Detection of Student Workgroup Identification using Passively Sensed WiFi Infrastructure

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Social identification: how much individuals psychologically associate themselves with a group has been posited as an essential construct to measure individual and group dynamics. Studies have shown that individuals who identify very differently from their workgroup provide critical cues to the lack of social support or work overloads. However, measuring identification is typically achieved through time-consuming and privacy-invasive surveys. We hypothesize that the extremities in-group norm affects individuals' behaviors, thus more likely to give rise to negative appraisals. As a more convenient and less-invasive technique, we propose a method to predict individuals who are increasingly different in identifying themselves with their working peers using mobility data passively sensed from the WiFi infrastructure. To test our hypothesis, we collected WiFi data of 62 college students over a whole semester. Students provided regular self-reports on their identification towards a workgroup as ground truth. We analyze the contrasts between groups' mobility patterns and build a classification model to determine students who identify very differently from their workgroup. The classifier achieves approximately 80% True Positive Rate (TPR), 73% True negative rate (TNR), and 78% Accuracy (ACC). Such a mechanism can help distinguish students who are more likely to struggle with negative workgroup appraisals and enable interventions to improve their overall team experience.

CCS Concepts: • **Human-centered computing → Ubiquitous and mobile computing design and evaluation methods**; • **Applied computing → Sociology**; **Collaborative learning**.

Additional Key Words and Phrases: WiFi, mobility, workgroup, social identification, education

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1 INTRODUCTION

The construct of *social identification – the degree to which individuals perceive themselves to be part of an in-group* – is often associated with workgroup productivity [36, 55] and psychological well-being such as stress and depression [6, 14, 23, 25]. Indeed, social identification is described as a "social cure", influencing one's perception of social support and well-being. Low identifiers are more likely to feel alienated from their peers, worsening their burdens of stress [7]. Identification is also a "motivational primer" for high identifiers to feel more committed, thus more likely to experience

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work overloads and burnouts [5, 24]. While the complexities of identification must be carefully balanced, its measurements remain defined by time-consuming and invasive survey mechanisms [10, 19, 33, 38, 41].

A seminal work by Turner *et al.* describes social identification as mediating the willingness of individuals to stick together; this social and dynamic phenomena is known as self-categorization [50, 51]. The more significant the category membership between an individual and their group, the more likely an individual becomes a 'conformist' [1]. Conformity to prototypical behaviors between team members is increased by individuals' agreement and perceived similarities with their group [1, 3]. In contrast, Thomas *et al.* proposed that team-level identification can occur from 'polarization' where members become increasingly different from each other in characteristics and experiences [48]. Similarly, Mackie *et al.* found that extremities in group norms depend on how group members perceive an individual's status opposing to theirs. [34]. We build on these arguments to investigate individual-level identification of working teams and determine contrasting behaviors of those who identify more differently from their working peers. In such cases, these individuals are more likely to elicit affective reactions from receiving little social support (associated with lower identification) or experiencing high workload and burnout (linked to higher identification). Note that moving forward, we will use the term *workgroup identification* in the rest of this paper to describe the psychological association of students with their assigned teams.

Our work explores the new possibility of using mobile data to predict workgroup identification [17, 18], influenced by prior large-scale passive-sensing research using WiFi data to analyze campus behaviors [54, 56, 58]. We hypothesize that user behaviors, derived from passively sensing location data using the WiFi infrastructure, could be used to determine members who identify far beyond the group norm; accordingly labeling our prediction outcomes as 'conformed' and 'polarized' identification [34, 48]. It is essential to mention that, for the rest of this work, one's behavior is determined by the time one spends on co-located work with group members. To the best of our knowledge, this is the first work that attempts to distinguish workgroup identification through technological means, complementing traditional survey methods for longitudinal analysis.

To demonstrate our approach, we conducted an IRB-approved user study among 62 college students over 81 days. All participants were pre-assigned to a 4-5 member group for an Information Systems (IS) core project, Software Engineering (SE). The course is suitable for our study as it requires students to be co-located in groups to work on their project (e.g., students pair-programmed to build a web application). Hence the project demands extensive communication and face-to-face interaction amongst group members. Group tasks took place mostly on campus. We obtained ground truth from their bi-weekly assessments on workgroup identification and interviews. We collected students' course material, a standardized artifact which logs all SE tasks in detail. Students supplied the MAC address of their mobile phones so that we could extract WiFi data directly from the campus infrastructure. Note: students did not install a mobile app or other software for the data collection.

Using the WiFi data and, by proxy, the phone user, we generate features representing students' participation in specific project tasks. Results from our statistical and qualitative analyses explain how and why workgroup identification is an essential measure of students' well-being. Our exploratory feature analysis and machine learning (ML) experiments demonstrate how we can utilize WiFi data to extract mobility patterns to predict workgroup identification. The contributions of this paper are:

(1) A cross-lagged analysis to understand how workgroup identification influences stress over time shows small but significant associations between identification and stress towards the later part of the project. We chose stress as an outcome measure since most students reported

SE to be a highly stressful course. Further, we supplement qualitative insights of students experiencing common group dysfunctions, which created psychological distresses. These findings validate the need to assess identification for nurturing student workgroups.

(2) A classification approach using mobility features to distinguish students who identify very differently from their group. We perform a group 5-fold cross-validation by setting aside 12 participants for testing (50 for training) in each fold. Input for our model is mobility features representative of major group tasks, extracted every two weeks. Output for our model is a binary outcome of individuals with polarized identification, performing at an overall accuracy (ACC) of 78%, 80% true positive rate (TPR), and 76% true negative rate (TNR). Out of 62 students, the model misclassifies one student who was more likely to appraise *negative* experiences with their workgroup.

2 RELATED WORK

Our focus is on understanding social identification in a workgroup and how location-based systems can be designed around identification.

2.1 Measuring Social Identification

Social identification is associated with *social identity*; that is, social identification is an affective aspect towards the group [38], whereas social identity describes a range of characteristics to which a person identifies with the group [38, 55]. Identification can affect both individual and team-level functions [23, 42, 48]. For example, a person who feels identified to an organization may be more committed to working. However, increased commitment may result in overworking and burnout, affecting overall productivity [36, 55]. Alienation from the team can influence one's self-esteem and social support.

Prior work has validated scales to measure the social identification on multiple dimensions [10, 19, 33, 41]. However, these scales are elaborate and complicated for users [38]. The simplification in Single-Item Social Identification (SISI) [38] strongly correlates with the referenced scales [33], while extending SISI, a Four-Item Social Identification (FISI) [16, 32, 38], demonstrates much stronger reliability [40]. These works influence our decision to utilize FISI in our study. However, utilizing surveys poses several limitations. First, questions restrict how we conceptualize the construct. Second, surveys do not cater to assessment's sensitive timing and become cumbersome to participants over repeated use. Seering *et al.* argues that communication technologies could characterize group members' prototypicality, informing different perspectives of social identity [43]. These findings motivate our research to investigate if it is possible to assess identification through technological means.

2.2 Location-Based Group Behavioural Systems

Using location information generally involves making direct observations on dynamic behaviours, or lack thereof, in human mobility. The ability to infer users' activities from location information helps associate traces with users' engagements in the environment [11, 12, 20]. For example, Zhou *et al.* derived students' classroom punctuality and attendance from analyzing WiFi association data [58]. At the same time, Brown *et al.* collected location data from RFID tags to infer interaction practices between colleagues in face-to-face meetings [8]. However, these works neither investigate workgroup processes nor assess dimensions of identification. We had previously investigated the use of passive WiFi signals to identify stress and depression among campus students [56]. Now, we extend the sensing capability to look at the social identification of students in a workgroup.

2.3 Workgroup Interactions And Location

Nemeth and Staw argued that workgroup tends to develop norms in their work practice [46]. This claim is supported by Jetten *et al.*, who describes highly identified individuals to incorporate salient in-group norms as a guide for "accepted" behavior [27]. However, a sudden change from these norms could indicate team friction or emotional upset within the group [4]. For example, members with high conflict tend to avoid each other [26]. Individuals who identify lesser to a group may engage in activities opposite of group norms [27]. Eagle *et al.* provides seminal work in investigating behaviors derived from analyzing mobile phone data, particularly Bluetooth signals, to predict job satisfaction and other organizational outcomes [17, 18]. We build on these findings to investigate if we can use location traces to distinguish individual differences in workgroup activities and analyze social identification. These questions remain unclear in the present literature.

3 FIELD STUDY

The following describes in detail our user study and data collection process. We summarize the key details of this study in Table 1.

Duration	81 Days, Fall semester
Total Users	76 (39 M, 37 F)
Active Users	62 (34 M, 28 F)
Age	19-25 (mean=22, median=20)
Year	Sophomore
Major	Information Systems (IS)
Grade	1.64-3.93 out of 4.0 GPA (mean=2.86, median=2.81)
Project	Software Engineering (SE)
Data Collected	Demographic survey of campus activities SE project schedule *Social Identification* (FISI) assessment (x5) Stress (PSS-4) assessment (x27) Semi-structured interview (x2) Mobile phone WiFi MAC address

Table 1. Summary of our primary participants and types of data collected.

3.1 Method, Participants, Environment

Our study employed an 81-day longitudinal design. 76 Sophomore college students from a Software Engineering (SE) cohort enrolled for the study over a full Fall semester between August to December. Two students dropped out, while 12 students were omitted due to insufficient participation (explained in Section 3.3). Students received up to US $30 compensation. We encouraged group and active participation by offering an additional prize of US $76.30. All participation was voluntary. Our study was approved by the university's Institutional Review Board (IRB).

Over the study, students assessed their workgroup identification from working in their SE group. They participated in additional assessments for stress and attended two semi-structured interviews to share accounts of their work practices. Surveys and interviews were intentionally scheduled during critical project milestones, as shown in Table 2.

Students supplied their mobile phone MAC address for us to collect WiFi data of their mobile connections within and around campus. Finally, they provided us with access to their project

Event Description	Period (in Day)
T_1: Collect assessment #1	3
M_1: Release of project specifications	04 - 08
T_2: Collect assessment #2	15
M_2: Team Goal	25 - 29
T_3: Collect assessment #3	36
Break week – Conduct interview #1	39 – 43
M_3: User Acceptance Test (UAT)	53 – 56
T_4: Collect assessment #4	57
M_4: Final deliverable	74-78
T_5: Collect assessment #5	75
Semester end – Conduct interview #2	77-81

Table 2. Data collection periods were timed before and after critical SE milestones (shaded rows and indicated as M#).

team schedule, a standardized graded material that logs all SE tasks in detail (i.e., the type of task, percentage progress of the task, location, duration, leader, member attendance).

Software Engineering (SE) Course. All students were enrolled in the Software Engineering (SE) course during the semester. SE is a mandatory course for students majoring in Information Systems (IS) and is uniquely suited to investigate workgroup identification for several reasons. First, students must work in pre-assigned teams of four to five, balanced across gender, nationality, and academic performance. Second, the curriculum places heavy emphasis on project work, requiring all technical implementations to be fulfilled through pair-programming sessions. Third and finally, students must exercise strict project management practices by maintaining detailed logs of all task involvement, including when and where these activities took place, who led and attended. The project management log is a graded component. Good project management practices entail the same amount of effort across the team, well-planned tasks for different project milestones, and a fair distribution of workload between and among every member. Senior students anecdotally cite SE as a stressful course because of its heavy workload and collaborative nature. We validated this anecdotal evidence during our study, with at least 50% of our participants reporting SE as their primary source of stress. Unlike other courses, SE demanded consistent work commitment throughout the semester.

3.2 Data Collection

Four-Item Social Identification (FISI) Survey. FISI is anchored on four questions: "I identify with *my SE-wokgroup*", "I feel committed to *my SE-workgroup*", "I am glad to be in *my SE-workgroup*" and "Being in *my SE-workgroup* is an important part of how I see myself", on a scale of 1 (strongly disagree) to 7 (strongly agree) [16, 32, 38]. There is no validated coding to the scoring. However, a high score indicates a stronger sense of belonging (N=62, median=21.5, mean=21.03, max=28, min=9, SD=4.09).

Perceived Stress Scale(PSS-4). Like workgroup identification, stress is associated with both negative and positive outcomes. In this study, we measured stress using the PSS-4 scale [13], with higher scores suggesting greater levels of stress (N=62, median=8, mean=7.66, max=16, min=1, SD=2.35).

Semi-structured Interview. Participants attended two interview sessions at midpoint and study's end. Sessions were guided by the questions stated below to understand how team experiences affected their perceptions of being part of the group or stress arising from SE.

(1) What is your main source of stress and experiences of critical (positive or negative) team events? Elaborate.
(2) Did any of these events change the dynamics of the team, and if so, how did it emotionally affect you?
(3) If applicable, were problems in the team solved and how did the group communicate?

WiFi Mobility Data. Participants were instructed to have their mobile phones connected to the campus WiFi at all times. They supplied the WiFi MAC address so that location and group data could be extracted from our system. We grouped MAC addresses of participants belonging to the same SE group to track group interactions between and among members. In total, we collected ≈310,000 pre-processed location data points and ≈50,840 pre-processed group data points for all 62 participants each day. This quantity is equivalent to an average of 7 hours of location and 2 hours of group data per participant (310,000/62 * 5 seconds and 50,840/62 * 5 seconds). Participants were altogether observed to have visited 96 different study room locations. We further explain how WiFi events are localized to specific rooms in Section 5.1.

3.3 Identification Labels

Fundamentally, social identification emphasizes an individual's conformity to the group. Specifically, conformity to prototypical behaviors between team members is increased by individuals' agreement and perceived similarities with their group [1, 3]. With conformity, individuals are more inclined to provide social support to one another. However, polarization can occur as members often exhibit differences in views and experiences [48]. Individuals displaying extreme differences are more likely to feel isolated and not receive/offer social support.

Building on prior arguments, our interest is to distinguish individuals with *conformed* from individuals with *polarized* identification. Recall, however, that in Section 3.2, FISI assessment makes no distinct coding of its scores except that a low score implies an individual feeling less identified with the team. In contrast, a high score implies an individual feeling more identified with the team. However, both low and high identifiers may be outside the group's norm. We believe that low-scoring individuals whose identifications do not conform to the group's norms are more likely to feel excluded from their group. Prior work argues that these individuals are at risk of stress and depression due to the lack of social support [14, 42]. Similarly, high-scoring individuals whose identifications are polarized from the group's norms are more prone to stress from over-commitment toward their work [36].

It is important to note the key assumption underlying our analysis is that students will report fluctuating identification during the 'forming' and 'storming' stages. However, identification will eventually stabilize towards (the end of their collaboration in) the 'norming' and 'performing' stages [49]. Polarized identification, regardless of high or low FISI score, is likely problematic to the group performance during the 'norming' and 'performing' stages.

To simplify the multilevel nature of identification, we present a heuristic to distinguish individuals with *conformed* from individuals with *polarized* identification. We interpret participants who scored within ± 1 SD (SD=4.09) of the mean (mean=21.03) to perceive a somewhat *conformed* identification among all other students in the sample. Participants who scored below or above the threshold are assessed as increasingly different (polarized) from their working peers in the level of identification.

The distribution of labels at the end of this grouping is 227 *conformed* (73%) and 83 *polarized* perception labels (27%) over 5 time periods. As we will later discuss in Section 5.4, we handle the poor prediction results of using an imbalanced dataset by tweaking the decision threshold [59].

4 CROSS-LAGGED ANALYSIS

We begin by investigating the effects of workgroup identification on students, including stress as a measure since SE is anecdotally cited to be a highly stressful course. Given our study's longitudinal nature, we conduct a cross-lagged analysis over five-waves from T_1 to T_5 and supplement qualitative evidence to explain our results.

4.1 Method

We utilize the IBM Statistical Package for the Social Science (SPSS) AMOS [37] version 26.0. This procedure allows us to investigate the stability and cross-lagged effects of both constructs over time [30]. As shown in Figure 1, we test for a model, M_{CL}, that controls for stability across time and cross-lagged paths from identification at previous time points to stress at future time points.

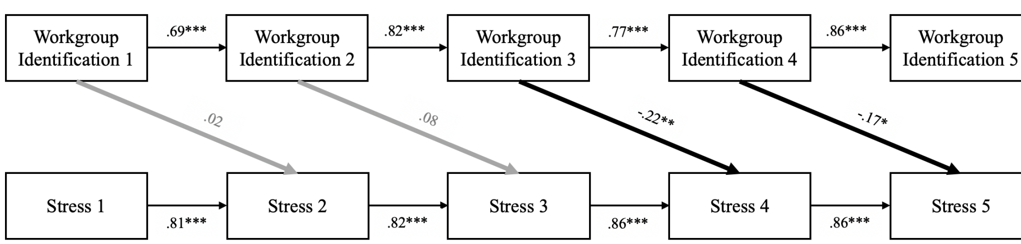

Fig. 1. Standardized stability and cross-lagged coefficients of M_{CL}. Pathways indicated in gray illustrate non-significant coefficients. *p<.01, **p<.05, ***p<.001.

4.2 Results

Pearson correlations and descriptive statistics (mean, SD) for all variables are shown in Table 3. The observed correlations of identification and stress, separately, across different time points

Variables	WI.1	WI.2	WI.3	WI.4	WI.5	S.1	S.2	S.3	S.4	S.5
WI.2	.69**									
WI.3	.61**	.82**								
WI.4	.50**	.70**	.77**							
WI.5	.50**	.66**	.72**	.86**						
S.1	-0.18	-.30*	-.27*	-0.24	-0.15					
S.2	-0.11	-.30*	-.26*	-0.23	-0.19	.81**				
S.3	-0.20	-.27*	-.27*	-.28*	-0.24	.70**	.81**			
S.4	-0.16	-.29*	-.26*	-.25*	-0.24	.65**	.77**	.87**		
S.5	-0.01	-0.17	-0.14	-0.22	-0.22	.63**	.73**	.79**	.85**	
M	21.23	20.71	21.03	21.13	21.11	7.26	7.6	7.79	8.24	7.5
SD	3.8	4.54	4.52	5.02	5.13	2.4	2.24	2.26	2.4	2.64

Table 3. Pearson correlations, means (M) and standard deviations (SD) of variables workgroup identification (WI) and stress (S) for five waves. *p<.01, **p<.05.

demonstrate strong and significant associations (r > 0.5). On the overall, the patterns of correlations between identification and stress are in an expected direction whereby a higher identification score is associated with lower stress score. Nonetheless, these correlations (r = 0.10 to 0.29) are small. It is important to note that the correlations presented here did not adjust for any other factors as we later present in the cross-lagged model.

Figure 1 illustrates the standardized stability and cross-lagged coefficients between identification and stress. Results from the autoregressive effects for both variables demonstrate lesser variance and more stability from T_1 to T_5. We can assume little differences between our participants from the large coefficients (r = .69-.86). Hence, results are not biased of any unobserved traits. The goodness of fit statistics for M_{CL} are Confirmatory Fit Index (CFI) whereby the cut-off for good fit is defined as $\geq .90$, Root Mean Square Error of Approximation (RMSEA) $\leq .08$, and p-value > .05.

Overall, M_{CL} ($\chi 2$=30.85, DF= 30) demonstrates a good fit to the data. Fit statistics are CFI = .998, RMSEA = .021 and p > .1. The correlations for identification at T_1 and T_2 to the following weeks of stress indicate positive (but small and non-significant) association − high identification score is associated with high stress score. In contrast, the correlations between identification at T_3 and T_4 and stress indicate negative association (black solid lines). While the associations are small (r = -.22,-.17), it is unlikely these relationships have arisen by chance.

We understand from prior studies that workgroup identification is linked to social support and affects one's stress in so many ways [24]. For example, the positive associations at T_1 and T_2 could suggest the possibility of over-commitment toward work arising from an increasing sense of obligation to perform successfully for the team [36], but this association is small and insignificant. On the other hand, the negative associations at T_3 and T_4 could indicate more positive consequences on individual well-being, especially in the presence of team support [24].

The reasons remain unclear up to this point. This analysis also does not prove a causal relationship between identification and stress, although we can render it probable. In what follows, we provide qualitative insights from our interview sessions.

4.3 Qualitative Insights

Main Stressor. More than 50% of our students (33) reported SE as their primary source of stress. Additionally, 14 of these students expressed negative appraisals with their team members. These experiences are commonly attributed to feeling devalued for their efforts. Students who believed their team did not make a concerted effort to meet their standards expressed a strong sense of obligation to lead. While 17 students did not explicitly state SE as the primary stressor, they had confirmed that academic factors, including juggling multiple courses along SE, made up a large part of their stress during the study.

Stereotypes of Competence. It quickly became apparent to us that students adopted social categorizations of *A/B/C-coders* based on their technical abilities, which manifested through a prerequisite course. Our findings support [34] that social categorization is the first step to social identification, as it inherently creates comparisons between and among team members. This comparison was regrettably punishing to the less technically-abled.

For example, two *C-coders* broke down in their first interview from overwhelming stress on SE, particularly from a relationship conflict with a team member. One student expressed, "the *A-coder* values someone with a higher IQ." Thankfully, they later shared (in the second interview) about receiving more social support from other members, especially in resolving disagreements with the *A-coders*. In contrast, *A-coders* were valued for their technical abilities across all teams. In most cases, *A-coders* took the lead even though the project required alternating leadership at every milestone. Others typically chose to maintain a subservient relationship with their leaders, suggesting: "As long as we stay on [*A-coder's*] path, the group work will be fine. So I stayed passive."

Negative Appraisals of In-group Members. We learned two very distinct patterns of *A-coders*. First, *A-coders* generally scored high on identification. They worked well with team members to achieve their goals and respect each other's contributions. However, cases of burnout were especially evident in the peak period of pair-programming, between T_3 and M_3 (see Table 2). There were more disagreements reported during this time, which caused higher stress to teams. However, these disagreements were somewhat spurious and never personal. Naturally, the work experiences became less stressful after M_3, when students got through the storming stage and grew more comfortable with their roles and responsibilities [49]. Most students also expressed a common sentiment that they had to work together by M_4 to perform for the final deliverable.

Unfortunately, we learned of a small group of *A-coders* whose work incivilities were tolerated. Other students remained stressed from mostly coping with the technical demands, but it was common for the *C-coders* to feel less identified from being disrespected. One student (P4) said, "I am the weakest in the group. It was quite shocking the way I was being treated [by the *A-coder*], and I do not dare to voice out my opinion." Another student clarified, "Scolding became [*A-coder's*] common practice on [our] Telegram group chat. Messages were sent in caps, and [he used] coarse language." Notably, for three students, they struggled with personal attacks by their *A-coder* leaders until the end of the project.

Conclusively, our analyses inform the complex influence of identification on stress. Higher identification is associated with lower stress, albeit in the later stages of the project, T_4 and T_5. We learn that distinct *identities* (*A/B/C-coder*) played a significant role in the students' team experiences and how much they viewed themselves as being a part of the group. The dysfunctions in leadership, communication, and teamwork distribution help explain some of the most damaging effects of workgroup identification, leading to individual stress in students.

5 DIFFERENTIATING IDENTIFICATION WITH MOBILITY PATTERNS

In what follows, we clarify how we assess identification through technological means. Figure 2 illustrates our processing pipeline. We briefly describe the critical sub-components used to acquire WiFi data and explain how features were extracted to build a binary classifier for identification.

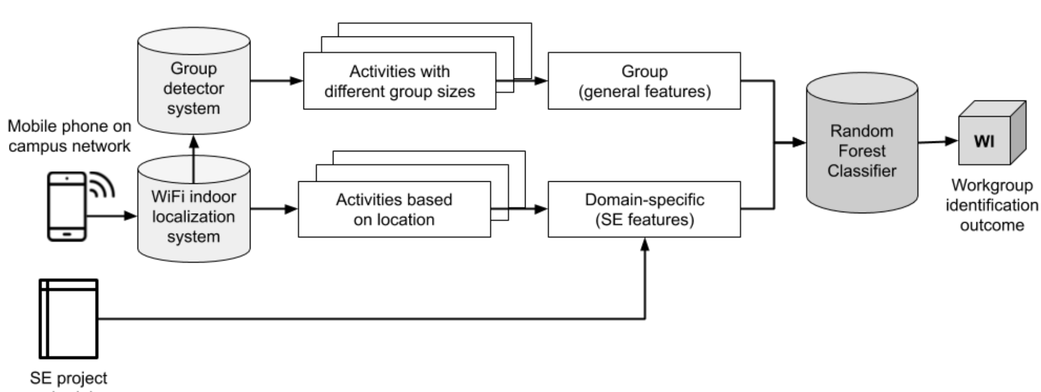

Fig. 2. Overview of our system in three parts: (1) location data sensed from the campus WiFi infrastructure, (2) preprocessing steps to extract mobility features and (3) a classification model for identification (WI).

5.1 Key Sub-components

Passively-sensed Location Data: Location data is sensed passively from our campus WiFi infrastructure, composed of two fully operational sensing systems in our university (since 2013) to collect our participants' location information. The first is a WiFi indoor localization system, which computes a mobile device's position using *reverse triangulation* as a reasonable proxy for human location [45]. Our deployment also included multiple phases of WiFi fingerprinting areas of interest to translate location coordinates into landmarks such as group study rooms and seminar rooms. Second is a group detector system, which leverages the location information from the first system to cluster devices into logical groups when they travel together [44]. Our system was tested accurately between three to eight meters to localize one or more devices to a specific room. It is important to note that the development and evaluation of the key sensing mechanisms are not part of our study, and accuracy numbers would change significantly in different environments. By default, the information from these systems is anonymized using a one-way hash function. Hence, users must consent to disclose their device MAC address for their location traces to be identified. It is important to note that these systems were evaluated in previous work, and they may produce erroneous data that could impact the results of our study.

5.2 Feature Extraction

Location data is sensed every five seconds and resulted in fluctuating signals, especially when users transit with their connected devices to other locations. A final location is determined based on the *mode* of a five-minute sliding window. Missing values resulting from unconnected devices were no more than a few days. Hence, we pre-processed the data by applying AKIMA interpolation, which affects only the curve of neighboring data points [2]. Next, location data is mapped to the most likely activity at that location based on several heuristics. First, we manually assign common activities to each campus facility (e.g., {"location":"<building name>_<level number>_Seminar Room3.2", " activities":["seminar", "study", "transit"]}). Second, the activity is further determined based on a simple decision-making statement of time and day (e.g., lectures take place at fixed time slots on weekdays). A SE group task is verified against the students' project schedule to overwrite a previously assigned activity. Finally, time thresholds for general campus routines are based on averaged samples among our participants, described in Section 3.

Domain-Specific and Group Features. Once activities are assigned to location entries, we extract features of students working in different group sizes. Specifically, the *Group* set captures activities carried out in different group sizes. For example, "solo" if a device is detected alone at an area, "small-group" if a device is amongst two to five collocated mobile devices. Separately, we extract *Domain-specific* features that only represent SE tasks. Recall in Section 3.1, we explained that as part of the course requirement, students must maintain a project management log of the tasks completed in groups, including where the event took place and who attended the event. We utilized this log to filter only location events relating to SE. The following describes all our mobility features. Feature names and information values are provided in Section 5.4, Table 4.

(1) *Amount of time spent on <SE activity>*: Activities include pair-programming, knowledge sharing, meetings, and schedule discrepancies. All except for schedule discrepancies are tasks logged in the project schedule. Schedule discrepancies reflect contradicting mobility patterns between logged events and actual user locations. We name this set as *Domain-specific* features.
(2) *Amount of time spent with <group size> and Number of times with <group sizes>*: Group sizes include solo and small-size. Solo implies no collocated devices. Small-size is two and up to

five collocated devices, a typical formation for our SE student groups. We name this set as *Group* features.

5.3 Exploratory Feature Analysis

Here, we draw comparison in mobility patterns between students of different identification groups (see Section 3.3) by (1) plotting the empirical cumulative distributions functions (ecdf) of features from T_1 to T_5, as in Table 2 and (2) conducting Kolmogorov-Smirnov (KS) non-parametric test.

Figures 3 and Figures 4 plot the ECDF of students' mobility patterns for schedule discrepancies and pair-programming. The distributions compared the feature in the first half of the semester, T_1, T_2 and T_3 (left plot), and at semester end, T_4 and T_5 (right plot). A group of students with conformed identification is indicated in the blue line and polarized perception in the red line. Note: we only present findings that indicate trends towards significance.

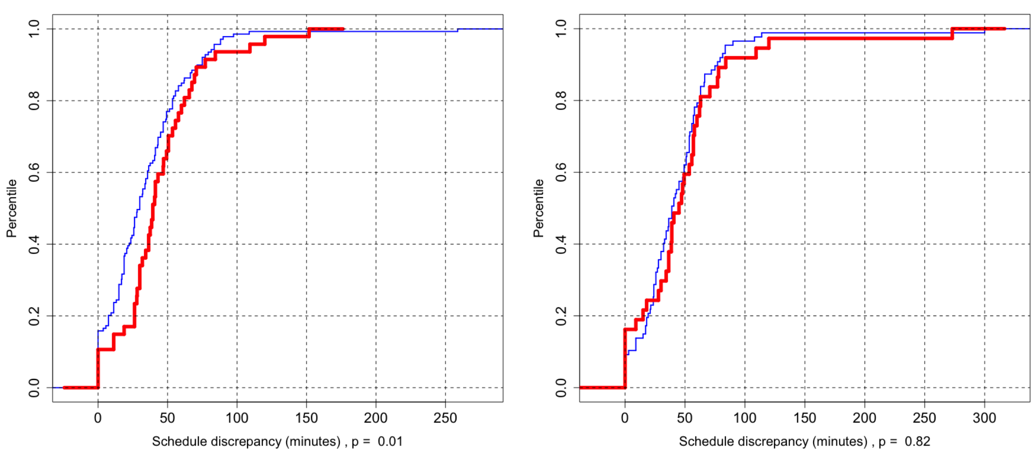

Fig. 3. Empirical cumulative distribution of the total duration in schedule discrepancies. Samples of students with conformed identification is represented in blue and polarized identification in red. Trends are plotted at two different periods, start of the semester (left – T_1, T_2 and T_3) and semester-end (right – T_4, T_5).

We observe significant differences (D-statistics = .28, p-value = .01) between both groups from T_1 to T_3. Recall, schedule discrepancies record the time differences between students' actual locations and reported locations in their project schedule. As shown in Figure 3, about 20% students with polarized identification spent lesser time on SE (approximately 30 minutes) than their actual reports between T_1 to T_3. Overall, about 95% of students with polarized identification recorded approximately 100 minutes of schedule discrepancies. The trends are relatively similar for both groups from T_4 to T_5 (right graph).

Next, we note the slight differences (towards significance, D-statistics = .20, p-value = .11) in the amount of time spent on pair-programming from T_1 to T_3, shown in Figure 4. For 60% of students with polarized identification, they had spent approximately three hours on pair-programming tasks – twice the duration recorded by other students. On the contrary, the trends at semester end (right graph) are relatively similar for both groups of students. Specifically, 60% of students with conformed identification have increased their pair-programming activities to three hours. As previously discussed in Section 4.3, we learned that the most critical pair-programming requirements must be met before T_3.

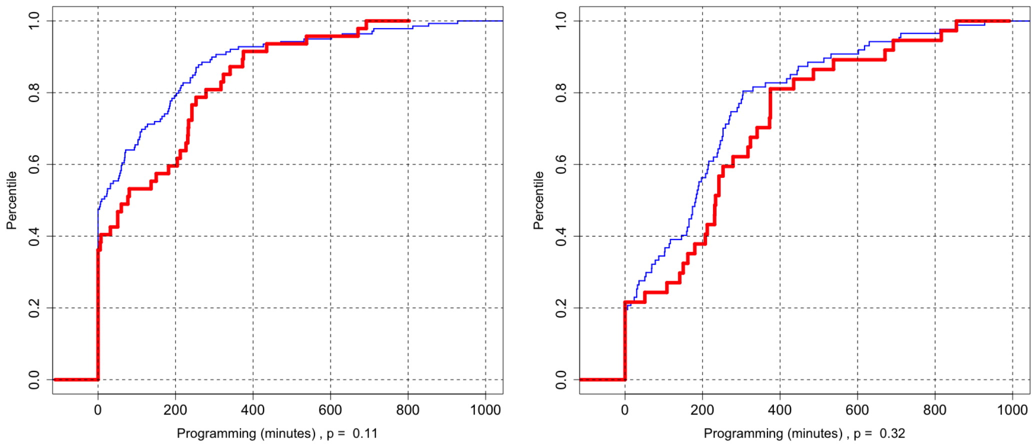

Fig. 4. Empirical cumulative distribution of the amount of time spent in pair-programming sessions. Samples of students with conformed identification is represented in blue and polarized identification in red. Trends are plotted at two different periods, start of the semester (left – T_1, T_2 and T_3) and semester-end (right – T_4, T_5).

While we did not observe significant differences in other SE group tasks, our analysis discovers an interesting relationship between schedule discrepancies and identification, which would otherwise not be reflected in project schedule. It is important to note that the KS test only compares the overall distribution, which might ignore significance in specific events.

5.4 Classifying Identification

Performance Metrics. Evaluation of our classification model is based on the following performance metrics; the area under the receiver operating characteristic curve (AUC), accuracy, true positive rate (TPR), and true negative rate (TNR). We perform a group 5-fold CV, splitting participants into 80-20 (%) for training and testing; that is, 50 participants exclusively for training and 12 participants for testing.

Dataset. We utilize features described in Section 5.2. Over an 81 day period, we aggregated features at critical time points corresponding to Table 2 (Day 3, 15, 36, 57 and 75). Each tuple consists of $[x_{a\_t1...tn}, x_{b\_t1...tn}, x_{c\_t1...tn}, y]$, where x_a to x_c represent different mobility feature, from T_1 to T_5, and y is a workgroup identification label, *0: conformed* or *1: polarized* identification.

Classifier Selection. Classifying social identification through machine learning techniques is the first of its kind; no prior work suggests which algorithm works best. Instead, published works that use location data to solve binary classification problems (not specific to social identification) have used algorithms such as Support Vector Machine (SVM) and Random Forest (Random Forest) [11, 20]. Figure 5 plots the AUC value from our 5-fold CV using SVM (left) and RF (right). Overall, using RF achieved an AUC = 0.88 on average, significantly outperforming SVM (average AUC = 0.62, p=.01). This metric is most useful for us at this stage in deciding the best classifier moving forward.

Feature Selection. Table 4 summarizes the Information Value (IV) and the mean Dropout Loss (DL) for each feature. IV measures the strength of the relationship between a feature and the identification outcome [39]. Having a higher IV indicates stronger predictive power. On the other

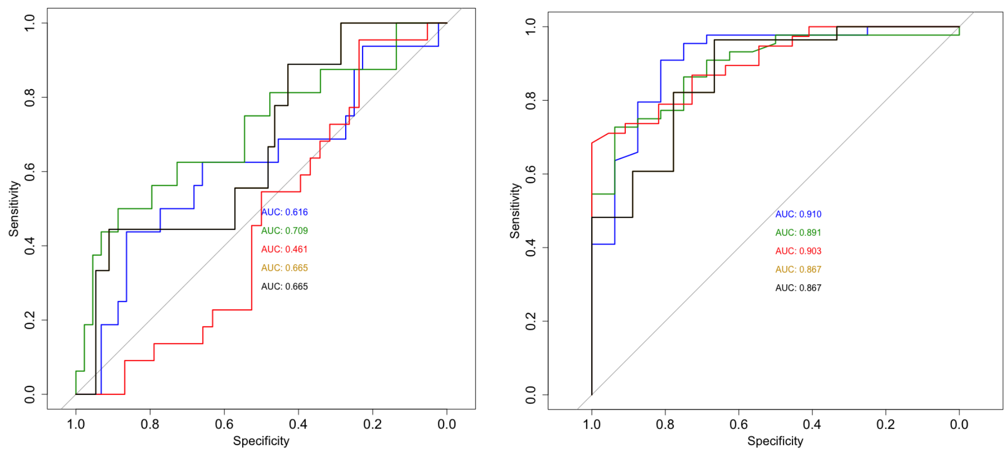

Fig. 5. The AUC values from 5-fold CV using Support Vector Machinee, SVM (left) and Random Forest, RF (right). RF significantly outperforms SVM at p=.01 level.

Type	Features	IV - PP	DL
DS	amount of time on schedule discrepancies	0.24 - medium	78.43
G	total amount of time with group	0.22 - medium	103.15
G	number of times with groups	0.19 - medium	84.41
G	number of times with small-size groups	0.15 - medium	82.14
G	number of times solo (group of 1)	0.14 - medium	93.05
DS	amount of time on pair-programming	0.10 - medium	73.57
DS	amount of time on knowledge sharing	0.05 - weak	75.99
DS	amount of time on meetings	0.03 - weak	69.33

Table 4. Summary of Information Value (IV), Predictive Power (PP) and mean Dropout Loss (DL) for all *Domain-specific* (DS) and *Group* (G) features, sorted in order of highest to lowest IV. Top features from using a RF classifier are highlighted.

hand, DL tells us how much loss is incurred from excluding the feature. All features are useful for prediction (no IV was less than 0.02), but none achieved strong predictive power.

While IV offers insights into the predictive powers of mobility features, feature selection using an RF classifier typically follows a recursive feature elimination (RFE) process to eliminate highly correlated predictors in the training set and benefit from post-hoc pruning of less important variables. The top five features from RFE are highlighted in Table 4. This process resulted in all *Group (G)* and *Domain-specific (DS)* features being used.

Threshold-moving. While we achieve a 0.881 score for AUC, the accuracy is slightly below 45%; this is an expected result (low TPR and high TNR) since our dataset is highly imbalanced with less than 30% students identified more differently than others. We adopt a simple cost-sensitive method in class imbalance learning of threshold-moving, which does not interfere with our AUC value [59]. The prediction threshold is shifted between 0.5 to 0.1 as shown in Figure 6, and we achieve optimal accuracy of 78.90% at threshold set to 0.2. We call this model, $\boldsymbol{Model_{WI}}$.

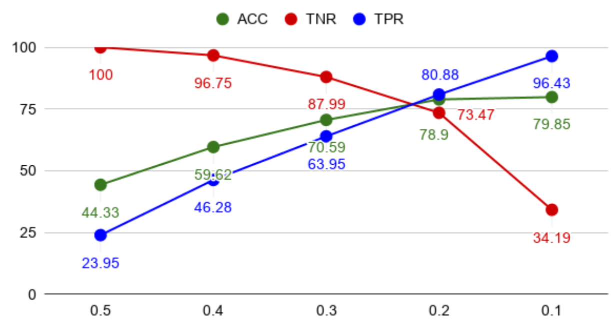

Fig. 6. The change of decision threshold from 0.5 to 0.1 shows improvement in TPR on an imbalanced dataset.

	fold-1	**fold-2**	**fold-3**	**fold-4**	**fold-5**
ACC (%)	83.33	81.67	78.33	76.92	69.23
TPR (%)	90.91	81.82	84.21	78.57	68.89
TNR (%)	81.25	81.25	68.18	66.67	70.00
AUC	91.90	91.60	90.80	85.20	85.20

Table 5. Results from a group 5-fold CV, where 12 participants were tested on a model, $\boldsymbol{Model_{WI}}$, trained on 50 different participants.

Results. Table 5 tabulates the performance from testing $\boldsymbol{Model_{WI}}$ on a set of 12 participants over trained data of 50 different participants. As expected, our model is able to better determine students with polarized identification (21) than others (40). Out of 21 students, 12 were wrongly detected during T_4 and T_5. This outcome supports our understanding of how students' SE participation grew less and less distinguishable towards the final milestone. Recall, we found from our feature selection process that mobility features representing the amount of time spent on meetings, pair-programming have the least predictive power and dropout loss. Unfortunately, none of our features has a strong predictive power, which could significantly improve model performance.

The inaccuracy of $\boldsymbol{Model_{WI}}$ primarily affects four students in this study; three students with polarized identification were disregarded entirely. From a practical standpoint, our model performance can be better tuned to correctly predict these cases, prioritizing TPR and compromising TNR. This would result in our model to not neglect the potentially troubling cases and introduce teamwork interventions.

6 DISCUSSION AND LIMITATION

Our study's objectives were to understand how identification influenced students' workgroup experiences and if identification could be detected using mobility patterns. Here we discuss the implications and limitations of our findings.

6.1 Expanding Assessment for Social Interaction

Our results confirm workgroup identification as a fluctuating valuation from emotional influences with working peers. With an aim to assess identification differently from traditional forms, these findings inform our decision to detect identification using mobility features that represent students' workgroup practices. Our qualitative insights hinted at students holding different identification with subgroups within the team. For example, we learned of several *C-coders* who reported feeling less identified with their *A-coder* leaders than with others in the team. In contrast, A-coders tend to be more identified with group members of similar skill sets.

While analyzing subgroup identification in teams is not part of our investigation, we believe our approach could distinguish the finer granularity of identification. More precisely, the mobility traces of grouped devices (i.e., a collection of devices belonging to all students in one workgroup) can be divided into subgroups that, in actuality, would exist if a set of members are fractured as a result of students forming cliques or feeling alienated. We could develop a new metric of participation within a group by analyzing the amount of time an individual spends with different team members. Conceivably, this could enable us to identify leaders, followers or support-enablers. However, developing this metric would require us to distinguish students' workgroup formation precisely, ensuring the same form does not overlap with multiple courses. Such an approach could complement traditional mediums, accounting for the emergence of subgroups and friendship networks (among other variations) to provide a more comprehensive understanding of workgroup phenomena.

6.2 Interventions and Assessment for Team Performance

Now more than ever, education is centered on teamwork so students can learn how to capitalize on expertise and perspectives from others. Nevertheless, team-based learning remains elusive and frequently disruptive. While every team has its unique blend of communication, we found that the most troubled teams would contain individuals who would characteristically display negativity in the form of 1) using profane language and/or 2) leaving the chat group prematurely. One student clarified, "Scolding became [*A-coder's*] common practice on [our] Telegram group chat. Text messages were sent in caps and [he used] coarse language." When asked how affected groups dealt with belligerent members, they chose to maintain a subservient relationship with the *A-coder*. Our findings support Lampinen's argument that users divide their communication platforms into separate spaces to manage conflicting situations and perform self-censorship [31].

We believe introducing group-level interventions enabled by detecting polarized identification could act as a proactive mechanism to help struggling members with task delegation and support for one another. One possible intervention is integrating predictive behavioral capabilities into common online communication platforms to encourage and assist students in taking a more proactive approach towards demonstrating team support.

Our cross-lagged analysis shows significant associations between identification and stress, which most of our students expressed, was as a result of negative SE experiences. It is not surprising that these appraisals can be self-limiting and impede one's performance for the group. Understanding students' health and campus behaviors using mobile data is a growing area of research; however, it lacks the investigation of workgroup indicators to evaluate scholastic performance [29, 52, 53] on individual and group levels. On other fronts, interventions to repair conflict within the workgroup and improve productivity [28, 47] still lack behavioral markers to evaluate changing group dynamics and automatically introduce appropriate mediation. Our findings are a necessary first step in testing and supporting questions central to one out of many workgroup measures.

6.3 Key Sensing Apparatus

Our detection mechanism is fundamentally driven by WiFi indoor positioning system deployed on campus. Our technique is susceptible to compounding errors if these sensing mechanisms are not highly accurate. The WiFi indoor localization systems' performance also depends on environmental factors (e.g., the layout of the building, the number of access points installed and changing crowd density). While the research to improve the accuracy of indoor positioning mechanisms is still ongoing, we believe there is sufficient progress in assuming that sensing solutions such as ours will produce location data for different collaborative spaces accurately.

Our approach can be easily extended with prior techniques that use RFID, Bluetooth, infrared and audio sensors to measure face-to-face interactions and support nearby work areas such as a cubicle setting [8, 35, 57]. One limitation in close-range detection techniques is gathering a comprehensive set of behavioral markers when members are not within close range but remain in the same vicinity. For example, we learned that the amount of time on schedule discrepancies among team members is a useful predictor, revealing movements that contradict their work records. Combining these sensors could offer a complementary or holistic approach to infer teamwork interactions at different workplace locations. It is important to note that sensing at the workplace, in general, often presents privacy concerns. Data privacy compliance, particularly in professional workplaces, must protect employees from exploitation by penalizing/rewarding based on these behavioral markers.

6.4 Remote Workgroup Arrangements

In our proposed approach, we did not investigate off-campus and online work behaviors. These behaviors are growing increasingly common among workgroups, especially relevant in the current context (i.e., COVID-19 pandemic), where schools must shut down during a health crisis, yet learning continues. Analyzing locations of group members for workgroup identification is not suitable under such circumstances. Fundamentally, our feature space measures attendance and the amount of time spent on different tasks. We showed how these features could be utilized via mobility data. However, it is conceivable that similar features may be obtained from other data sources. A potential source is Git, an open-software repository that is commonly used in the software development culture and was, in fact, an educational resource among our student teams keeping records of their tasks.

In a different endeavor, Dabbish *et al.* examined team participation and commitment through text-based interactions in an online game and argued that communication is likely to increase one's commitment [15]. Our findings remain pertinent to examining identification using online communication platforms. For example, all teams maintained a Telegram chat group, primarily purposed to schedule meetings, delegate tasks, and resolve conflicts. While analyzing commit logs and text messages were not part of our work, research dedicated to using Git and other communication platforms to assess team collaboration and support teaching [9, 21, 22] can be extended to investigate identification.

6.5 Model Generalizability

Our sample size of 62 students requires us to investigate these results with a more extensive set of student workgroups. The *Domain-specific* features used to build $\boldsymbol{Model_{WI}}$ required validations from a project schedule, which working teams might not always maintain. Besides, most courses allow for flexible learning spaces and collaboration with their peers. It remains a challenge to automatically sense student workgroups without verifying the project schedule provided by the course. Our study includes analyzing ad-hoc teams and thus requires evaluation for long-term teams. While our sample selection for this study is biased to SE students, many characteristics are not dissimilar to workgroups in education and professional environments. These characteristics include working with strangers, varied skill sets, and demanding project deadlines.

7 CONCLUSION

The interplay between individuals and their social structure has grown increasingly crucial for technologies to adapt to human behavior complexities. Prior work related to social identification has argued to be a valuable contribution to Systems research [43]. In this paper, we analyzed the temporal dynamics of workgroup identification among college students. We provided qualitative evidence to understand social identification influences on their stresses and analyzed students' group participation from generating mobility patterns sensed directly from a WiFi infrastructure. Then, we proposed an approach that could identify group members who are more likely to identify more differently than their peers. We conducted a field study over 81 days to demonstrate its feasibility, with 62 undergraduates all enrolled in the Software Engineering (SE) course. Our solution, $\boldsymbol{Model_{WI}}$, detects identification every two weeks and achieves an overall accuracy of 78%, 80% TPR, and 76% TNR. Conclusively, our findings point to a new research direction to assess identification, complementing existing methods for longitudinal analyses.

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