Higher Education Check-Ins: Exploring the User Experience of Hybrid Location Sensing

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A large body of literature is dedicated to understanding people's check-in behavior when they use location sharing services to pair their location with a venue, e.g., a restaurant, a park, etc. Check-in behavior in higher education settings, e.g., where students and instructors have academic purposes for check-ins, is under-studied. In this work, we explore how university students apply two different mechanisms, i.e., automatic and manual location-sharing services, to conduct check-ins for an academic purpose (i.e., students sharing their class attendance with their instructor). More specifically, a Bluetooth Low Energy beacon-based technology is applied to enable automatic class check-ins. We conducted two field trials with a total of 141 university students. Our findings showed that several social, technological, and psychological factors impacted the use of auto and manual check-ins. Feedback from the student participants suggested that future higher education check-in systems may need to consider the integration of check-ins for a variety of purposes.

CCS Concepts: • **Human-centered computing → Collaborative and social computing**.

Additional Key Words and Phrases: check-ins, location sharing, Bluetooth Low Energy beacon, hybrid sensing, automatic location sensing

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1 INTRODUCTION

The prevalence of smart phones and location-sharing services promote check-ins, where people post their location status by coordinating their location with venues such as restaurants, movie theaters, and shops [7, 109, 112]. Through check-ins, people can inform their friends of their location [63], disclose their personality traits [105], and exhibit their social lives, lifestyle, tastes, and self-presentation [104]. Users' check-in data can be useful in multiple ways. For example, Bannur and Alonso found that Facebook users' check-ins at popular venues like restaurants and movie theaters can be used to analyze people's temporal patterns and dynamics, thereby informing the design of new search experiences to help users meet their information needs [7]. Ying et al.

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illustrated that users' check-in behaviors can be employed to design systems for urban Point-of-Interest (POI) recommendations, such as for restaurants [41, 112].

However, little work has studied check-ins in academic settings, e.g., a higher education institution [55]. Prior HCI and CSCW research addressed a variety of check-ins, e.g., users may inform others of their visit to a venue or disclose their location for fun or other social reasons such as social capital [95]. Scholars examined motivations behind location check-ins [9], privacy issues [45], human mobility [22], users' location information needs [87], and inaccurate check-ins [109]. Nevertheless, check-ins for academic purposes in a college or university setting are under-studied [55]. Unlike many check-ins on social media platforms where one user shares his/her check-ins with many others who may not need the check-ins, when an instructor takes students' class attendance [95], there is an explicit inquirer (the instructor) who needs the check-ins of the senders (students).

In addition, prior check-ins used one location sharing mechanism, e.g., manually sharing the user's GPS location [18, 45, 66]. Recently, a leading proximity location-sensing technology, Bluetooth Low Energy (BLE) beacon, has been proposed to automate location sensing (e.g., for class check-ins [5, 27, 58, 74]). The technology is projected to be the key player in the industry [88, 102], because it provides location sensing with high accuracy, low cost and low energy consumption [32, 46]. However, there is a lack of user experience (UX) research and understanding of social implications of this location service. Most location-sharing systems applied only one location-sensing technology, and very few applied hybrid sensing solutions [43]; those that applied hybrid sensing approaches did not address user behavior (e.g., [68]).

To address this research gap, we designed and developed a hybrid location-sensing system for academic check-ins. We conducted field trial studies of two iterative designs of the system. The first design offers automatic location sensing with BLE beacons alone, and the second provides hybrid (both automatic, using BLE beacons, and manual, using either GPS or WiFi) check-in mechanisms. A total of 141 students from four classes participated in the studies, with each lasting two months. The hybrid sensing design received much higher adoption than the one that had automatic location sensing with beacons alone. Interviews with a total of 32 participants showed that several social, technological, and psychological factors impacted the use of auto and manual check-ins. For example, some student participants had misunderstandings of BLE beacons and had varied concerns about battery consumption depending on when they used the app. Some student participants shared that the availability of manual check-ins promoted their adoption of auto check-ins. The use of the check-in system also had unexpected social implications, e.g., some student participants used the system to check in to classes earlier in order to create a positive impression on their instructors. In addition, student participants expressed their desire to leverage the system that was originally designed for an academic purpose (i.e., taking attendance) for social purposes (e.g., getting to know their classmates better).

This work makes the following contributions to HCI and CSCW research. First, the work contributes the design and evaluation of a check-in system in a higher education setting, which fills the research gap of a lack of empirical research on check-ins in academic settings. Second, the study contributes user experience (UX) research findings about a hybrid location sharing design (with automatic location sharing via BLE beacons and manual location sharing using GPS or WiFi) and the social implications of its use within and beyond the higher education context.

2 RELATED WORK

In this section, we first present an overview of check-in literature. We then discuss check-ins in higher education settings. We proceed with two popular fundamental check-in mechanisms. Then, we introduce the rising popularity of Bluetooth Low Energy (BLE) beacon technology, a proximity based location sensing technology. We also address the differences between BLE beacons and other popular location sensing technologies. Finally, given the reviewed literature, we propose our research questions.

2.1 Check-ins

Check-ins are essentially about people sharing their locations. Instead of logging a geographic coordinate, a check-in is typically paired with a venue (e.g., a restaurant, a park, etc.) [22]. Scholars have been studying such behavior from different perspectives, e.g., addressing people's check-in patterns, where people conduct check-ins, e.g., [108], with whom they share locations, e.g., [23], why they do so, e.g., [51], issues with check-in data, e.g., [109] and how people's check-ins can be leveraged for building more intelligent systems, e.g., [62, 103].

Tang et al. proposed two ways of describing location sharing [95]. One way is to consider the size of the recipient group, where recipient size can vary from one-to-one [85, 94, 106], one-to-few [83, 89, 90], and one-to-many [63, 105, 109]. The other involves reasons of location sharing, e.g., purpose-driven (where a person's location is needed by others) and social-driven (where people share location because it is fun for them to do so or for other social reasons, e.g., social capital [95]). Tang et al. observed that purpose-driven sharing often involves one-to-one and one-to-few, and social-driven sharing is more aligned with one-to-many. However, the distinctions between the two motivations can be fluid.

Scholars found that the identity of the person who sent the request for location significantly influenced the others' willingness to check in [24, 60, 80]. For instance, people were willing to share their location when the receivers had close relationships with them, e.g., as spouses, friends, or family [24]. However, when co-workers and managers requested location sharing, people were not quite as willing to share [24]. Similarly, scholars found that participants would not reply to location requests from strangers, and they would feel comfortable sharing their location with their acquaintances who went through the trouble of asking [45]. In general, greater privacy concerns are associated with lower motivations of conducting check-ins [9, 51].

In addition, check-in data can be used to reflect the users' characteristics, preferences, and lifestyle [41, 103, 116]. For example, the distance of a location from a user's previous visits is an important factor in predicting whether she will visit a new location or not [103]. People's personal interests can also be inferred from friends [69], because people with common preferences are more likely to be friends [26]. However, a recent CSCW work also shows that advertising and promoting the locations of users' businesses and self-presentation can be primary motivations for users to generate fake check-ins [109].

In college and university campuses, location sharing can be both one-to-many (e.g., sharing one's location with others on campus to make friends) and one-to-one (e.g., helping instructors to take class attendance). In this research, we focus on one-to-one check-ins in a higher education setting. In the next section, we provide the background of check-ins in higher education.

2.2 Check-ins in Higher Education

Academic check-ins are suggested to be useful for both academic purposes and social engagement on campus [55]. However, location sharing systems used for academic purposes are under-studied. Mainly, location sharing is proposed to improve social interactions among students on campus [28, 113]. For example, location-based services are designed for current and prospective students to engage with their surroundings and each other [49, 50].

Collecting check-ins for academic purposes is a pressing need for many institutions, but it is not yet widely supported by location sharing services/systems. For example, class attendance is proven to have a positive impact on students' academic performance [65, 77]. Attendance records are often used by administrators or by parents to understand students' learning status [48, 77]. In the United States, according to the Federal Title IV funds policy, students who receive government financial aid but never attend class (i.e., students are absent for three consecutive weeks [99]) should be reported, as they may need to return their financial aid [76].

The attendance taking policy is mainly implemented by college administrators and registrar offices, though instructors are often relied on to report students' attendance. However, taking attendance can be a tedious and burdensome task for instructors. To relieve instructors from attendance taking, automated class attendance taking solutions, e.g., via face recognition [89] or by using a fingerprint reader [85], were developed. But these solutions can be expensive or take time to set up. Clickers, a two-way communication system that consists of a student responder and a computer receiver [29], or RFID-enabled card readers [79] are also used by students to check in to classes. However, these often require students to take time to participate. Campus WiFi networks were also proposed to automatically track students' locations[2]. However, in a recent study, it was found that Bluetooth-based technologies are better than WiFi for localizing students in a classroom, because Bluetooth consumes less smartphone battery power and is more reliable than a WiFi signal [58].

Our work examines students' class check-ins using a beacon-based check-in mechanism with a variety of factors (e.g., class attendance behavior, phone platform, and time of use) involved. In the next section, we will present major check-in mechanisms.

2.3 Check-in Mechanisms

The CSCW community has extensively studied location-sharing systems [47] where two main check-in mechanisms are applied, i.e., manual and automatic [43].

The manual approach requires users' explicit participation but also gives users more flexibility by allowing them to decide when to share data and how privacy mechanisms are to be set up each time [59]. The manual approach is often used when users explicitly share their GPS location (e.g., [94, 113, 114, 117]). The automatic approach, on the other hand, does not require users' explicit participation; it leverages sensors on users' devices whenever changes (e.g., changes in geographic location) are detected [59, 92]. A variety of applications apply the automatic approach when they need to collect user data contiguously for a long time and when it is difficult to maintain constant user participation [98, 111, 113]. Automatic sensing is particularly valuable to leverage users' existing itinerary without requesting users to share information, e.g., tracing a bus rider's trip after the rider gets on a bus [119]. Automatic check-ins may raise privacy concerns where people worry about being spied on [45].

Scholars suggest combining these two approaches [40, 43], such that the quality of the collected sensor data through the automatic approach can be improved with the explicit participation of human intelligence [40]. However, prior systems mostly applied only one of the sensing approaches [37, 59, 92], and very few location-based systems applied hybrid sensing solutions [43]. Those that applied hybrid sensing approaches, e.g., [1, 30, 115], either did not study user behaviors (e.g., [4, 68] or cannot support automatic proximity-based location sensing [35, 40].

Our system implemented two mechanisms and the empirical work allowed us to study the relationship between the two location-sharing mechanisms. In the next section, we present the BLE beacon technology that is used to enable the automatic sensing mechanism and briefly compare it with other location sensing technologies that can be used to support manual check-ins.

2.4 Bluetooth Low Energy (BLE) Beacon

BLE beacons, e.g., [32, 46], are small devices that only broadcast Bluetooth signals without receiving signals; each beacon has a unique identifier. If a user's smart phone installs a mobile app that can sense the Bluetooth signals and can recognize the unique identifier (knowing where the beacon is installed), then when the user moves in the area covered by the beacon's signals, the location of the associated beacon can be used to estimate the location of the user.

Unlike GPS [6, 19] or WiFi [78, 81, 101] which may provide user location in terms of latitude and longitude at a given moment, BLE beacon technology [32, 75] is used to sense whether a user is close to a location where the beacon is installed. GPS is often used for outdoor location tracking [72, 100] but has poor accuracy for indoor localization. Using WiFi for indoor localization requires either prior knowledge about Access Points or a fingerprint map with complicated matching algorithms to improve the accuracy of the location-sensing [39, 106].

Compared to GPS or WiFi, BLE technology has several benefits for indoor localization, including: low power consumption; short-range indoor sensing [67] with high accuracy; better smartphone support (since Bluetooth is widely supported by different phone models); and low cost in terms of the expenses for required hardware and system design for initial set-up and system maintenance [61, 86, 118]. For example, the power consumption of smart devices is lower for BLE beacons than for WiFi [34]; Bluetooth is shown to be about 30% more energy efficient than WiFi [84] when transmitting occupancy data. System developers can adjust the signal strength of a beacon in order to adjust the sensing area ranging from one meter to 30 meters or more. To cover a large area, multiple beacons may be needed to increase the total coverage. Its automatic location sensing requires users to turn on Bluetooth on their phones and to share their location with the system [33, 73]. BLE beacons have been used in many venues, such as restaurants, museums, and airports [14, 17, 71]. They are also proposed to support students' classroom check-ins [5, 27, 58, 74].

Current studies of BLE beacons focus on addressing technology issues and proposing the application of beacons in different domains, e.g., stores, museums, and transportation systems [14, 17, 70, 71, 90], instead of understanding how users adopt them. For example, beacons can be used to promote in-store sales by continuously tracking customers' in-store activities and movements to identify popular areas [93]; to manage energy consumption by tracking the number of people in different rooms and adjusting the heating, ventilation, and air conditioning systems accordingly [25]; and to organize crowds at events by continuously detecting visitors' movements and sending them real-time push notifications about recreational and bus shuttle services [36].

However, people's attitudes towards beacon-based services were studied in interviews and survey studies e.g., [96, 110]. For example, interviews showed that some people had misunderstandings of beacon-based technologies, e.g., they thought beacons could store user information [110]. A survey study showed that, given sample situations for the use of the beacons, 40% of the respondents were willing to consider using beacon-based services [96]. None addressed how users used location-sharing services enabled by BLE beacons in real use settings, e.g., their adoption, challenges, and social implications. There is a lack of empirical investigation of BLE beacon-based check-ins.

In our work, we designed and developed a system that provides auto check-ins through BLE beacons and manual check-ins using GPS. Our field trials allow us to study the use of different check-in mechanisms in a higher education setting and to gain a better understanding of their social implications. This work, however, is not meant to justify whether attendance should be taken. Exploring how instructors may use the system differently is also not in the scope of this work.

Given the above literature, we focus on the following research questions:

- **RQ1:** *How do users check in to classes using the proposed hybrid sensing system that provides both automatic and manual location sharing mechanisms?*
- **RQ2:** *What are the social implications of using the proposed hybrid check-in system in the context of higher education?*

3 SYSTEM DESIGN

The design of the system evolved from automatic location sensing with beacons alone to offering a hybrid (both automatic and manual) location-sharing solution.

3.1 1st Design: Automatic Sensing Only with BLE Beacons

The first design of the system was informed by the related work we reviewed, where BLE beacons were adopted to automate students' class attendance-taking in classrooms [5, 27, 58]. Thus, the first version of the system only accommodated the automatic sensing approach via BLE beacons. The key features of an automatic attendance-taking system include: 1) a student should be able to log in to the app with a unique account; 2) once an instructor provides class enrollment information and an enrolled student uses the app for taking class attendance, the system will be able to show the instructor the class attendance of the student users; 3) in order to automate class attendance taking, beacons should be installed in the classrooms where the classes are given; and 4) if a student user chooses to automate his/her attendance by using the app, then the student's attendance should be automatically taken by the system upon arriving to the classroom at the lecture time.

To realize the above features respectively, we took the APIs provided by our university's IT department to connect to the university's identity server, such that only students who had official university accounts could log in to the app; their login accounts match with the roster information. We applied LTI (Learning Tools Interoperability) APIs to integrate our system with the university's Blackboard system–a content management system for learning that is officially used in the university–so that the roster information of participating classes could be loaded into our app. With the university's permission, we installed beacons by attaching them to classroom walls, and configured the beacon's signal strength to cover the classroom. We also developed both beacon-based Android and iOS apps and a tutorial for the check-in methods.

Figure 1 illustrates the system model. The app screenshot shows the interface where students can find their classes and check-in statuses. When a student first launches the app, the app sends a request to the attendance server to look up the student's class information. The server returns course title, time, instructor, and classroom location. If beacons are installed in any of the classrooms, the app will keep the beacons' identifiers locally. When the smart phone's Bluetooth is on and location sharing is allowed, the phone will sense the beacons. Once the app senses the student entering the area of a classroom's beacon, and it is about the lecture time, the app logs the student's attendance to the server. Instructors may have different ideas on when students can check in to a class. Our system allows students to check in 15 minutes before the class has started and 15 minutes before the class is over. This condition is included in the tutorial and can be customized to each class. Before attendance is taken, if the present time is within the check-in window, then the status is in orange, suggesting the student is not checked-in yet; otherwise, the status is grey signifying "unavailable." Once attendance is taken, the status will change to green, meaning the student has successfully checked in.

We also implemented a web app that displays students' first/last names, emails, check-in times and status by each class. The web view is not accessible to students, and can be used by instructors to look up students' check-ins. If a student does not want to use the app, his/her instructor can confirm their attendance through the web interface. In our field studies, the instructors applied the same practice, in that they opened up the web interface at the beginning of the lecture, and confirmed the attendance of those students whose attendance was not showing up in the web view. How other instructors will use the web app differently to check their class attendance is outside the scope of this work.

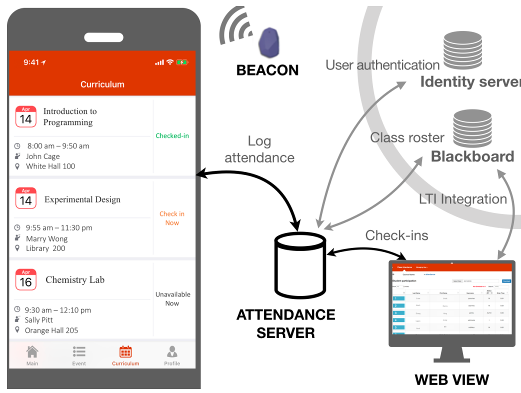

Fig. 1. An illustration of the system model. Our work focused on examining how student participants used the mobile app to check in to classes (class content displayed on the app screenshot was revised for anonymity). Students' attendance records are organized by each class and displayed in a web view, which is not accessible to students.

In summary, to enable automatic location sensing using BLE beacons, a student user needs to: 1) install the app; 2) log in to the student's university account; 3) turn on Bluetooth before going to the class; and 4) choose the option of sharing location with the app. Steps 1 and 2 are required, where student users typically do it only once before using the app. Depending on users' preferences, some students may choose to keep Bluetooth and location sharing on all the time; some may switch on and off the two settings at different times. The iOS and Android platforms provide location sharing options a little bit differently. For example, for the iOS platform, when the iOS app was first installed, there were three options from which users could choose: "Only While Using the App," "Always Allow," or "Don't Allow." In order to enable automatic location sensing where the app can detect when students walk into a classroom (by sensing signals of the installed beacon) without opening the app, participants were required to choose "Always Allow." For the Android platform, location sharing settings only had two options: "Share" and "No share." By default, Bluetooth and location sharing are not turned on; users have to turn on the required options, otherwise, students' attendance will not be automatically taken.

3.2 2nd Design: Hybrid Sensing (Auto and Manual Location Sharing)

We conducted a field trial of the first system design and found several non-technical issues (e.g., not keeping Bluetooth on, or not being willing to always share location with the app) that challenged the use of the beacon-based automatic sensing approach. Inspired by the idea of hybrid location sharing [40, 43], in the second system design, we added a participatory approach, where students did not need to keep Bluetooth on, nor did they always need to keep location sharing on. The hope was that those who did not want to use the BLE-beacon enabled approach to automatically check in to classes may use the manual approach, therefore increasing the adoption and usage of the app.

More specifically, when using the manual approach, students can share their GPS or WiFi location in classrooms to check in to classes. When a manual check-in is made, the app will validate the user's location by calculating the distance between the student's reported location and the location of the classroom. Therefore, this manual approach still requires users to share their location at the moment of clicking the check-in button. We do not consider automatic indoor localization (constantly sampling location in the background) using GPS or WiFi, as it drains battery significantly and GPS and WiFi have low accuracy for indoor localization [44, 53]; having students share their location upon arriving to the classroom when the class starts can alleviate the concerns.

If a student plays with the system by trying to check in from another place, then the app will reject the check-in request and pop up with an alert: “you are too far from the classroom.” In the field trials, we set up a 30-meter threshold value based on the size of the classroom, i.e., if a student’s location is not within 30 meters of the classroom, the student’s manual check-in request will be rejected. The threshold value can be adjusted to each room.

It is worth emphasizing that in the system design and follow-up field studies, we carefully considered privacy and ethics. The app does not sense participants’ location beyond the classroom or outside the lecture time. The app only collected student participants’ location when they attended the class with both the instructor and the participant’s consent to collect and willingness to share this piece of information with the instructor. Students had options for not using the app for attendance; using the app and consent is voluntary. Non-participants’ attendance was taken by the instructors manually as they did before using the app. Attendance was only shared with the corresponding instructor who took attendance to count participation points.

4 FIELD TRIALS

We conducted the first field trial with the beacon-only design during the Winter 2017 semester with an undergrad course in economics. After revising the design with the hybrid sensing approach, we conducted the second field trial during the Spring 2018 semester with another class of students who took the same undergrad course offered by the same instructor. However, because only 6% of undergraduate student participants in the spring class were Android users, we further recruited a class of graduate students who took a programming course, where 34% of participants were Android users. Note that the low ratio of Android to iOS student users was not surprising, as it was reported that college students use iPhones more than Android [3].

Table 1 provides an overview of the two field trials, including the design version of the system; when each study was conducted; and the number of students involved in the study. This project is approved by our university’s IRB.

Table 1. An overview of the field studies with different student groups and two instructors.

Check-in Mechanism	Time	Instructor	Student Group
Student Automatic only	Winter 2017	A	43 undergrad students of an Economics class
Students' Automatic & Manual Instructor Validation	Spring 2018	A	45 undergrad students of the same Economics class
		B	25 grad students of the morning database class
		B	28 grad students of the afternoon database class

4.1 Participant Recruitment

When recruiting student participants, we needed to make sure students knew that the research was not related to their courses and their decision whether or not to participate in the study would not impact their grades; these should only be determined by their instructors. Thus, we first sent out messages to our school’s listserv to seek instructors who would be willing to pass the recruitment script on to their students. We targeted classes where student attendance was already included as part of their final grades. In this case, only their attendance mattered to the grades; their decision whether to use the app (and participate in the study) and whether to participate in the follow-up interviews would not impact their grades. Using the app in each class was voluntary during the field study period.

In this work, we focused on studying students' usage of the app for taking class attendance instead of exploring how instructors would use the system differently or whether attendance should be taken. We targeted classes where the instructors had already established a practice of validating attendance information in the class (e.g., calling students' names) before using the app. We had two reasons for doing so: (1) we were able to collect real attendance records even if participants did not use the app to check in; and (2) using the check-in information provided by the app to validate student attendance would not create an additional burden on the instructors since they would validate attendance individually otherwise.

In total, 43 undergraduate students (one third were female) from an economics course voluntarily participated in the winter field trial; 45 undergrads (one third were female) and 53 graduate students (54% were female) participated in the spring field trial. Ages of the student participants varied between 19 and 25 and averaged at 20.

Seventeen enrolled students in the winter class and three enrolled students in the spring classes did not use the app to participate. Because participation was voluntary, we did not ask their reasons, though three of them told the instructors that their phones were too old to run the app. In each class, the instructors used the web interface to review/update students' attendance, so that those who did not participate in the studies and those participants who did not check in through the app could still have their attendance confirmed by the instructors.

4.2 System Log Analysis

Throughout the trial, the system was instrumented to reliably log users' behaviors (e.g., checking in to a class using a particular method) with corresponding timestamps. Information about their phone platforms (the iOS version or Android version of their phones) was also logged, as this information would be helpful to troubleshoot if they reported issues on their apps. We conducted system log analyses to examine which methods participants used to check in between different settings (e.g., varied phone platforms and times of use).

4.3 Interviews

After each field trial, participants were eligible to be invited to a one-hour semi-structured interview. The interviews were designed to understand participants' app adoption and usage and to collect their feedback about the system design. We tried to diversify the interviewees based on their app usage (auto and manual check-ins), phone platform (iOS/Android), and class session (morning/afternoon). Interviewees' app usage and phone platform were provided by system log analysis. Each participant was paid $5 for finishing one interview.

4.3.1 Interview Protocol. During the interview, we asked participants to describe the typical scenarios in which they used our app and their own understanding of how the system worked. Because the automatic sensing approach relies on Bluetooth and location sharing, we also asked our interviewees about their daily usage and perceptions of Bluetooth, as well as their settings of location sharing with this app and other social applications on their phones. For the hybrid-sensing design, in addition to the above questions, we asked why they chose either of the approaches. If they switched between the two sensing approaches, we asked them why and to describe the situations when it happened. Finally, we asked our interviewees if they had any questions, comments, or suggestions regarding this system.

A total of 12 participants (seven male and five female) from the first trial were interviewed after using the beacon-only design of the system, and a total of 20 participants (nine male, 11 female) were interviewed after using the hybrid sensing design of the system. We recruited participants until theoretical saturation was reached [20].

4.3.2 Interview Data Analysis. All the interviews were audio recorded with the interviewees' consent and all the audio interviews were transcribed. We conducted a thematic analysis [10] that was commonly used to analyze qualitative data. We immersed ourselves in the data by listening to the audio recordings and reading through the transcriptions multiple times. Two researchers jointly coded two interview transcriptions at the sentence level which resulted in an initial code book. Then the two coders coded the rest of the interview transcriptions independently using the code book. When they had new codes that were not included in the initial code book, they added the new codes to their own copy of the code book. When finished, the two coders compared their coding and discussed and reconciled any differences. In the end, the code book of the first study contained 77 unique codes, e.g., "bluetooth consuming battery," "bluetooth leaking information," "accurate check-ins," "turning off location sharing," and "checking in to classes early." The code book of the second study contained 139 codes, e.g., "preferring manual check-in," "preferring auto check-in," "started with manual," "security issues of Android phones," and "leaving early." The intercoder reliability of both interview studies was above 0.87 (Cohen's Kappa), which is considered acceptable [56]. All the codes were grouped into six themes, including: perceived benefits of auto check-ins, perceived benefits of manual check-ins, challenges of using the auto-sensing approach, switching between the two sensing approaches, issues of the manual approach, and suggestions for improvements. Finally, we read the interview excerpts from each theme to make sure they were coherent with the theme.

5 FINDINGS - USER EXPERIENCE OF DIFFERENT CHECK-IN MECHANISMS (RQ1)

5.1 Overall Check-ins

Overall, our system log showed that 1) only auto check-ins using BLE beacon-based location sensing did not fulfill the needs of academic check-ins in the classroom setting; to ensure 100% coverage, both the check-in inquirers (instructors) and the senders (students) had to collaborate on it; and 2) given two check-in mechanisms, some participants constantly used one mechanism and more participants switched in between.

First, our initial round of study with only auto check-ins failed. In the Winter class, 43 students installed and used the app. The app coverage started with 60% but gradually declined in the following weeks. Overall, the average success rate was 38%. After a month, most of the students stopped using the app by doing one of the following three: 1) they stopped sharing their location with the app; 2) they turned off Bluetooth; or 3) they uninstalled the app. In Spring 2018 with the same instructor, 45 undergrad students installed the app. The coverage of the hybrid sensing approach–including auto and manual–started at 67% and reached 95%, with an average of 80%; the coverage of the auto sensing alone started at 43% with an average of 59%. On average, the instructor helped check in 5 students during each class.

Note that the percentage was calculated based on the number of check-ins using the app over the total actual class attendance (the ground truth of the participants' class attendance) provided by the instructors. For example, if a participant went to 10 classes (missed one class for sickness), and used the app eight times to check in (regardless of which method was used), then the app usage was 80%. If the participant had five (three) auto (manual) check-ins, then this participant's auto (manual) check-in usage was 50% (30%).

Second, in the graduate participants' setting, there were more auto check-ins (195) than manual check-ins (147). On average, each graduate participant checked in to 95% (SD = 0.10) of his/her classes using the app. Overall, a very small portion of the participants used only one sensing method; the majority of the participants applied both sensing methods. More specifically, out of the 53 participants from both classes, 8 participants (15%) used only auto check-in; 5 participants (9%) used only manual check-in; the remaining 76% of the participants used both sensing methods. On average, 92% (96%) of the participants checked in to the morning (afternoon) class using the app. To ensure 100% coverage, the instructor marked students' attendance when they did not check in using the app but they showed up in the class.

When asked which check-in mechanism they used and why, our participants shared several factors that contributed to the selection of check-in mechanisms. Participants' feedback showed their perceived benefits and challenges, as well as their social perceptions of the academic check-ins in this higher education setting. Below, we present participants' feedback. We use U to denote student participant.

5.2 Perceived Benefits

Throughout the interviews, our participants shared a variety of methods their instructors used for taking class attendance, including name cards (e.g., U19, U9), using codes in Blackboard (e.g., U10), RFID (e.g., U21), WiFi based automatic check ins (e.g., U21), swiping ID cards (e.g. U37), using a sign-in paper (U9, U27), calling names (e.g. U38), another Bluetooth beacon app that only provided auto sensing check ins (e.g., U28), and clickers (e.g. U14). In summary, participants perceived that the two check-in mechanisms *"saved lecture time"* compared to instructors' calling individual students' names in the class and were *" less error prone"* compared to circulating paper sheets for students to sign in. Below, we present unique values perceived by participants of using the two check-in mechanisms.

5.2.1 Unique Benefits of Students' Auto Check-ins. The unique benefits of using auto check-ins include: its immediacy, accuracy, and low transaction cost when availability is limited.

Immediacy and Accuracy Several participants (e.g., U37, U9, U21, U41, U53, and U28) perceived that beacon-based automatic location sensing generated instant and accurate information. For example, U41 (male, checked in to 79% of his classes) was pleased by the automatic feature and its low cost compared to other attendance methods he was requested to use in his other classes: *"It's just the right time when I arrived to the class. Yes, it instantly recognized my attendance. It is much better compared to the clickers, where we have to buy the device, which costs $50."* Similarly, U21 (male, checked in to 85% of his classes) also liked the accuracy of the auto sensing feature: *"I think it was cool, as it even tells you the time. It's like a bonus, for the time especially with attendance, you're supposed to be in class at 12:45. But if you come in at 12:46, you're late. It's very accurate."*

Low Transaction Cost Another common reason why participants chose auto check-ins was because of its perceived low transaction cost. For example, U27 (male, checked in to 75% of his classes automatically) said *"Most of time I was checked in automatically, so I don't even have to open the APP."* Similarly, U53 shared that: *"I don't want to take my phone and then open that app every time before class. I feel it's a little bit a trouble for me if I have to do that. "*

Reliability Sometimes students forget to manually check in and auto check-ins provided better reliability. For example, U15 (male) started with manual check-ins. Once, when he forgot to check in, the app helped him check in automatically: *"The first several times, I just manual checked in because I didn't trust Bluetooth. But after certain times, I forgot to check in and when I opened the app the app already checked (me) in automatically, so I trusted it and kept using the auto check-in method."*

5.2.2 Unique Benefits of Students' Manual Check-ins. The unique benefits of using manual check-ins include the feeling of being in control and feeling more available.

Feeling of Being in Control Several participants (U9, U10, U40, U27) manually checked in because they enjoyed seeing the change in their check-in statuses, i.e., seeing the status change from an orange button "check-in" to a green status "checked-in." For example, U9 (male) manually checked in to 86% of his classes. He explained that clicking the button and seeing the status change made him feel very satisfied. He emphasized that it had to be him doing it: *"Because I would like to confirm that "I" actually pushed the button. I just want to make sure that "I" touch the button and the status changed."* Similarly, U40 (female) echoed that the manual check-in process gave her psychological satisfaction: *"It is some sort of psychological trigger. When I personally push the button, then I am certain that the action has been initiated. It is a reassurance that what I wanted this to be done."* U37 (female), who manually checked in 6 times and checked in automatically only once, thought manual check-in made her more aware of her check-in activities, *"I want to be aware of that (my check-in behavior). Because it can be possible that if it's automatic and there's some problems. I attend the class but after the class I see that I wasn't checked in."* She further added,*"It even bothering than to check whether I checked in the class or not."*

Feeling More Available There were cases where participants (e.g., U10, U53) switched from auto to manual check-ins. For example, U10 (female) chose the sensing approach based on her availability. Her first check-in was made automatically because she was late for that class, but she went to classes earlier thereafter and then she manually checked in to them all: *"Because I usually arrive early, so I prefer to use manually, because I have time. When I arrived late, I didn't want to use cell phone, then Bluetooth [auto check-in] can help."* In another case, U53 (female) checked in automatically four times and then switched to manual check-in. She recounted: *"Since I still have to open the app [to enable the beacon sensing for auto check-in], why not just check in by myself [manually]."*

5.3 Perceived Barriers

There were several barriers perceived by the participants during check-ins. Some were well discussed in prior literature, e.g., U10 and U38 didn't want to share their location in any location-based sensing apps. In addition to the common barriers of check-ins, in this section, we present the unique challenges perceived by the participants when using different check-in mechanisms.

5.3.1 Unique Challenges of Students' Auto Check-ins. The unique challenges of using auto check-ins include Bluetooth use; a user-perceived contradiction of BLE beacon-based location sensing; and time of use for BLE beacon-based check-ins.

Not Keeping Bluetooth on BLE beacon-based automatic location sensing requires participants to keep their phones' Bluetooth on, as the app needs to constantly detect BLE beacons' signals. Therefore, not keeping Bluetooth on failed automatic check-ins.

Three participants (U9, U41, U11) turned off Bluetooth because they were worried about battery drainage. For example, U9 (female, checked in to 56% of her classes) explained that battery was one major reason why she turned off her Bluetooth: *"Because it tends to lower my battery. I only switch my Bluetooth on before class and then try to check in with the app [for attendance]. I usually have it switched off to save battery."* Similarly, U41 (male, checked in to 79% of his classes) said: *"I think when I turn on something that I'm not using at the time that it makes waste of the battery."*

User-Perceived Contradiction of BLE Beacon-based Location Sensing We identified a user-perceived contradiction of BLE beacon-based location sensing as another barrier of using the auto check-ins. The situation is that a BLE beacon has a limited effective sensing area (within meters), but the automatic location sensing feature requires the location sharing option on the phone to be on all the time [33, 73]. Therefore, some participants had an illusion of being tracking everywhere. This is probably also because participants did not interact with beacons directly; instead, they interacted with the mobile app that detects the beacon. Since they were not sure of the sensing areas of beacons, they raised privacy concerns.

Because of the privacy concerns about "always" sharing location with iOS phones, sometimes participants failed to check in automatically. For example, U38 (female, checked in to 84% of her classes) mentioned that she chose "Only While Using the App" instead of "Always Allow." This caused her to fail to check in automatically. She noticed her classmates had the same problem: *"In the beginning of the class, a lot of iPhone users like me had trouble automatically checking in because we didn't turn the location on as always. I feel it will be better if the app can check your location even if the location doesn't have to be shared all the time."* Similarly, U53 (female) only shared location "While Using the App," instead of "Always" sharing. Therefore, she needed to keep the app open when she walked into the classroom so that the app could detect the beacon.

Time of Use Our interview results also showed that even though the battery concern was shared by both morning and afternoon participants, its impact on these participants might be different depending on what time of day the participants used the app. For example, in the second half of the day, worrying about losing battery might be more of a concern, such that participants did not take auto check-ins in the afternoon.

More specifically, participants (e.g., U28 and U53) in the afternoon session mentioned that it was challenging for them to use auto check-in in the afternoon because they thought keeping Bluetooth on drained the battery quickly. The system log showed that participants in the afternoon session had significantly more manual check-ins than those participants in the morning session, as illustrated by Figure 2 (the check-ins of the graduate participants). Given that a three-hour class, U28 (female) switched from auto to manual check-ins: *"Ninety percent of the times I switch off my Bluetooth was because of the battery. I never keep Bluetooth on for like three to four hours in the afternoon."* U53 (female), another afternoon participant, had similar check-in behaviors as U28 and

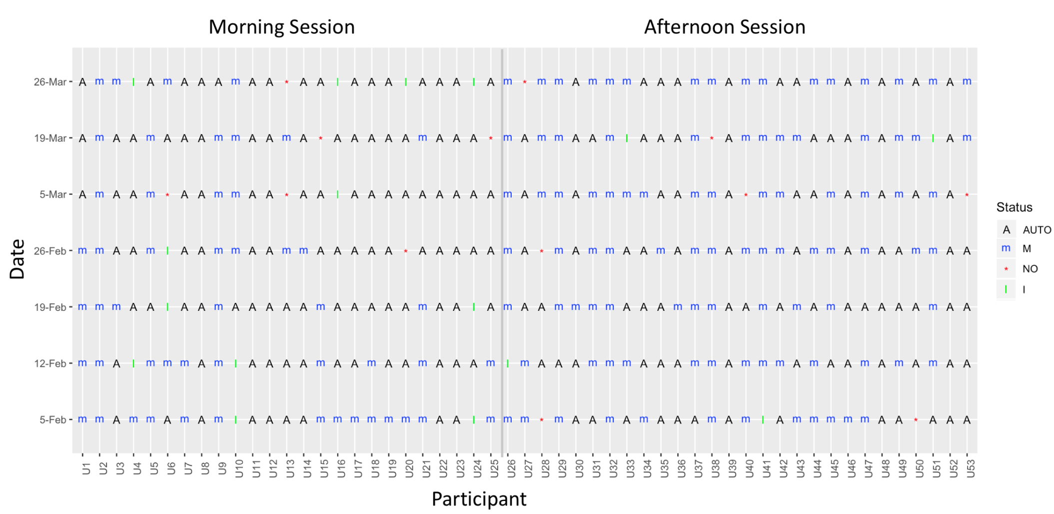

Fig. 2. Attendance records of the graduate participants. Each node identifies the attendance status of one participant in a class, including: A (checked in automatically); M (checked in manually); I (the student attended the class but didn't check in using the app), and a red dot (the student did not show up in that class). U1-U25 were from the morning session and U26-U53 were from the afternoon session. There was a significant difference between the number of manual check-ins in the two sessions ($H(1) = 4.70, p < 0.05$), i.e., the morning session ($M = 2.55, SD = 1.88$) and the afternoon session ($M = 3.84, SD = 1.95$).

shared exactly the same concern: *"Because my battery will run it out easier if I turn Bluetooth on [in the afternoon]."*

In fact, the battery concern of the auto sensing approach was also mentioned by several participants (e.g., U9, U11, U19) from the morning session. However, as we presented their feedback in the early findings, there were other factors that impacted their decisions of still taking the auto sensing approach. For example, U19 preferred auto check-ins because she didn't want to worry about spending time on manual check-ins; U11 liked auto check-ins because it was effortless and reliable especially when she forgot to check in manually.

5.3.2 Unique Issues of Students' Manual Check-ins. It was not surprising that participants perceived a higher transaction cost of using manual check-ins. Though the instructors did not catch any cases of students faking check-ins, some participants expressed related concerns.

Relatively High Transaction Cost Some students (e.g., U10, U11 and U19) felt it troublesome to check in manually. For example, U19 (female) began with manual check-ins to learn how the app worked. After she figured out how the automatic check-in worked, she switched to it and kept using it thereafter: *"I manually check in only for the first two weeks. Now I don't manually check in, because I know it [auto check-in] worked and just love it. I'm getting used to the system."* She also added, compared to the manual approach, auto check-ins helped her better concentrate in her class: *"I prefer Auto check-in. It's easy because of the time management. If I am still on my phone [manually] checking in, I can't concentrate."*

Potential Fake Check-ins Manual check-ins could be misused. The system required participants to log in to their university accounts before using the app. U37 (female) figured a way to cheat the system: *"I can manually check in for two people. I can log in for check-in then log out, and check in for others."* Though we expected this to be less likely to happen, because others' university account passwords were needed to re-login, U37 commented that it could happen and the system should prevent it from happening. On the other hand, it was harder to check in for others automatically than manually once the class was started, because the automatic sensing feature was implemented to detect when students entered the classroom. Therefore, to check in for others by taking the auto-sensing approach, the student needed to go outside and re-entered the classroom with a new login account.

6 FINDINGS - SOCIAL IMPLICATIONS OF ACADEMIC CHECK-INS (RQ2)

6.1 Shared Social Value of Student Check-ins

Participants all thought instructors' awareness of students' attendance was important and that the app helped their instructors be more aware of their attendance status.

Early Bird Impressions One important social implication of students' check-ins is that students were able to record early attendance even before the instructor's arrival; this was also perceived as a unique value of the check-in system by participants (e.g., U37 and U38). For example, U37 (female, checked in to 88% of her classes) explained: *"I want credit for being early so it's nice for showing the early arrival time. I mean not that it makes a difference but at least Professor will acknowledge that I've been there since 12:30pm when the class started at 12:45pm."* The instructors also told the researchers that there were early birds who constantly checked in to the classes early, which did leave them with good impressions of the students.

In fact, most of the participants interviewed shared that because the app captured fine-tuned information about when they arrived to class, they not only tried to come on time but also tried to be early. As U28 (female) explained, *"(When) college students come late, if they think that they are not noticed, they're likely to come late, and they think it will be OK. But (when) they know the professor noticed that you're coming late to the class, then you will try to come earlier."* Since our app provided the specific time of participants' arrivals, it successfully nudged the participants to arrive earlier. From the interviews, quite a few participants shared their experiences of trying to be punctual or even coming early. For example, U27 (male) started to take an earlier bus to campus, as the bus he used to take was always a few minutes late. His roommate who used the app in the morning class chose to leave home 20 minutes earlier and walked to campus to make sure he arrived on time, and U40 (female) shared that one time when her bus was late, she and her classmates booked an Uber to make sure they were not late for the class.

Participants also shared other anecdotes about how the system helped them beyond the class attendance taking. For example, U27 (male) appreciated the positive impact on him in terms of improving his time management skills as a result of using the app: *"I think it's a positive change. Because I have to learn about time management, like sometime right when I start my job I can't give that excuse to my boss that I'm late."*

Sense of Community All students were told by their instructors that it was their choice whether to use the app for taking class attendance. If they chose not to use the app, their instructors would still mark the remaining attendance using the web app interface in the class by checking each student's attendance status, so that in the end the attending students received credits accordingly. The credits were not affected by the way in which the attendance was recorded.

The motivations for students to use the app are manifold. The aforementioned perceived benefits of using either of the check-in methods (in section 5.2) were considered from the functional (e.g., immediacy and accuracy) and emotional (e.g., feeling of being in control) perspectives. There were also social benefits perceived by the student participants as a result of being in a classroom community.

First, the majority of the participants explained that they liked to use the app to record their own attendance because it saved their lecture time for the whole class; e.g., U40 (female) and U41 (male) mentioned that they were concerned that it would take more time for their instructor to take attendance. Participating in the attendance taking activity that was originally the instructors' sole responsibility made some student participants feel more responsible in the student-teacher relationship. For example, U43 (female) noted, *"I think it creates a sense of responsibility towards the instructor. It doesn't make me more attentive towards my classmates, but definitely towards my relationship with my instructor and my organization, presence and accuracy."* She mentioned that *"the sense of responsibility"* strengthened the relationship between her and her instructor.

Second, participants shared that participating in check-ins themselves increased their awareness of each other's attendance. For example, U15 (male), missed one class because of a health issue. He shared that he received four classmates' messages asking if he was well, though none of them were his close friends. They knew each other because they took the same class. Receiving these messages, U15 commented, *"I feel people concern about me."* He also said that when he noticed his classmates' absence, he would ask them as well. Though he did not know 90% to 95% of his classmates, he would still show he cared about them if they did not show up. He commented, *"I come to the class and I see the same people every time. One time I didn't see him, then I just asked him 'is everything fine' in the next lecture."*

6.2 Interpreting Classroom Check-in Data

Participants shared how they interpret other classmates' check-ins. For example, they raised questions about fairness of how check-ins should be used or collected and they also explained how classmates' check-ins helped them get to know others better.

Fairness of Check-ins Participants were given attendance credits as long as they checked in to classes. U38 (male) worried that this could be leveraged by some students: *"We came in [to] the class and took attendance with the app. But in the middle of the class, some students left after they* *checked in. So how to ensure that the student was there throughout the [entire] class time?"* A similar concern was raised, however regarding late check-ins, from a participant (female) from the first field trial: *"Whenever there's people coming late in like 20 minutes before the class ends and signs in, I kind of get angry because I was here early for the participation [credits], so it's kind of unfair."*

Interpreting Others' Check-ins Our results showed that late attendance could be interpreted in different ways. U53 (female) shared her perceptions of one of her classmates who constantly came late. She thought that the student who came late regularly might have a reason for being late that he couldn't control: *"because he's always 5 minutes late. I think it is normal between this is a routine, and something that he cannot control."* But if someone had irregular late attendance, that indicated that the student might find ways to better manage his time.

As another example, U9 (male) had bad impressions of students who constantly came in late and thought of not teaming up with the late student: *"I'll think he or she is a little bit lazy or something. People can have a critical situation that they can't be in the class but if someone keeps doing it for several times, I may not team with him [or her]."* Thus, providing check-in records could have influence on students' perceptions of their peers and subsequently impact their team work behavior.

When students were familiar with each other, they showed more understanding. For example, U37 (female) understood another student's constant lateness because she knew the person's health condition: *"I know one person since we meet outside the classes. So I know that she's usually late because she has a leg problem."*

6.3 Emerging Needs and Potential Issues of Academic Check-ins for Social Purposes

Some participants also shared their desire to leverage academic check-ins for social needs and proposed new features to improve the system; in the meantime, concerns were raised in terms of the hypothetical changes that might reveal students' absence to classmates.

Potential Values of Academic Check-ins Used for Social Purposes Forty percent of the interviewees mentioned that they did not know half of their classmates, and they (e.g., U10, U19, and U40) shared their desire to get to know their classmates by leveraging the check-in features of the system. For example, U10 (female) wanted to know more of her classmates and suggested adding photos next to students' names: *"adding pictures would be good, because students can know each other better and maybe instructor can recognize students better."* U19 (female) also said, *"It (adding photo) would actually help, because just by name we won't know people. (Some) people have the same name. It is very common for two or three people have the same names. So having photos would help us get to know each other."*

Concerns of Sharing Class Check-ins with Classmates The proposed idea of sharing academic check-ins among the attending students could potentially promote social interactions on the one hand; on the other hand, participants (e.g., U21 and U27) raised concerns about the hypothetical scenario where students' attendance and absence were shared among their classmates. For example, U27 (male) recalled that he skipped a class because of an interview: *"if you have a private reason that you don't want to disclose to others, then that might be a problem. Like my reason was not that private, I can just say that I had a job interview. That's OK. But others may have a more private reason. I can't think of any examples right now. But probably in that case they don't want their absence to be noticed."*

7 DISCUSSION

We designed and implemented a hybrid check-in system–offering automatic and manual location sharing–for students and instructors to collaboratively take class check-ins. We conducted an empirical investigation of when and why different check-in mechanisms were used, as well as explored its social implications. In this section, we reflect on our findings of the two proposed RQs and discuss insights for future CSCW research.

7.1 Manual Check-ins Promoting the Adoption of Auto Check-ins (RQ1)

While the concepts of auto and manual location-sharing (check-ins) were not new, most of the prior work studied them separately [43]. Indeed, scholars hypothesized that the two mechanisms can be complementary to each other [40, 43], where manual sensing allows users to be in control and auto sensing keeps users' efforts at a minimum. Note that the manual approach was also referred to as participatory sensing and the automatic approach was considered as opportunistic sensing [40, 43]. However, no empirical work examined their relationship by integrating them into one system and reporting how people switched in between. Our work made two major contributions in this line of research.

First, we identified several factors that impacted participants' decision to choose one check-in mechanism over the other. More specifically, these include but are not limited to social (e.g., privacy concerns), technological (e.g., the immediacy of Bluetooth enabled automatic check-ins), and psychological factors (e.g., being more concerned about battery consumption in the afternoon than in the morning, wanting to be in control). In particular, our findings showed that participants changed their perceived benefits of check-in mechanisms upon battery contingency, and they traded battery power (by using auto-sensing) for convenience given limited time in the morning. Thus, our UX research contributed new discoveries and empirical evidence that supports the complementary roles of the two sensing approaches, which cannot be received by conducting interviews or surveys without situating users in real scenarios. For example, some participants switched to taking the *participatory* sensing approach (i.e., manually checking in) when there was limited battery on their phones to run *opportunistic* sensing (i.e., automatically checking in). When there was limited time available for taking the *participatory* sensing approach (i.e., opening the app and manually checking in), some participants preferred *opportunistic* sensing since it was hassle free.

Second, more importantly, our findings revealed a new relationship between manual (*participatory*) and auto (*opportunistic*) check-in mechanisms, which was that the use of manual check-ins promoted the adoption of auto check-ins. This relationship enriches our understanding of the two mechanisms, since prior scholars only hypothesized a complementary relationship. In particular, participants shared that after taking class attendance using manual check-ins, they built a better understanding and more trust with the hybrid sensing system, which in turn promoted participants' use of the automatic sensing approach enabled by BLE beacons.

This new relationship between the two check-in mechanisms needs to be further evaluated in more diverse contexts, e.g., collecting noise spots [8, 64] and real-time traffic conditions [54, 107], where both automatic (different sensors on smart phones can be used to automatically collect relevant information) and manual (users share their observed data) approaches can be applied.

7.2 Rethinking and Mashing up Check-ins with Different Purposes (RQ2)

Our system work with two rounds of field trial studies brought us new insights into designing future social systems that collect and leverage people's check-ins in various settings.

First, we may not limit the role of inquirers as pure receivers of check-in data. The original design of our system was for senders (students in this case) to fulfill academic check-ins. Most of the check-in systems do not involve inquirers to check-in for the senders, e.g., [24, 60, 80], . However, our field trial results showed that in order to ensure 100% coverage, oftentimes, the inquirer (instructors in this case) needed to participate as well. This was because students who did not like to use auto check-ins came late to the class and forgot to manually check-in, and the instructor helped validate the student's check-in during the class or at the end of the lecture. In fact, this collaboration may not be unique in the higher education setting, where instructors co-locate with the students when the check-ins happen. Such scenarios can be familiar in other situations as long as the senders and inquirers co-locate, e.g., if producers of tourist events [38] or organizers of conferences [12] and trade-shows [82] try to collect check-ins from event participants.

Second, our work identifies that a new temporal factor, i.e., being early, punctual or late, could impact people's check-in behavior. It's a relationship between people's actual check-in time and the expected check-in time from the location requester. Prior work addressed the timing of check-ins more in terms of examining or comparing traffic patterns at different times, e.g., weekdays vs. weekends and morning vs. night [7, 22]. The public venues include restaurants, movies, stores, auditoriums, and resorts. For example, the popularity of certain venues changes significantly across four seasons [7]. A recent CSCW work [109] studied four different check-ins, i.e., real check-ins, delayed check-ins, nearby check-ins, and fake check-ins, but they focused on check-ins' accuracy. For example, the delayed check-in was defined as the user being beyond the predefined distance from the perimeter of the interest area but having visited the place within the previous 24 hours [109], which is different from being late in our study. Our empirical findings showed that this new temporal factor not only contributed to the use of the check-in system, but also had social implications, e.g., early birds (student participants) wanted to leave good impressions on instructors so they chose to use the app to check in even before the arrival of their instructor. This finding has a broader implication in other contexts, e.g., sporting events, conferences, and auditoriums [7]. For instance, will an early check-in to a sporting event indicate the level of fan-ship of a person to the sport team, or can we leverage this information to identify fans and promote the relationship between the fans and the team? Do early or punctual check-ins at a conference talk indicate higher interest in the presentation than late check-ins? Further, do late exits suggest an interest in socializing with the speakers?

With the consideration of this new temporal factor, e.g., late check-ins, some of our student participants also raised concerns regarding fairness of using the check-in data. Technically speaking, BLE beacons can be used to automatically capture when students leave the class as well as when they arrive. However, this may indicate students who check in manually upon arriving to the classroom should also check out manually. Such additional manual efforts need to be better incentivized, otherwise, students may not be motivated to do so. Given the potential of fake check-ins using the manual approach, new features may also need to be developed to prevent students from checking in for others. For example, the attendance system may provide photos of the attending students to the instructor so that, if needed, a more reliable validation can be processed. Another method could be "locking" a student account with the installed app once a student successfully logs in. In this way, in order to check in for others, the student would need to uninstall and reinstall the app to wipe the associated information from the pre-installed app.

Third, we need to carefully address the inter-sender relationship before/during/after collecting their check-ins; namely, we need to address senders' social needs and challenges while trying to fulfill their academic needs. In our case, several participants mentioned that they did not have a lot of social connections on campus and in the classes and they hoped to use the check-in data (people in the class) to expand their social connections and to improve their learning (being able to work with classmates outside of the classroom). To serve these social needs, one suggestion shared by many student participants was to display students' photos for those attending students in the class, so that they can become more familiar with each other. Essentially, this suggests mashing up check-ins with different purposes (e.g., academic and social). However, showing attendance may reveal absence, which was not favored by certain participants. Therefore, how a privacy-preserving solution in the check-in system can be designed to promote social networking on campus is another open question.

Fourth, using our check-in system, students have an opportunity to demonstrate community involvement in several ways, which is important for building a campus-community partnership. In the context of higher education, a healthy and mutually beneficial campus-community partnership can be stimulated by encouraging students to "participate in an organized service activity that meets identified community needs" and "reflect on the service activity in such a way as to gain an enhanced sense of civic responsibility" [13, 97]. It was also found that students who are moderately or highly involved in campus activities perceived a greater sense of campus community than those who had lower levels of involvement [31]. Collaboratively taking class attendance using the app is an organized activity to address the class's needs. We had participants who shared a feeling of stronger responsibility to the instructor and who felt they were cared about and expressed willingness to care for others. According to Schlossberg's theory of college students' mattering and marginality [91], students need to feel that their presence on campus is noticed and important to others (including peers, family members, faculty, and staff) and mattering to others at their colleges helped students feel a sense of belonging. Thus, collaborating on academic check-ins provides an opportunity to promote the sense of community in a college or university campus [11, 21].

Most of the location sharing literature addressed the social phenomenon of a check-in system given one system design primarily focusing on any type of check-in, e.g., one-to-one [57, 58], one-to-few [55, 82, 92], or one-to-many [54, 63, 112]. Transitions of a check-in system from one design (often influencing the type of check-ins) to another system design, or switches in between, are under-studied. Lederer et al. studied the relative importance of two factors, inquirer and situation, [60], and found that privacy preferences varied by inquirer more than by situation. Specifically, people were more likely to have the same privacy preferences with the same inquirer across different situations than to use the same privacy preferences with different inquirers in the same situation. Namely, in our case, introducing new designs for promoting social interactions among students into the existing academic check-in system could impact students' privacy preferences and possibly their associated check-in behaviors. For example, maybe the students no longer want to be early birds once they realize their early check-ins will also be visible to their classmates. Our work calls for addressing the state transition of a check-in system: how to safely transition the design from an academic purpose only (one-to-one) to mash-up with different purposes where the relationship can be one-to-many?

7.3 Seamful Design of BLE Beacon-based Location Sharing Systems

Our system applied BLE beacon-based automatic location sensing technology, which has been proposed by other works to automate classroom attendance-taking [5, 27, 58, 74]. BLE beacon technology is a leading proximity-based location sharing technology that has been applied in a variety of application domains, e.g., for better navigation [52], to send location-based messages [14, 42] and to analyze users' indoor movements [25, 83, 93]. However, user experience of beacon-based systems was not evaluated through field trials in prior work. Understanding user experience of this mechanism is important for designing check-in systems. Thus, our research fills a critical gap and also contributes novel findings.

In particular, a user-perceived contradiction of BLE beacon-based location sensing was revealed from our study. The signal range of the BLE beacons we installed was only within the size of the classroom. Participants were confused about the "always" location sharing requirement, especially for iOS participants. This confusion was caused by the fact that the permission for location access was bundled with BLE beacons in iOS, and beacon-based APIs and other location services (for sampling GPS location) are obtained through the same iOS's Core Location framework. Therefore, using BLE beacons requires the location service permission to be enabled for the app. With the "Always Allow" setting, the app can detect beacons while the app is in the background; with the "While Using the App" setting, the app must be in the foreground/active to detect beacon signals. That is why when students first installed the app and were prompted by the request for always allowing location sharing, they had an illusion that this auto-sensing technology constantly monitored their location anywhere within and beyond the classroom. Some participants even thought they could be tracked when they were in the parking lot.

These user experiences were not be able to be identified/discussed in prior work because their participants were introduced to imaginable situations during interviews and survey studies, e.g., [96, 110]. To ease the adoption and usage of BLE beacons, iOS and Android platforms may consider separating BLE beacon sensing APIs from the other location service (e.g., GPS) so as to improve the clarity of how beacon-based location services really work behind the scenes.

On the other hand, if beacons were misplaced in other rooms, users' locations would be interpreted incorrectly. Similarly, if there were more beacons than expected, users would be located unexpectedly. Because beacon-based app users typically do not interact with beacons directly, beacon sensing and location estimation happened seamlessly behind the scenes without participants' awareness. One idea of addressing this is to take a *seamful design* approach. The notion of seamful design is to allow users to perceive both the weaknesses and strengths of the system and appropriate them for their own uses [16], where *seams* are used to describe the above situations, including technical limitations, e.g., inaccurate location detection and unstable signal strength [15]. For example, since our participants were concerned about unwanted location tracking, future designs of BLE beacon-based systems may need to release where beacons are installed to users. In this case, the exact location and sensing areas of the beacons are *seams*. Then, the app can let users choose which beacons to sense, figure out if the signal coverage is accurate and validate if the interpreted location is correct. This design is not limited to class check-ins on campus. This design implication may be also applicable to conference, event and grocery settings (e.g., [17, 71, 90]).

8 LIMITATIONS AND FUTURE WORK

This work does not aim to investigate if class check-ins should be taken or not. The goal was to understand students' user experience of different check-in mechanisms in an academic setting. Thus, we chose instructors who specified attendance credits in their syllabus and took attendance regularly (by calling students' names) in their classes, such that using the application was meant to reduce time spent on attendance checking instead of creating additional overhead. In the field studies, the two instructors took the same approach of taking class attendance. Consistent with the student participants' feedback, the instructors shared that the system saved them a significant amount of time from taking class attendance and that it was effortless to validate no-attendance students. In our future work, we plan to examine user behavior in classes where instructors have varied practices and requirements on class check-ins.

Both two-month field trials were conducted mainly in the first half of the semester. There were several reasons why we chose that time period. First, it was better to introduce an attendance taking practice from the beginning of a semester. Once classes already started, it was hard for instructors to introduce a new attendance practice in the classroom as students had already adapted to an existing one. Second, in the second half of the semester, there were mid-terms, student presentations, and finals when the instructors did not take attendance as regularly as they did at the beginning of the semester. It was hard to maintain the same practice, therefore we were not be able to collect the ground truth of student attendance in the later part of the semester. Given that the findings were produced in the context where instructors took class attendance regularly, they may not be generalizable to the weeks or those classes where attendance is not required or taken regularly. We plan to run studies semester-long to explore the patterns of system usage over time.

Additionally, the participating classes were not very large (more than 100) or very small (below 20), thus the findings may not be generalized to other sized classrooms. Studying the app usage in different sized classrooms is also part of our future research plan.

9 CONCLUSION

Check-ins are extensively studied on social networks and limited work was conducted in the context of classroom check-ins in higher education settings. We designed and developed a check-in system with two mechanisms enabled and conducted two rounds of field trials with 141 university students. Our findings showed that several social, technological, and psychological factors impacted the usage of auto check-ins (BLE beacon-based) and manual check-ins, and the use of manual check-ins promoted the adoption of auto check-ins. The findings also revealed unexpected barriers of adopting BLE beacon-based location sensing. In addition, we identified the needs and potential issues of integrating check-ins with different purposes. Our findings provide design implications for future check-in systems within and beyond the higher education context.

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