the identified clusters. Clustering is an unsupervised technique which leverages the inherent patterns within the data to discern and group similar data points, and it is apt for our case as we aim to identify and cluster students based on similar behavior disregarding any predefined labels or categories. Profiling the participants with behavioral inferences enables us to distinguish and recognize different groups of participants then make inferences and identify behaviors within the identified groups. We use 59 features derived from the passive smartphone sensing data for the cluster analysis. More precisely, we chose the K-means clustering as the clustering algorithm since it is designed to optimize similarity within data points of the same cluster and reduce similarity between data points in distinct clusters by utilizing Euclidean distance. Then we used silhouette method (Rousseeuw, 1987) to determine the hyperparameter K, the most suitable number of the clusters to generate, to ensure effective segmentation of the data across the clusters. We obtain the highest average silhouette score of 0.28 for K = 9. We then group data into 9 clusters and select top important features within each cluster and seek to provide a representative description that profiles the characteristics of the participants' behavior within these clusters. For each obtained cluster, we select the top important features by applying permutation feature importance approach. Based on these features, we analyze, interpret and identify behaviors through behavioral inference.

Association Analysis We utilize bivariate Generalized Estimating Equations (GEE) (Liang & Zeger, 1986) to examine the relationship between identified behaviors and the levels of learning motivation. We first combine the passive sensing dataset collected form smartphones, the self-report responses dataset (the responses from one participant are received at different time during the study) and the previously obtained cluster labels into a unified dataset, then we apply the GEE to this combination. Finally, we execute the two-stage Benjamini-Hochberg procedure (TSBH) (Benjamini et al., 2006) to manage/regulate the false discovery rate (FDR).

RQ1: How Do College Students' Daily Behaviors Relate to Their Learning Motivation Levels?

After clustering and selecting the top importance features within each cluster, we interpret and identify the behaviors with behavioral inference, it draws us an overview of the participants' usual daily behaviors via passive sensing and provides the foundation for analysis in the next step. Table 1 lists the identified behavior of each respective cluster in detail, indexed by the number of data points contained within each cluster. Explicitly, C1(we use the label code of each cluster to represent it) describes the students who spend much time on social media and like to socialize and chat with others on the phone; C4 describes students who like to study using productivity type of apps (e.g., office apps, collaboration apps, etc.) in the library; C2 portrays that the students who regularly watch short videos on the short video platform; C5 describes students who tend to play online multiplayer games in the dorm and sleep late; C7 suggests students who like to watch learning related videos or search for learning related resources on the phone and use learning tools/apps with social attributes or functions (e.g. tandem apps); C9 describes students who are likely to spend a lot of time listening to the music in dormitory (there is no extension to infer concurrent music playback behavior); C6 suggests students who are prone to browse contents related to entertainment, beauty and lifestyles, and shop frequently on their smartphones around bedtime; C8 profiles students who like to watch livestream video with the phone and frequently order food or beverages for delivery; C3 describes students who inclined to wake up early and like jogging outdoors during the daytime.

Table 1: Behaviors identified by clustering behavioral features

Features	Behavior
duration of using social, IM (instant messaging) and communication apps, long sedentary duration	(C1) Spend a lot of time on social media and chatting on the smartphones
long stay in the library and duration of using productivity app, high number of unlocks	(C4) Frequently use of productivity tools in the library.
duration of using social-video apps, duration of unlock	(C2) Regularly watching short videos on smartphones
duration of using multi-game apps, long stay in the dormitory area, late sleep start time, duration of voice-call	(C5) Playing online games and sleep late, mostly stay in the dormitory
Duration of video play, duration of using educational, utility and social apps	(C7) Watch learning related videos and read learning resources on smartphones and use learning tools with social attributes or functions
Stay in the dormitory area, duration of audio play, duration of using music apps, ambient sound level, duration sedentary	(C9) Spend a lot of time listening to the music and be sedentary in dormitory
Duration of using shopping, lifestyle，entertainment and beauty apps，sleep start time	(C6) Shopping and browsing content related to life sharing，entertainment and beauty around sleep time
Duration of using livestream apps and frequent use of food/drink apps (with function of food delivery)	(C8) Spend a lot of time watching livestream video and ordering takeout for food or beverages via smartphones frequently
sleep end time early, sleep duration, jogging, ambient light level, stay in outdoors (sports field/ playground)	(C3) Wake up early and like to jog outdoors at daytime

As previously mentioned, we investigate the relationship between the obtained clusters and SRQ-A scores by utilizing GEE then FDR to analyze the associations between the behaviors identified from the clusters and the learning motivation levels. A positive association indicates that individuals with matching behavior are more likely to have elevated levels of learning motivation, while a negative one suggests that individuals with matching behavior are more likely to have lower scores in survey, implying a potential lack of learning motivation. As a consequence, in Table 2, we find that behaviors identified from C1, C4, C7, C9, C6 and C3 are positively associated with the level of learning motivation, whereas behaviors identified from C2, C5 and C8 negatively associated. Among them, behaviors identified from C4(Frequently use of productivity tools in the library.) and C7(Watch learning related videos and read learning resources on smartphones and use learning tools with social attributes or functions) exhibit a strong positive association with learning motivation levels, implying that students who habitually use educational and learning-related apps may tend to have higher levels of learning motivation. Conversely, behaviors identified from C5 and C8 are observed to have strong negative associations with learning motivation levels, suggesting that students with prolonged or excessive engagement in mobile gaming and livestreaming on smartphones may result in a decline in learning motivation.

Table 2: Behaviors associated with learning motivation level

Positively associated behaviors	Negatively associated behaviors
Behavior - C1, **Behavior - C4**, Behavior - C6, **Behavior - C7**, Behavior - C9, Behavior - C3	Behavior - C2, ***Behavior - C5***, **Behavior - C8**

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

RQ2: What Are the Behavioral Changes of Students with Different Learning Motivation Levels?

To compare and analyze the behavioral changes among students with distinct learning motivation levels, we divide the participants into two groups based on their SRQ-A scores, corresponding to high and low motivation levels, respectively. As a result, the high learning motivation level group achieves the overall mean of 3.6 with the standard deviation of 1.28, while the low group achieves the overall mean of 2.0 with the standard deviation of 1.47. Furthermore, as we have obtained the behavioral features computed and extracted from passive sensing data, we analyze the behavioral changes by exploring features that exhibit variations between the high-level and low-level groups. We conduct the comparison by using Wilcoxon signed-rank test (Woolson, 2007) and show the results in Figure 1. After applying the Benjamini/Hochberg FDR correction procedure for multiple comparisons, the displayed results reveal statistical significance with a p-value below 0.05. Additionally, please note that our statistical comparisons specifically pertain to daily averages. The y-axis represents sensing behavioral features that reveal significant differences between the two groups, while the x-axis illustrates the percentage change. The bars in Figure 1 diverge to indicate whether a feature undergoes positive or negative changes between the two groups (e.g., a positive change indicates that the particular feature is more prominent in the high learning motivation level group). The positive percentage changes are signified by blue bars, while the negative percentage changes are denoted by red bars. More specifically, we observed from the figure that for the positive changes, the features including duration of using productivity apps (+48%), duration of using education apps (+31%) and duration in the library (+39.6%) change with a relatively higher rate. It is reasonable to infer that students with high level of learning motivation might have the habit of using learning supportive apps. Correspondingly, duration in the gym (+18%), duration of using music apps (+14.5%), duration of using social apps (+12%), duration of walking (+9%), sedentary duration (+5%) and duration of using lifestyle apps (+1.3%). An interesting finding is the positive change in sleep start time (+23%) and the negative change in sleep duration (-5%), which might indicate that students with the higher level of learning motivation are likely to go to bed and rise early. As for other features that change negatively, we find that features including number of unlocks (-45%) and video play duration (-41%), duration of using multi-game apps (-37%), total unlock duration (-35%), duration in the dormitory (-23%), duration of using shopping apps (-22%), duration of using livestream apps (-11%), duration of using instant messaging apps (-7%) and number of visited locations (-2%). This suggests that students with lower learning motivation levels overall spend more time using their phones for entertainment purposes.

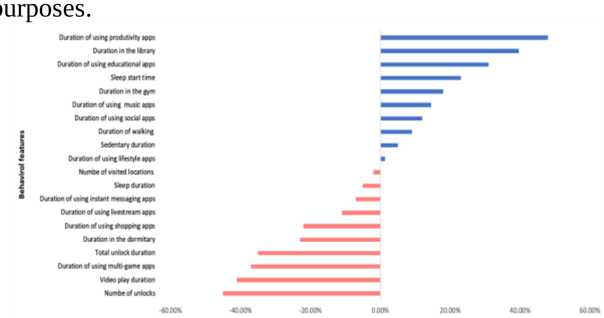

Figure 1: Features with significant differences between high and low learning motivation groups

Discussion

To gain deeper insights into daily behaviors associated with learning motivation levels, we employ various computational methods. Our approach enriches the current psychological methodologies for measuring learning motivation, serving as a paradigm that could be applied in other domains.

Implications

Our approach enhances conventional psychological measurement methods in learning motivation levels by utilizing the computational methods. The use of passive sensing via smartphones highlights the importance of incorporating multi-modal data to assess different aspects of learning motivation. More importantly, our study demonstrates a comprehensive process of using clustering techniques for behavior identification and illustrates how to conduct the analysis of identified behaviors associated with targeted variables. Comparing with the labor-intensive methods like traditional EMAs, our approach suggests a continuous assessment method that could be generalized to measure other psychological variables (e.g., students' attention or cognitive load during learning).

Moreover, as a preliminary study, our work also provides the foundation for the future learning motivation perdition and intervention research. HCI researchers may explore building models to offer tailored interventions for students with diverse needs. For instance, systems integrating learning motivation assessment and supportive interventions, similar to cognitive behavioral therapy, could be a potential design option for future studies.

Furthermore, in educational psychology, researchers can utilize our method to enhance existing educational psychology models. For instance, within the SDT framework, researchers can conduct more continuous tracking and quantifiable measurements of other basic psychological needs and mediating variables, contributing to a more robust theoretical development.

Limitations

Our study faces several limitations. It primarily focuses on a specific demographic of students within a single college in China, which limits the generalizability of our findings. Caution should be exercised when extending these results to broader populations, and further research is essential to validate the applicability of our findings across various settings, including other colleges. The restricted demographic representation in our sample may lead to an underestimation of clusters in the broader population, underscoring the importance of our cluster analysis and encouraging similar analyses in future studies. Additionally, we acknowledge that our study did not fully exploit multimodal sensing, as it solely relied on smartphones without integrating other devices with diverse sensor capabilities. Despite these limitations, they serve as a foundation for future research opportunities.

Conclusion

In this study, we conduct a preliminary investigative study of measuring learning motivation level by integrating passive smartphone sensing and self-report survey. We identify a number of daily behaviors of 118 students with objective passive sensing data on a clustering approach and analyze the associations of these behaviors alongside self-reported measures. We study the behavioral changes of students with different learning motivation levels and find the differences at the level of behavioral features. Our study proposes a novel integrated approach of measuring learning motivation level with multimodal data, laying an enlightening foundation for future research on measuring and intervening in learning motivation.

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