IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 5 May 2025, accepted 7 June 2025, date of publication 11 June 2025, date of current version 24 June 2025.

Digital Object Identifier 10.1109/ACCESS.2025.3578718

RESEARCH ARTICLE

Integrating Indoor Localization Technologies for Enhanced Smart Education: Challenges, Innovations, and Applications

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This work was supported in part by Ministerio de Asuntos Economicos y Transformación Digital and European Union-NextGenerationEU within the framework Recuperacion, Transformación y Resiliencia y el Mecanismo de Recuperación y Resiliencia under the project MAORI, and through the University of Malaga under Grant Agreement for Open Access Charge: Universidad de Málaga/CBUA.

ABSTRACT This comprehensive study investigates the integration of indoor localisation technologies in Smart Education (SE) environments, emphasizing their transformative potential to optimize educational systems. Moreover, this work reviews various technologies such as WiFi, 5G, Bluetooth, IoT, Ultra-Wideband (UWB), and Radio Frequency Identification (RFID), analysing their advantages, limitations, and applicability within educational settings. Special attention is given to privacy concerns, exploring compliance with international regulations such as the GDPR. A novel Proof of Concept (PoC) is presented, demonstrating the effectiveness of an Automatic Attendance Control (AAC) system leveraging WiFi and 5G technologies. By combining these radio technologies, the PoC achieves real-time localisation with a high degree of accuracy and scalability, even in resource-constrained environments. The results highlight the significant improvements in attendance management and other potential applications, such as real-time navigation and occupancy monitoring, contributing to enhanced efficiency and quality in educational institutions. This study underscores the potential of indoor localisation technologies to advance SE and offers insights for future innovation in smart, technology-driven learning ecosystems.

INDEX TERMS Smart education, indoor localization, WiFi, 5G, automatic attendance control, machine learning, IoT, educational technology, resource optimization.

I. INTRODUCTION

In the last years, the impact of precise location services is growing in society with the advancements in technology, leading to the use of location-based services by autonomous robots, self-driving cars, or context-aware applications to provide personalized services [1]. By providing more accurate and reliable location information, these services can help improve safety, efficiency, and overall effectiveness in a wide range of industries and applications. Location-based services have also had a transformative impact on Smart Education (SE) [2], where they can be used to improve the overall efficiency and effectiveness by providing real-time information about the location of resources [3], such as classrooms and labs, and the location of students or teachers.

Students are now more connected and engaged when carrying out their academic activities with digital devices. Given the increasing inclination of students to work digitally, educational institutions must adapt to meet this digital demand. SE consists on the use of the technology to optimize the whole educational system for a personalized teaching and learning process for each student [4], [5]. This includes the use of advanced algorithms, data analytics, and Artificial Intelligence (AI) to create flexible and interactive learning environments that can adapt to the unique needs, preferences, and abilities of each learner. SE utilizes a diverse range

The associate editor coordinating the review of this manuscript and approving it for publication was Miguel López-Benítez.

of digital tools and platforms, including mobile devices, learning management systems, educational apps, and Virtual Reality (VR) technologies, to develop captivating learning environments [6].

In the context of SE, the need for accurate location estimation is crucial for personalized services. The most common approach for precise localisation is the use of Global Navigation Satellite System (GNSS), which provides high accuracy in outdoor scenarios. However, GNSS is not available indoors, where many applications for this field are being developed, due to signal blocking or signal reflections. To overcome this limitation, various technologies and techniques such as 5G and WiFi are being used to provide accurate and precise location information indoors and in built-up areas [7], [8]. Additionally, some applications require the network to estimate the location of end-users in order to save energy and reduce computational complexity [9]. Network-based location is a better solution for these functions, as it allows the network to estimate the location of terminals based on data collected in the network infrastructure without requiring cooperation from the terminals.

This paper provides an overview of the role of localisation within the services existing in an SE vertical scenario while also offering insights into potential forthcoming services in the upcoming years. In addition, this work contributes to the development of an Automatic Attendance Control (AAC) system that is carried out as a Proof of Concept (PoC) to demonstrate a location-based service within a resource-constrained SE.

The rest of the paper is organized as follows. Section II delves into localisation technologies that are in the context of SE. In Section III, various localisation techniques commonly applied in the educational settings are explored. Section IV provides a comprehensive analysis of various use cases for location-based services in SE. It delves into the requirements and challenges of localisation associated with these services. In Section V, privacy concerns of localisation within an educational context are explained. Section VI explains the PoC, highlighting its objective of AAC through Machine Learning (ML) and detailing the methodology as well as employed classification and regression models. Additionally, the experimental setup and the results are presented and discussed. Finally, the conclusions are carefully reviewed in Section VIII. Figure 1 presents the structure of the paper. The acronyms in this paper are listed in the Table 1.

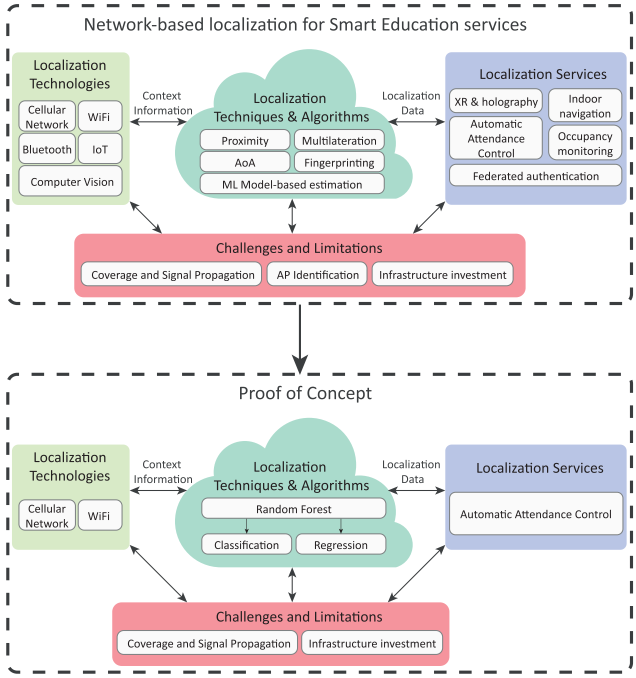


FIGURE 1. Structure of the paper.

II. LOCALIZATION TECHNOLOGIES FOR SE

This section explores the radio technologies that are commonly present in educational environments. These technologies are often installed for network access, serving as a backbone for SE services. The purpose of this paper is to present them and define how they can also be opportunistically used for indoor positioning.

A. CELLULAR NETWORK

Cellular networks offer a myriad of services based on voice and data traffic. Currently, this technology is prevalent in educational institutions as it enables us to access any information source at any time. Many infrastructures are deployed in educational institutions by operators to handle high densification, and experimental networks are deployed by certain universities for research and development purposes.

Although we are at an early stage of 5G deployment, the 3rd Generation Partnership Project (3GPP) has formally declared its commitment to achieving an accuracy of less than 3 meters in both horizontal and vertical dimensions, and up to 10 meters in the vertical plane in open spaces for 80% of the cases 3GPP. To this end, various protocols and techniques will be employed, including the deployment of the multi-Round Trip Time (RTT) protocol [10], which uses timestamps to measure the distance between the UE and the different cells to improve the accuracy of the system. The 3GPP has noted in technical reports, such as [11], that the use of RTT can be effectively employed in both frequency spectrums defined within the 5G framework. These spectrums encompass Frequency Range (FR) 1 for frequencies below 6GHz and FR 2 designed for the millimeter band (mmWave). This protocol will be used in both upstream and downstream communication channel, not only from the serving cell but also from neighboring cells. This approach is aimed at obtaining precise location of users without incurring higher energy costs.

The implementation of 5G operating at high frequencies presents new technical challenges in comparison to lower and mid-band services [12]. Initially, mmWaves have a centimeter-level location precision [13] but a shorter propagation distance, resulting in greater Line-of-Sight (LoS)

TABLE 1. Overview of acronyms.

Acronym	Definition
AoA	Angle of Arrival
AP	Access Point
ANN	Approximate Nearest Neighbors
AI	Artificial Intelligence
AR	Augmented Reality
BLE	Bluetooth Low Energy
CSI	Channel State Information
CDF	Cumulative Density Function
DTA	Data Transfer Agreement
DFL	Device-Free Localisation
EU	European Union
FR	Frequency Range
GDPR	General Data Protection Regulation
GNSS	Global Navigation Satellite System
gNB	gNodeB
IMU	Inertial Measurement Unit
IoT	Internet of Things
LMS	Learning Management System
LOS	Line-of-Sight
LS	Least Squares
MIMO	Multiple Input Multiple Output
ML	Machine Learning
MR	Mixed Reality
NB	Narrow Band
NFC	Near Field Communication
NRPPa	New Radio Positioning Protocol A
PAN	Personal Area Network
PIR	Passive Infra-Red
PoC	Proof of Concept
pRRH	pico-Remote Radio Heads
RF	Random Forest
RFID	Radio Frequency IDentification
RSSI	Received Signal Strength Indicator
RTT	Round Trip Time
SE	Smart Education
SSID	Service Set Identifier
ToF	Time of Flight
UWB	Ultra Wide Band
UE	User Equipment
VR	Virtual Reality
XR	eXtended Reality
3GPP	3rd Generation Partnership Project

path loss than sub-6GHz waves, necessitating smaller cell sizes and/or more powerful radio stations [14]. Additionally, mmWaves do not propagate through many of the external/internal building materials such as concrete walls [15]. Although covered, signal fluctuations or connectivity gaps may create challenges, leading to inconsistent availability of SE services.

It is important to consider the evolving landscape of mobile networks, which are increasingly moving towards the deployment of smaller cellular units. These smaller cells are expected to be highly integrated into SE [16]. The adoption of advanced technologies like beamforming [17] and the densification of cells will allow the presented services in SE. Further network densification results in UEs' receiving greater contextual information, such as distances/angles between APs and UEs, that substantially improves location services, among others. Nonetheless, some cellular network manufacturers have opted for pico-Remote Radio Heads (pRRH) -based infrastructure in industrial deployments. This means that there exist different 5G APs that are operating as a single cell, in a synchronized way. This approach provides several benefits such as the avoidance of handovers between APs when the users are moving. Nevertheless, it makes more difficult to use the 5G APs for localisation, since it is not possible to distinguish which AP the user is connected to [18].

B. WiFi

Due to its widespread availability and worldwide deployment, WiFi networks offer global coverage in educational areas that can be the backbone for location-based services within SE. Eduroam is the secure, worldwide roaming access educational network developed for the international research and education, accessible to all students [19]. This network, based on a single shared SSID (Service Set Identifier), has become a standard that selects APs and enables roaming, guaranteeing continuous connectivity while moving between campuses or affiliated institutions [20]. Eduroam stands out for providing a secure worldwide service through the implementation of robust authentication protocols like EAP and WPA2-Enterprise encryption [21].

When WiFi employs the IEEE 802.11mc standard, it incorporates a feature known as Fine Time Measurement (FTM), which facilitates precise distance estimation from the UE to the AP. This estimation is accomplished by the insertion of timestamps and the utilization of the RTT protocol [22], [23]. This release is intended to transform the indoor positioning industry in the coming years, as new smartphones are adopting the IEEE 802.11mc protocol universally.[1] Implementing a 5G network and the necessary infrastructure can be expensive [24], and may not be feasible for all schools or educational institutions. Thus, WiFi technology with eduroam network only needs to change the APs to implement the IEEE 802.11mc protocol to provide an accurate localisation service.

The protocol estimates with an accuracy of around one meter the distance of any user that supports the protocol without the need to be connected to the AP [25]. The information is calculated on the UE side to safeguard user privacy, since the location information is not shared among the nodes in the network. Nevertheless, it is also remarkable the extensive study of the conventional WiFi for localisation using signal power [26], [27] known as *fingerprinting*.

C. BLUETOOTH

Bluetooth is an ubiquitous technology owing to its widespread adoption in Personal Area Networks (PANs) such as smartwatches, headphones or smartphones. It is a short-range wireless communications technology which facilitates cost-effective, low-bandwidth, and energy-efficient communication thanks to the BLE protocol [28]. Notably, BLE-based positioning relies on the measurement of signal

[1] Wi-Fi location: ranging with RTT, https://developer.android.com/guide/topics/connectivity/wifi-rtt, Accessed: 18/02/2025.

power as a key determinant [29]. However, this technology offers low precision in localisation terms. Under specific LoS conditions and with proximity to APs, an accuracy of only a few meters error can be obtained [30]. Furthermore, BLE holds considerable promise for forthcoming sensor implementations in the Internet of Things (IoT) [31]. Consequently, while Bluetooth technology demonstrates considerable potential, it is not yet as implemented as cellular networks or WiFi in this educational context.

Attendance control via Bluetooth has already been implemented in SE [32]. Despite BLE provides the benefit of broadcasting mode without the requirement for pairing, this characteristic makes BLE vulnerable to passive sniffing attacks [33]. Additionally, BLE has limited coverage; therefore, the most feasible approach for user localisation is fingerprinting, as demonstrated in [32]. However, fingerprinting is a non-scalable technique that necessitates a comprehensive measurement offline phase.

D. INTERNET OF THINGS (IoT)

A wide range of sensors (e.g. smoke detectors, temperature, and proximity sensors) or beacons (e.g. WiFi or Bluetooth) fall under the category of IoT devices, which play a crucial role in the educational sector as a fundamental enabler [34]. The integration of IoT systems and devices enables multiple applications such as resource monitoring or occupancy tracking [35]. IoT information is typically centralized into a system that cross-correlates data from various IoT enablers to provide localisation information [36].

The use of low-cost sensors in IoT allows effective control and monitoring of large areas, contributing to the optimization of spaces and resources. Nevertheless, IoT devices are vulnerable to security breaches that may compromise confidential information and personal privacy [31]. In addition, it is crucial to consider the diversity of the infrastructure across educational institutions, including universities and schools, as well as the resources and advantages afforded by any financial investments made.

The success of a location-based service is largely determined by the chosen educational establishment. It is evident that universities prioritize the allocation of greater resources towards infrastructure technology in comparison to primary or secondary schools. Some universities, such as the University of Malaga, utilise IoT networks that monitor and investigate the effect of vegetation conditions (temperature, humidity, etc.) on students' comfort levels [16]. The University of Zaragoza utilises a spatial and geographic information system to provide ongoing access to the inventory of its facilities and available classrooms [37]. Similarly, the University of Alicante employs a vehicle mobility management system to monitor use of its car parks [38].

E. COMPUTER VISION

Multiple camera-based applications exist for real-time monitoring of educational facilities, such as libraries, cafeterias or classrooms [39]. Furthermore, it is possible to determine levels of occupancy in these spaces using the computer vision, allowing for more efficient use of resources [40].

Image processing constitutes the fundamental element of localisation and tracking with computer vision. It provides accurate navigational data which correlates both localisation and motion information with centimetric precision [41]. This technology relies on fixed cameras placed at strategic locations within the infrastructure, such as campuses or educational settings. Implementing navigation and tracking services in SE requires a building map and a configuration phase to mark stationary camera positions [42]. The algorithms employed constantly update the navigation status of multiple students based on their current foreground state and previous positions [43]. By examining changes in the image structure, computer vision objectively identifies the foreground elements through pixel correlation [44]. Nevertheless, enlarging the monitored areas results in a significant increase in expense, both in terms of effort and infrastructure, in order to uphold a high level of accuracy.

F. ULTRA-WIDEBAND (UWB)

UWB is a wireless technology designed for high-precision indoor positioning. It utilises extremely short pulses in the nanosecond range, making it resistant to multipath interference. Additionally, UWB employs the RTT protocol to locate a device with remarkable accuracy, down to centimetres. The use of a wide range of frequencies for data transmission enables UWB signals to penetrate materials such as concrete, glass and wood, due to their low frequency components. However, this wide frequency range is accompanied by a trade-off of a limited operating range, typically less than 100 metres, due to power density transmission limitations.

UWB also allows accurate estimation of the Angle of Arrival (AoA) when our receiver integrates two antennas synchronised with the same clock for signal reception [45]. In this way, UWB makes it possible to know the orientation of a UE as well as its position very precisely [46].

Despite of its high power consumption due to the requirement for a wide bandwidth, UWB has been integrated in different SE services such as eXtended Reality (XR) applications [47], [48] or indoor navigation [49]. UWB is ideal for XR applications due to its high data transfer rate and precise positioning.

G. RFID

Due to its low price and availability, Radio Frequency Identification (RFID) is a versatile and cost-effective solution in the realm of indoor localisation for smart education environments. RFID can be employed as a placeholder for some location-based services, including occupancy monitoring [50], attendance control [51] and geo-fencing [52].

RFID positioning utilises electromagnetic fields to automatically identify and track tags attached to objects. These tags contain electronically stored information which can be read from several metres away, even without line of sight [53].

RFID tags can be either active and passive elements, which is mainly based on how each device is powered. Active tags have their own power source and can transmit signals over a longer distance, which can cover several metres. In contrast, passive RFID tags (e.g. Near Field Communication (NFC)) lack an internal power source and are activated by the electromagnetic field generated by an RFID reader. RFID readers emit radio waves to receive signals back from RFID tags. They can be strategically placed at entrances, exits, and other key points within the school to track movement and the presence of tagged individuals.

Table 2 presents a comprehensive comparison of the advantages and disadvantages of the various technologies employed for location-based services for SE purposes. This comparison elucidates how each technology can be utilized to enhance educational environments, while also identifying potential challenges and limitations that must be addressed to ensure effective implementation.

III. LOCALIZATION TECHNIQUES

Depending on the nature of the data information, e.g. signal power, distance or angle to the AP, different approaches are commonly utilized to locate users, including location by proximity, ranging-based methods, AoA, fingerprinting and model-based localisation.

Location by proximity is the simplest method for determining the User Equipment's (UE) location, assuming it to be the same as the AP location. This method is employed when high accuracy is not a strict demand [54].

Ranging-based techniques, such as multilateration, involve computing distances to APs using metrics such as RSSI or Time of Flight (ToF) [55]. These methods achieve a high accuracy if the ranges are precise. The final location estimation is determined by the intersection of spheres (or circles in 2D). Nevertheless, range estimations are prone to result into non-convergence of the circles or hyperbolas used in the trilateration process. To mitigate this uncertainty, techniques such as Least Squares (LS) are applied [56].

AoA measures the angle at which the signal arrives at the UE from the AP. This approach is employed in Multiple Input Multiple Output (MIMO) systems because of their ability to utilize beamforming techniques [57]. Indoor environments present challenges for both range-based models and AoA due to signal blocking and reflections [27].

In cases where received power remains relatively constant over time, despite not following a predetermined propagation model, it can serve as a stable reference. For instance, in a location close to an AP, if the measured power is consistently reduced due to an obstacle like a wall, this power level remains constant as long as the obstruction remains unchanged. Each point in space is associated with paired values comprising reference point identifiers and unchanging received power levels, forming a unique signature known as a *fingerprint* [58]. However, fingerprinting has notable limitations, including sensitivity to variations in training and testing conditions caused by dynamic propagation attributes like temperature, humidity, and obstacles [59], [60], [61]. It also requires an initial radio map construction phase that limits the covered area, unrecorded data points cannot be used for positioning during operational phases [62].

While fingerprinting is a specific indoor localization technique, ML encompasses a broad range of methodologies that can enhance localization by generating a comprehensive model of the scenario through the information provided in the training phase with a reduced number of *fingerprints*. ML techniques enhance fingerprint-based localization, providing substantial performance improvements in accuracy, adaptability, and scalability that enable a localisation service encompassing the entire designated area [63], [64].

IV. INDOOR LOCALIZATION SERVICES IN SE

Education is one of the key pillars of modern society. As human knowledge advances, the topics that are taught become more and more complex and profound, and the teaching methods must evolve and adapt to new layers of complexity [16], [65]. Education is an evolving field shaped by technological advancements and pedagogical innovations. Localisation, in particular, introduces a diverse range of services aimed at actively involving and inspiring students. In this section, an overview of different localisation-based applications in SE are presented.

A. XR AND HOLOGRAPHY

eXtended Reality (XR) is a comprehensive term encompassing a range of immersive technologies that merge both digital and physical worlds. It includes VR, Augmented Reality (AR) and Mixed Reality (MR), enabling users to simultaneously immerse themselves in and interact with virtual and real environments [66]. Holography refers to the technique of encoding a light field as an interference pattern of phase and amplitude variations. When appropriately illuminated, a hologram diffracts incident light, creating a faithful replica of the initial light field, resulting into a realistic representation of the recorded 3D objects [67]. Both technologies enable an immersive experience that transcends the boundaries of conventional media, offering unique opportunities for diverse applications in fields such as entertainment, education, healthcare, and engineering.

Within the realm of SE, the utilization of techniques like gamification, which involves converting educational concepts into game-like formats and leveraging the brain's dopamine response to improve the learning experience, presents an opportunity to captivate students more effectively and to foster student engagement [68], [69]. There is a broad range of gamification strategies available. Certain strategies may be dependent on advanced technologies such as XR or holography [70], which impose substantial demands on processing power and communication capabilities, while also emphasizing the need for physical portability and non-intrusiveness.

By incorporating gesture recognition [71] and location [5], interaction with AR/VR objects can be facilitated, thereby simplifying the complexity and cost of the end devices [72]. Furthermore, location serves as a crucial factor in the traffic generated by SE applications, enabling efficient network management [73]. XR requires a latency below 50 ms [74] and depend on localization accuracy in the range of 0.1 meters for optimal performance [75]. Holography can experience a latency as high as 100 ms [76], [77] while localisation accuracy must be below the centimeter-level [76]. When students are situated within a classroom, broadband traffic becomes concentrated in a hotspot. This traffic is similar among students but varies slightly based on their precise location, such as different viewing angles of the same XR object. Hence, if the location is known, the usage of edge resources can be optimized [77].

In the next decade, XR and holography could also be used to create virtual classrooms, where students can attend classes remotely and interact with teachers and classmates in real-time. This could open up new possibilities for education, such as providing access to education to remote and underserved communities [78].

B. INDOOR NAVIGATION

Indoor navigation is a technology that can be used to provide positioning, guidance and wayfinding for people within a building or campus [79]. To provide a reliable and seamless indoor navigation service, localisation accuracy must be enhanced to the level of meter-level in horizontal plane [1] and floor-level in height [80]. This level of precision is necessary to ensure that users can confidently navigate within indoor spaces, avoiding obstacles and reaching their intended destinations accurately. However, by leveraging a combination of position and inertial sensors, including Inertial Measurement Unit (IMU), it becomes possible to achieve a comprehensive and accurate navigation experience even when the localisation precision is diminished [81].

Different technologies have claimed to provide precise localisation down to some meter-level or lower. For instance, Ultra Wide Band (UWB) technology achieves centimeter-level accuracy with time-based estimations [82] meanwhile WiFi 802.11mc obtains an accuracy of 1-2 meters with the same protocol [23]. 5G claims to provide <3 meters for 80% of the cases, encompassing both horizontal and vertical planes [11] with the aim of indoor navigation. Bluetooth Low Energy (BLE) fulfills the requirements of precision for indoor navigation when mapping the whole scenario in a previous step for fingerprinting [83]. However, fingerprinting is not practical for precise navigation around a whole campus due to the cost of deployment [84]. While 5G or WiFi Access Points (APs) would provide services, mainly internet access, as well as localisation features, a BLE-based deployment would not offer additional functionalities except for localisation. Furthermore, for indoor navigation systems to be truly effective, a real-time location service is required. Users require instant updates and guidance to make informed decisions while traversing indoor environments. Therefore, the system should operate with a maximum latency of 1 s [85], minimizing any perceptible delays for a fluent navigation response [1].

Indoor navigation can be used to improve the overall efficiency and experience of SE by reducing congestion and making it easier for people to find their way to the desired classroom or laboratory [79]. Moreover, it can set up virtual boundaries, a feature called geo-fencing that triggers an action when a device or a person enters or exits that boundary [52]. Geo-fencing is a powerful tool that is often used in security systems to restrict access to certain areas and ensure that only authorized personnel are present in sensitive areas.

TABLE 2. Advantages and Disadvantages of technologies for SE purposes.

Technology	Advantages	Disadvantages
Cellular Network	- Universal coverage and integration - High positioning accuracy with 5G - Advanced protocols for energy efficient	- Need for increased network densification - Challenges with mmWave - Complex positioning with indistinguishable APs
WiFi	- Widespread availability in educational settings - Eduroam provides secure and seamless connectivity - Low cost to upgrade APs to support IEEE 802.11mc	- Accuracy up to one meter - Location estimated by the UE
Bluetooth	- Cost-effective and low power - Widely supported	- Limited to coarse localisation accuracy - Vulnerable to passive sniffing attacks - Limited range and scalability
IoT	- Low-cost sensors for versatile applications	- Vulnerable to security breaches - Effectiveness varies across institutions due to infrastructure diversity
Computer Vision	- High localisation accuracy - Efficient real-time applications	- High implementation and maintenance costs - Raises privacy concerns due to the use of cameras and image processing - Obstructions limit the use of this technology.
UWB	- Centimeter-level accuracy - Resistant to multipath interference - Signals penetrate various building materials	- Limited scalability and operating range - High power consumption - Narrowly implemented
RFID	- Low-cost solution for various location-based services	- Limited scalability and operating range - Limited to coarse localisation accuracy

Indoor navigation is also used in emergency situations such as fires, earthquakes, or other disasters where time is crucial, and having a reliable indoor navigation system can be critical to save lives. It can also be integrated with other emergency systems, such as fire alarms, smoke detectors, and emergency lighting, to provide a comprehensive solution for emergency preparedness [86]. In the event of an emergency, the system would automatically trigger an alert, providing immediate guidance to individuals in the affected area making it easier for people to quickly and safely evacuate the building while avoiding certain spaces [87].

C. OCCUPANCY MONITORING

Occupancy monitoring is an important issue in SE, as overcrowding can lead to safety concerns, reduced comfort and productivity, and increased wear and tear on facilities [35], [88]. It allows administrators to track the occupancy of different areas in real-time and enforce safe capacity limits. In addition, real-time occupancy monitoring can provide valuable insights into how different areas of the campus are being used, allowing administrators to optimize the use of resources and energy efficiency by combining with different actuators such as lighting or air conditioners, e.g. identifying areas of low occupancy and adjusting the lighting and temperature accordingly.

To accomplish this task, Device-Free Localisation (DFL) is a technology that can be used to track the presence and movement of people in a given environment without the need for them to carry any device. There are two types of DFL: based on images and signal propagation.

Camera or vision-based systems combined with ML algorithms provide a centimeter-level accuracy [41]; however, partial occlusion results in coverage blind spots and privacy concerns make this method unfeasible for urban areas [89]. Alternatively, DFL systems based on signal propagation typically rely on WiFi, Zigbee and UWB technologies [89]. When utilizing Channel State Information (CSI), DFL systems capture the multipath propagation during the wireless transmission offering a nonintrusive approach with high sensitivity to channel variations [90]. These inherent characteristics make CSI-based DFL systems within an horizontal error of few meters [91]. Moreover, DFL systems offer a latency below 1 s [89]. DFL can also be based on the Received Signal Strength Indicator (RSSI) between a transmitter and a receiver with LoS [92]. Given that the human body consists of approximately 70% water, it absorbs radio signals, leading to shadowing effects [93]. This process primarily focuses on human movement and tracking [94], [95]. Signal propagation-based DFL systems can be categorized as either model-based [96] or fingerprint-based methods [97].

There are several less effective technologies for nonintrusive DFL, including air-pressure sensing and ultrasound signal reflections [98], Passive Infra-Red (PIR) which detects thermal energy radiation from the human body [99], and CO2 concentration measurement in buildings [100].

D. AUTOMATIC ATTENDANCE CONTROL

Early attempts at attendance control was a labor-intensive and time-consuming process, and the accuracy and reliability of the attendance data could vary depending on the expertise of the educators. Attendance control is critical for learning, ensuring that students are participating in classes and receiving the education they need to succeed [101].

Over time, advancements in technology have made localisation in education more efficient and effective. Up to date, the use of AI and ML has allowed institutions to automatically translate the geo-location of a teacher to attendance control of its workplace when they are in the nearby of the institution [102]. Thus, the rise of SE have evolved to encompass the need for accurate localisation data to track students' attendance during lectures [103].

There are different solutions to control the attendance of the students. Camera-based systems identifies with high probability the face of the student to track their attendance [104]. However, this type of system carries significant privacy concerns with additional issue of the subjects often being underage [105]. Barcode or QR scan [106] or RFID identification systems [107] solves these privacy concerns. In barcode or QR systems, students must log in through the institute portal by an application to ensure their attendance by face id [108] or biometrics [109]. RFID identification systems check the attendance based on an NFC system that detects the students at the beginning of the class. QR scanning systems are more time efficient because it makes all students to ensure their attendances in a time interval. Nevertheless, this process halts the lecture for a brief duration.

Automatic attendance control eliminates these processes on the user's side to reduce the time consumed in this process to zero. Moreover, it aids educators in identifying and addressing any issues or challenges that students may be facing, such as absenteeism or lack of engagement. Additionally, attendance data can be used to evaluate the effectiveness of educational programs and make improvements where needed. In short, attendance control is an essential aspect of ensuring that students are receiving a high-quality education.

Beyond their administrative utility, location-based attendance systems have the potential to offer insights into pedagogical practices. Through the analysis of spatio-temporal movement patterns, instructors can develop a more comprehensive understanding of how students interact with different zones of the learning environment, thereby identifying areas of both high and low engagement. This data facilitates the conceptualization of adaptive learning environments that dynamically respond to students' presence and movement, thereby promoting active learning. Additionally, real-time localization can facilitate collaborative learning analytics by identifying group behaviour and enabling proximity-based peer interaction. These affordances are consistent with

TABLE 3. Comparison of different use cases.

Use Case	Location Accuracy	Latency	Description
XR	0.1 m	50 ms	Immersive and interactive systems to improve the learning experience
Holography	1 cm	100 ms	
Indoor Navigation	3 m	1 s	Guidance for finding people/offices within a building or campus
Space Usage and Occupancy Tracking	10 m	1 s	Capacity control with DFL systems for safety concerns
Attendance Control	5 m	1 s	To detect the presence whether a student is in a classroom

learner-centered educational paradigms and constructivist models, in which context and interaction are pivotal to the construction of meaningful knowledge.

In [32], an automatic attendance control system based on localisation is developed based on BLE. This system matches the localisation of the students during the lecture with the attendance control. During this process, neither students nor teacher intervene during the process of attendance control. For this process, time is not critical, so even a latency of up to a few seconds is valid. The location process is done with Approximate Nearest Neighbors (ANN), which is an ML model, that estimates the position of the user by a previous modelling of the scenario. Radio technologies that are usually present in SE scenarios, such as 5G, WiFi or BLE, can also be leveraged for this use. By using the RSSI information, the system can automatically detect the presence of a student in a classroom within a localisation accuracy of 2-5 meters [110].

Table 3 shows an overview of the different use cases with their minimum location accuracy and latency required for the 80% of the cases for 5G commercial use cases [11] and a brief description of their use in SE.

V. PRIVACY CONCERNS

A potential limitation of using localisation in SE are the privacy concerns of students. Institutions may need to implement safeguards to ensure that students' location data is not misused [111]. To address these concerns, this section places GDPR compliance in an international context, comparing it with frameworks such as CCPA (California Consumer Privacy Act), CPRA (California Privacy Rights Act) and PIPEDA (Canada) to highlight the robust privacy measures of the proposed system.

A. GDPR AND INTERNATIONAL COMPARISONS

The General Data Protection Regulation (GDPR) is an European Union (EU) regulation that governs the protection of personal data. In relation to localisation privacy, GDPR establishes several requirements for companies that collect, process, and store location data [112]. These requirements include transparency, ensuring that only the minimum amount of data is collected, ensuring that data is accurate and up-to-date, implementing appropriate security measures, limiting data retention and giving individuals the right to access, rectify, and erase their location data [113]. GDPR also requires institutions to conduct Data Protection Impact Assessments (DPIAs) to identify and mitigate risks associated with sensitive data processing, particularly relevant for student location tracking. Additionally, GDPR requires institutions to appoint a data protection officer if they process or monitor location data on a large scale or if the core activities of their business involve regular and systematic monitoring of individuals [112].

In the United States, there is no single regulatory framework equivalent to GDPR. Instead, privacy regulations are fragmented and vary by state. The California Consumer Privacy Act (CCPA) is one of the most comprehensive state-level privacy laws and shares some principles with GDPR, such as granting individuals the right to access and delete their personal data [114]. However, it is more limited in scope, focusing primarily on consumer data collected by businesses. The California Privacy Rights Act (CPRA), an extension of the CCPA, introduces additional protections, including data minimization requirements and mandatory privacy impact assessments, aligning more closely with GDPR principles [115]. Other states, such as Virginia and Colorado, have enacted similar laws, but these frameworks remain less comprehensive than GDPR. In Canada, the Personal Information Protection and Electronic Documents Act (PIPEDA) is the legislative instrument that governs data privacy in the private sector [116]. PIPEDA, analogous to the GDPR, requires organisations to obtain consent when collecting personal data, implement security measures, and provide individuals with access to their data. Nevertheless, the scope of the GDPR and the mechanisms of its enforcement are broader and more rigorous.

B. GDPR COMPLIANCE IMPLICATIONS FOR SE LOCALIZATION SYSTEMS

Educational institutions implementing GDPR-compliant localisation systems need to consider several factors that include deploying data sovereignty, data minimization, transparency and ensuring continuous monitoring and auditing of data practices to detect and mitigate any privacy risks promptly.

1) DATA SOVEREIGNTY

Data is subject to the laws and governance structures within the nation it is collected. Educational institutions must implement Data Transfer Agreements (DTAs) ensuring that data shared with third party service providers maintains the same levels of security.

2) DATA MINIMIZATION

The GDPR principles advocate for the collection of only the location data that is necessary for the specific educational purposes for which it is being collected. In a SE context, this may entail the collection of data for the purpose of verifying student attendance within designated zones (e.g., classrooms, libraries) during specific times, as opposed to continuous monitoring of student location throughout the school day. Furthermore, wherever feasible, the anonymisation or pseudonymisation of location data can serve to enhance privacy.

3) TRANSPARENCY

Schools or faculties deploying indoor localisation systems must have clear and accessible privacy policies. These policies should explain how student location data is collected, used, and stored. Informed consent, obtained from students (and their parents/guardians if applicable), is essential.

4) CONTINUOUS MONITORING AND AUDITING OF DATA PRACTICES

Robust security protocols are in place to safeguard location data from unauthorised access, breaches or loss. This entails the implementation of encryption measures, access controls, and periodic security assessments to identify and address potential vulnerabilities. For instance, educational establishments are required to define transparent retention periods for student location data, contingent on its intended purpose. This may include data collected for the purposes of monitoring attendance, which may be retained for varying periods of time, such as months, semesters, or years. The periodic examination of data management procedures can facilitate the expedient identification and mitigation of privacy hazards, thereby ensuring the continued compliance of data processing operations with the stipulations set forth in the GDPR.

VI. PROOF OF CONCEPT

In this section, the PoC is described in full detail. It implements an attendance control system for SE that locates students within a laboratory using cellular technology and WiFi networks, both operating independently and combined. Different techniques for classification and regression are explained, and the different challenges and limitations that this PoC can encounter are defined. In addition, the experiments and the scenario setups are described. Results of the different techniques and technologies are discussed. Finally, a proposal for an architecture that integrates this service within an OpenRAN derived from this PoC is given.

A. OBJECTIVES

The implementation of a real system at an educational institution, whether a campus or a school, would streamline the process of monitoring student attendance, thereby reducing the time spent on this task. This would allow for an increase in the time dedicated to lectures, which would, in theory, enhance the overall quality of the educational system.

The decision to combine WiFi and 5G technologies was driven by their extensive availability in educational settings. WiFi is a pervasive technology in most institutions, while 5G offers enhanced signal strength. The integration of these two technologies aims to enhance the precision of location-based services, particularly in scenarios where one technology may face coverage challenges. Furthermore, this approach increases the resilience of the system by providing redundancy in case of network disruptions.

Furthermore, modern smartphones, which are widely used by students, operate in a dual mode, enabling simultaneous utilisation of WiFi and cellular networks. This dual functionality facilitates efficient data transmission between the student's device and the server, ensuring seamless integration and reducing latency in the attendance control process. The dual-mode capability of mobile devices not only facilitates real-time data communication but also supports continuous monitoring without disrupting the user experience, making it highly suited for this PoC setup.

Based on these objectives, we define the following Research Questions to guide the study:

- How effective is the proposed system in automating student attendance monitoring in a SE environment? Is it useful for educators?
- Which is the accuracy of different approaches for indoor localization in SE scenarios?
- What are the benefits of integrating WiFi and 5G for real-time location-based services in education compared to isolated technologies? What are their limitations? Is it worth it to fuse these technologies?

The main objective of this PoC consists on localizing the students within a specific classroom depending on their radio signal information for an automatic attendance control system in real-time. To achieve this goal, a comparative analysis is conducted between two different methodologies of Random Forest (RF).

The first approach utilizes a purely classification-based ML model, which determines whether the student is in a laboratory or not based on the provided input. Conversely, the second approach entails a location regression model that estimates the student's position and subsequently classifies whether the student is situated within a laboratory area. Thus, both systems use, as input, the RSSI signal obtained from 5G and WiFi networks working both together and independently. In this case, the system uses an RF method that is straightforward to implement and can accomplish high precision in classification and regression processes. The objectives of this PoC are disclosed as follows:

- Performance validation of the automatic attendance control system.
- Comparison of classification and regression success rate.

- Demonstration of the viability and benefits of the opportunistic fusion for location-based services for SE.

B. METHODOLOGY

The RF model was selected due to its capacity to process data that is subject to noise, which is a prevalent issue with wireless signals in indoor environments. RF are ensemble learning methods that operate by constructing multiple decision trees during training and outputting the mode of classification (majority voting) or the average prediction (regression) of the individual trees [117].

Furthermore, RF is advantageous due to its efficiency in combining multiple features, such as RSSI from both WiFi and 5G, to provide high precision in both classification and regression tasks. Furthermore, RF is particularly well-suited to scenarios where signal fluctuations caused by environmental factors, such as reflections and interference from objects and walls, can affect the accuracy of localisation. This technique combines the predictions from various single models, known as *base models*, to create a final outcome. RFs are a versatile tool for a range of ML tasks such as classification, regression or anomaly detection [118]. RFs are particularly effective in classification and regression tasks as they can effectively merge the predictions of multiple decision trees to provide a final location of the UE [117].

RFs create decision trees through a process called bootstrapping aggregation (bagging), which involves randomly selecting a subset of the training data and using this subset to create a decision tree, this process is repeated multiple times, resulting in a large number of decision trees that are all trained on different subsets of the data [118]. The final prediction is then made by averaging the predictions of all the decision trees in the forest as illustrated in Figure 2. In the case of the classification process, as shown in Figure 2 (a), a majority voting mechanism is employed to determine the final output, which corresponds to the most commonly voted label. In contrast, in the regression model process, depicted in Figure 2 (b), the estimation of the location is achieved by averaging the positions across the trees. RFs are robust to the presence of noise in the data, as the averaging process helps to reduce the impact of any individual decision tree that may be making incorrect predictions [119].

RFs are an straightforward implementation with minimal hyperparameter tuning requirements that made it an ideal choice for resource-constrained environments, such as educational institutions with limited technical infrastructure. While other ML models were considered, their limitations made them less suitable for the specific requirements with low infrastructure investment. For example, Neural networks require significantly larger datasets, Support Vector Machines (SVM) are sensitive to kernel selection or gradient boosting methods, while powerful, demand extensive hyperparameter tuning and are computationally expensive to train [120].

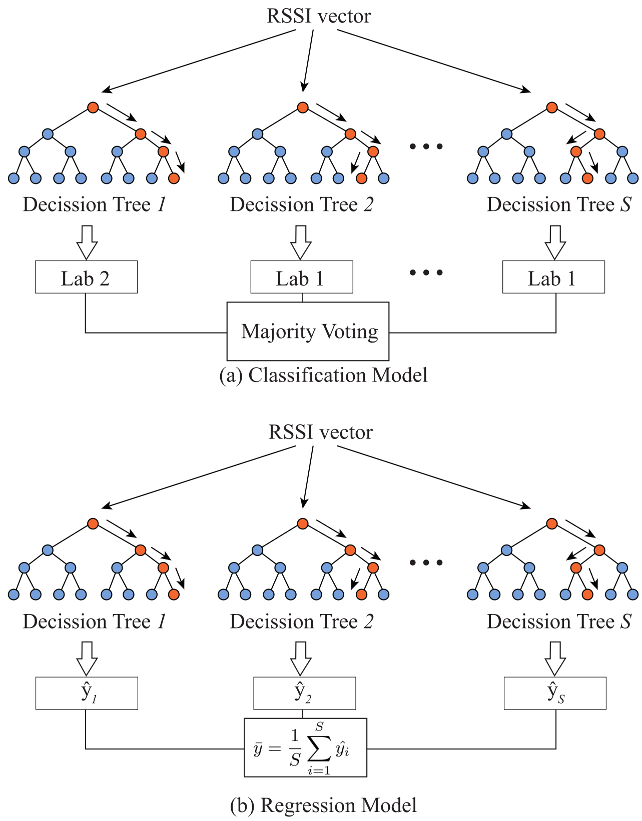


FIGURE 2. RF schema.

C. CHALLENGES AND LIMITATIONS OF THE POC

The main challenges encountered during the experiments were related to signal interference and multipath propagation, due to the presence of metallic objects and other elements within the surrounding environment. These challenges are intrinsic to real-world SE environments, where classroom structures, furniture placement, and student movement can significantly impact signal stability and positioning accuracy.

Due to the high concentration of students within a classroom environment, the personal devices utilized by these students possess the potential to introduce interference within the radio frequency spectrum degrading the end-user position estimation. Additionally, educational institutions often operate in mixed-device environments where older devices may not support advanced localisation techniques, further complicating uniform implementation.

Areas without coverage may be generated, relying solely on 5G or WiFi localisation for attendance control becomes problematic since students may encounter difficulties in establishing network connections. Moreover, ensuring real-time data transmission in dense classroom environments remains a challenge, as network congestion can lead to delays in attendance verification.

One critical challenge specific to SE applications, particularly in AAC, is the cost associated with False Positive (FP) and False Negative (FN) errors. False positives occur when the system incorrectly marks a student as present when they are absent, potentially leading to issues in monitoring student engagement and compliance. Conversely, false negatives result in students being incorrectly marked as absent despite being present, which can have significant consequences, such as unfair penalties for attendance-based grading or unnecessary administrative interventions. Addressing these errors requires a balance between sensitivity and specificity in the implemented classification algorithms, along with redundancy mechanisms, such as fusing multiple positioning technologies to improve detection reliability.

In this PoC, the focus is on the basic infrastructure commonly found in primary or secondary schools, including cellular networks and WiFi. As a result, this PoC can be conducted at any educational institute with limited resources.

D. EXPERIMENTAL SETUP

The scenario where the PoC was deployed is located at the University of Malaga and composed by two different laboratories as shown in Figure 3. It is a medium-cluttered scenario with instrumentation equipment that create signal reflections in the whole area. Both 5G and WiFi networks were utilized to conduct the measurement campaign.

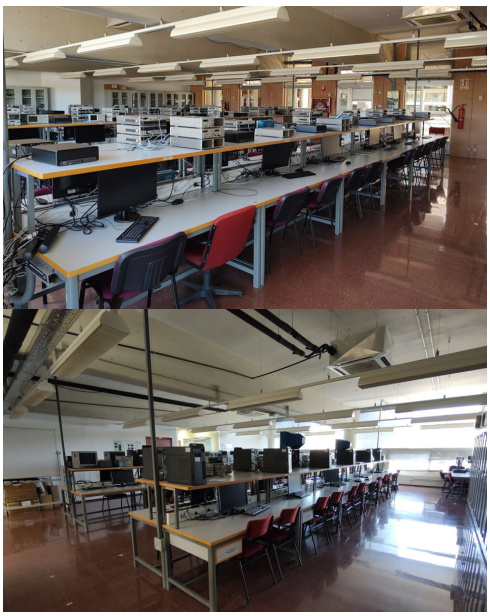


FIGURE 3. **Images of both laboratories.**

To minimize interference with commercial networks, three gNodeBs (gNBs) were configured for the 5G network, with the stations located at different heights (2.5 m and 3.5 m), as shown in the map of the scenario map in Figure 4. Additionally, Google WiFi mesh routers were used as WiFi APs, placed on shelves at a height of 2 meters. For the 5G network, the gNBs were located in the ceiling to provide good visibility and transmit at a frequency of 3774.990 MHz with a power of 20 dBm. The arrangement of the gNBs and routers were a legacy layout. The scenario consisted of two laboratories, with an additional laboratory where there is a 5G AP, which included metallic elements that could potentially cause signal blocking, attenuation, and multipath effects.

E. IMPLEMENTATION DETAILS OF THE AAC SYSTEM

To ensure a comprehensive understanding of the proposed automatic attendance control (AAC) system, this section details its architecture, data collection process, and integration into educational environments.

1) SYSTEM ARCHITECTURE AND COMPONENTS

The AAC system is composed of the following key elements:

- Client Devices: Student smartphones equipped with WiFi and 5G connectivity, which serve as localization sources.
- Network Infrastructure: WiFi access points and 5G gNBs installed within the classroom environment to provide connectivity and positioning data.
- Processing and Storage Unit: A cloud-based or local server responsible for collecting, analysing, and storing attendance records.
- Machine Learning Model: A RF algorithm trained on RSSI data to classify student presence accurately.

2) DATA COLLECTION AND PROCESSING WORKFLOW

- Signal Measurement: The system continuously gathers WiFi and 5G signal strength data from students' mobile devices. To collect the RSSI of serving and neighboring cells in both 5G and WiFi networks, a smartphone application has been created. The application reads the 5G and WiFi connection information that can be used for real-time services due to its refresh rate is up to 2Hz. The application is made of multiple threads called *services*, which represent a software entity that either performs a long-running operation without user interaction in which extract WiFi and 5G NR information from the chipset.[2] A Motorola Edge 20 smartphone, operating on Android 11, serves as the target UE for determining location. RSSI information is collected in an snapshot time by this application is subsequently transmitted via the 5G network to a server, where the measurement samples are stored in a MySQL database for future analysis. The application also includes a feature for indicating the ground truth location, which is then included along with the measured data. By using this setup and collecting data application from real-world scenarios, we aimed to accurately evaluate the performance of the classification system.
- Localisation Analysis: Using a trained RF model, the system processes collected signal data to determine student presence in predefined classroom zones. In this study, a dataset comprising more than 250 samples was

[2] Service in Android Developer, https://developer.android.com/reference/kotlin/android/app/Service, Accessed: 18/02/2025.

employed.[3] To facilitate RF training and evaluation, the data was divided into a training set and a testing set, visually depicted in Figure 4 as orange and green dots, respectively. The 20% of the measurements were designated for testing. To ensure reliable statistical outcomes, the experiment was repeated a thousand times, with each iteration involving random selection of training and testing points using the Monte Carlo method. In addition, this approach allows for the assessment of model sensitivity under realistic conditions, such as signal interference caused by metallic structures, user density, and device variability. As a result, it enables a robust estimation of classification performance and provides insights into the influence of environmental variability on model reliability. Figure 4 illustrates one instance of this iterative process, ensuring precise statistical results.

- Attendance Validation: Once a student is classified as present, the system records attendance in a central database.

In terms of actual implementation, the AAC system may have the capacity to be integrated into a Learning Management System (LMS), such as Moodle or Blackboard. The automatic synchronization of attendance records facilitates real-time updates to class rosters and attendance logs. Educators are able to monitor and retrieve attendance data through an administrative portal, thereby streamlining attendance management and reporting.

F. RESULTS

This section presents the performance of the localisation and classification results achieved from the PoC, which aimed to assess the reliability of the system for classifying a student's location within a specific classroom. To achieve this goal, the performance of both RF models are evaluated by comparing the accuracy of final classification obtained from 5G and WiFi networks, both together and independently.

1) COMPARING ACCURACY OF CLASSIFICATION AND LOCALIZATION-BASED REGRESSION MODELS

To assess the effectiveness of the classification and localisation-based regression models, it is crucial to compare the accuracy of the classification process in correctly identifying the laboratory where the student is placed. Figure 5 illustrates the percentage of accuracy performance of the classification (orange) and localisation-based regression (blue) models for 5G, WiFi, and their fusion.

The findings demonstrate that the regression model and the fusion of different technologies significantly enhance the overall classification performance of the system. In indoor environments, signal propagation conditions tend to be challenging, resulting in a random reception of RSSI by the UEs due to blockages and multipath effects. Based on the user's position estimation, the system determines whether the user is situated within a classroom. Consequently, in regions closer to the classroom boundaries, there is an enhancement in performance compared to the pure classification method. This enhancement is attributed to the fact that regression systems first estimate the UEs' location and subsequently assign it to a particular classroom.

[3]This dataset is upload in [121] in order to allow the reader to perform new ML algorithms to improve the final accuracy. For reproducibility purposes, the full configuration of the RF model is reported: 100 decision trees were used, with a maximum depth of 20 and Gini impurity as the splitting criterion.

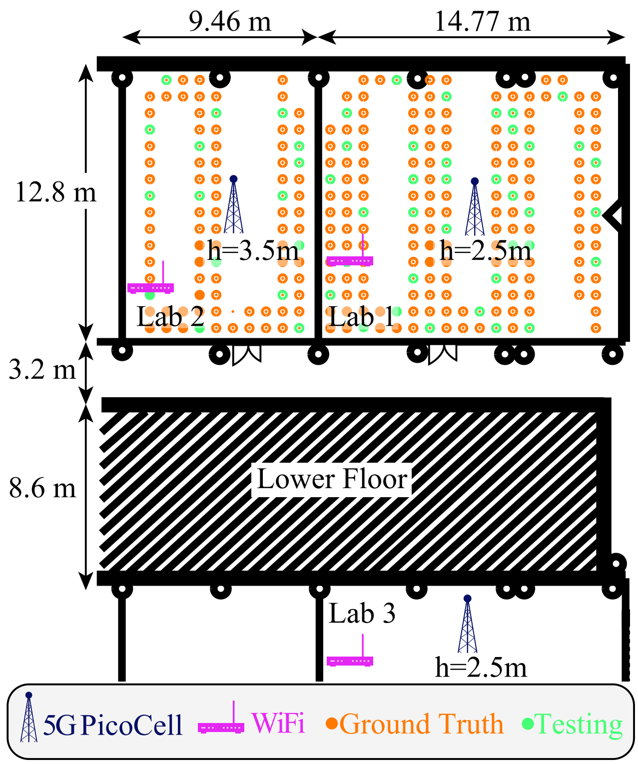


FIGURE 4. Map of the scenario.

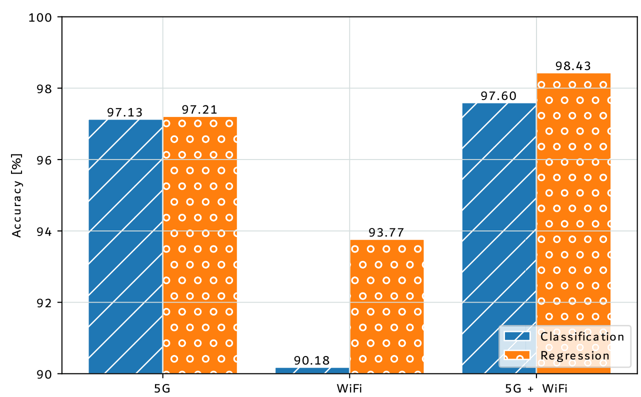


FIGURE 5. Comparative accuracy analysis of classification and regression RF models for 5G, WiFi and Fusion.

2) LOCALIZATION PERFORMANCE BY REGRESSION

the system classifies the student's location as being within a specific laboratory. Figure 6 represents the Cumulative

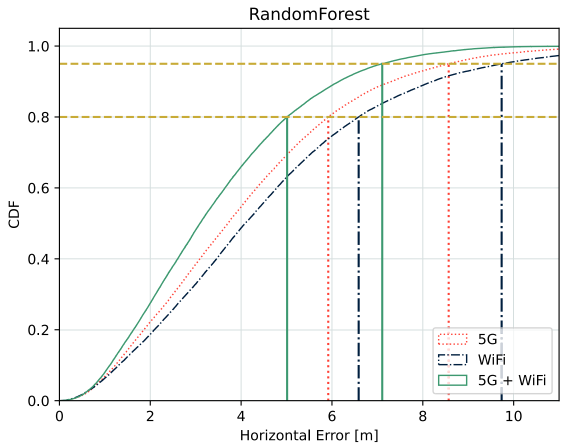


FIGURE 6. CDF of localisation regression for 5G, WiFi and Fusion.

Density Function (CDF) of the horizontal localisation error. The localisation error is relative to the disparity between the estimated final position of the user and the ground truth position. As it can be observed, the performance of 5G (red dotted line) is better than WiFi (blue dashed line). However, the fusion (green line) of both technologies improves the overall performance compared with each technology in isolation. Fusing 5G and WiFi achieves a location error of 5 and 7 meters in 80% (pink) and 95% (yellow) of the cases, respectively. Thus, it satisfies the location requirements stated in Table 3 as originally mentioned.

The better precision of the regression, the better performance at the classification process is expected. Notably, when examining the data independently, 5G obtains higher localisation precision resulting in a higher accuracy classification results. Consequently, when combining 5G with WiFi data, there is a noticeable enhancement in classification accuracy than in isolation.

By combining two technologies, the system not only improves its classification accuracy but also extends its coverage area beyond what could be achieved with a single technology. Simultaneously employing two supplementary technologies offers redundancy in case of system failure or outage, further enhancing the robustness of the system.

VII. DISCUSSION

While the proposed system effectively demonstrates the integration of WiFi and 5G for automatic attendance control in SE, it is essential to critically assess its merits and limitations to provide a balanced evaluation.

A. MERITS OF THE PROPOSED IMPLEMENTATION

The system leverages widely deployed WiFi and emerging 5G infrastructures, ensuring broad applicability. It eliminates manual processes, reducing administrative workload and minimizing human error. The fusion of WiFi and 5G was found to be an effective method of mitigating some of these issues, resulting in more accurate localisation overall. Additionally, real-time data processing ensures seamless integration with educational management systems for immediate attendance validation.

B. SCALABILITY OF THE SYSTEM

The proposed PoC demonstrates inherent scalability, primarily due to the extensive pre-existing network infrastructures typically found in educational institutions. The ubiquity of WiFi networks, in conjunction with the pervasive coverage of mobile networks, establishes a robust foundation for large-scale implementation without necessitating significant additional investment in communication infrastructure. Consequently, the scalability challenge shifts from infrastructure deployment to the seamless integration of the localization system within existing educational management platforms. In order to extend the PoC across a number of classrooms or buildings, it is first necessary to perform an initial measurement campaign within each targeted area. This is the prerequisite for the successful training and calibration of the localization models. Upon completion of the calibration phase, the system is able to operate autonomously, thereby providing scalable, low-latency attendance tracking services across a range of educational environments.

C. LIMITATIONS AND CHALLENGES

The system relies on students carrying their mobile phones, which introduces potential deception scenarios where a student's device is present but the student is not, although this is an unlikely scenario as it is rare for students to leave their phones behind or lend them to others. Additionally, the system can also serve as a preliminary step before manual attendance verification, helping to speed up the process and allowing students to check if their attendance has been correctly recorded. Factors such as network congestion, multipath effects, and indoor signal interference may reduce system performance in certain environments. The continuous tracking of student locations raises ethical and regulatory concerns, necessitating strict compliance with GDPR and other privacy frameworks. While WiFi is widespread, 5G infrastructure deployment is still limited in many institutions, which may hinder immediate large-scale adoption.

D. FUTURE RESEARCH

To mitigate these challenges, future research could explore device-free localization techniques, multi-sensor fusion with Bluetooth Low Energy (BLE), and alternative authentication mechanisms to enhance robustness against device-based deception. Additionally, the inclusion of privacy-preserving methodologies, such as anonymization and decentralized data handling, would further strengthen the system's compliance with privacy regulations.

VIII. CONCLUSION

Location-based services are increasingly used in education to enhance the learning experience and increase efficiency, with the implementation of XR and indoor navigation on campuses. In this paper, we explored the application of indoor localisation technologies, specifically WiFi and 5G, in the context of SE. Through the development and implementation of a PoC, we demonstrated the viability of integrating widely available technologies to create cost-effective, scalable solutions tailored to resource-constrained educational environments. The insights gained from this work highlight several significant contributions and suggest promising directions for future development.

This paper aims to provide an overview of localisation in SE with real-world examples, analysing the main technologies and techniques employed to improve the quality of education. After analysing the challenges and limitations of the different technologies in this educational context, we conducted an experiment on a system created to automate attendance control in education settings. The PoC emphasizes the use of affordable and widely available infrastructure, such as existing WiFi and cellular networks, making it accessible to a broad range of educational institutions, particularly those with limited budgets. The system effectively demonstrated the advantages of combining various available technologies within educational institutions to overcome limitations related to signal coverage and accuracy, achieving robust and scalable location-based services, as shown by real data.

This PoC illustrates that a localisation-based regression model performs better than a simple classifier model. The proposed AAC system can be readily implemented in academic settings, offering a straightforward and unobtrusive method for enhancing teaching and learning efficiency. The attendance monitoring procedure may be executed using students' mobile devices, as all such devices come equipped with both cellular and WiFi technologies. Additionally, the system's data can be analysed to identify attendance patterns, allowing teachers to optimize class scheduling and delivery. The proposed system streamlines attendance tracking and could provide other location-based services for students, including space usage and occupancy tracking. The potential of wide-spread 5G and WiFi technologies in the education sector to revolutionise how students learn and interact with their surroundings is significant. Furthermore, the approach paves the way for future advancements in smart education, such as enabling adaptive learning environments where location data supports personalized and context-aware learning experiences, and improving accessibility and efficiency through real-time guidance systems for navigating complex campus environments.

The proposed system has the potential to seamlessly integrate into existing educational management systems. By providing dynamic, real-time data on attendance, classroom occupancy, and student engagement, it could serve as a comprehensive tool for automating administrative tasks, such as attendance tracking, informing data-driven decisions on scheduling and resource allocation, and enhancing overall institutional efficiency and transparency. This work not only showcases the practical applications of indoor localisation in education but also sets the stage for future innovations. By leveraging existing technologies in a cost-effective and scalable manner, we contribute to the ongoing evolution of smart education systems, aiming to enhance the learning experience, improve institutional efficiency, and democratize access to advanced educational tools.

REFERENCES

[1] H. Obeidat, W. Shuaieb, O. Obeidat, and R. Abd-Alhameed, "A review of indoor localization techniques and wireless technologies," *Wireless Pers. Commun.*, vol. 119, no. 1, pp. 289–327, Jul. 2021.

[2] V. Terzieva, T. Ivanova, M. Ivanova, S. Ilchev, E. Djambazova, and I. Petrov, "Intelligent educational environments: Recent trends, modeling, and applications," *Appl. Sci.*, vol. 15, no. 7, p. 3800, Mar. 2025.

[3] T. Sayapogu, K. Dsa, and P. Kaul, "AR smart navigation system," in *Proc. 2nd Int. Conf. Emerg. Technol. (INCET)*, May 2021, pp. 1–4.

[4] D. Schiff, "Education for AI, not AI for education: The role of education and ethics in national AI policy strategies," *Int. J. Artif. Intell. Educ.*, vol. 32, no. 3, pp. 527–563, Sep. 2022.

[5] R. Chengoden, N. Victor, T. Huynh-The, G. Yenduri, R. H. Jhaveri, M. Alazab, S. Bhattacharya, P. Hegde, P. K. R. Maddikunta, and T. R. Gadekallu, "Metaverse for healthcare: A survey on potential applications, challenges and future directions," *IEEE Access*, vol. 11, pp. 12765–12795, 2023.

[6] Y. Koumpouros, "Revealing the true potential and prospects of augmented reality in education," *Smart Learn. Environ.*, vol. 11, no. 1, p. 2, Jan. 2024.

[7] B. El Boudani, L. Kanaris, A. Kokkinis, M. Kyriacou, C. Chrysoulas, S. Stavrou, and T. Dagiuklas, "Implementing deep learning techniques in 5G IoT networks for 3D indoor positioning: DELTA (DeEp learning-based co-operaTive Architecture)," *Sensors*, vol. 20, no. 19, p. 5495, Sep. 2020.

[8] G. Kia, J. Talvitie, and L. Ruotsalainen, "RSS-based fusion of UWB and WiFi-based ranging for indoor positioning," in *Proc. CEUR Workshop*, vol. 3097, 2021.

[9] H. A. de Souza Mourão and H. A. B. F. de Oliveira, "Indoor localization system using fingerprinting and novelty detection for evaluation of confidence," *Future Internet*, vol. 14, no. 2, p. 51, Feb. 2022.

[10] S. Dwivedi, R. Shreevastav, F. Munier, J. Nygren, I. Siomina, Y. Lyazidi, D. Shrestha, G. Lindmark, P. Ernström, E. Stare, S. M. Razavi, S. Muruganathan, G. Masini, Å. Busin, and F. Gunnarsson, "Positioning in 5G networks," *IEEE Commun. Mag.*, vol. 59, no. 11, pp. 38–44, Nov. 2021.

[11] *Study on NR Positioning Support*, document TR 38.855, 3GPP, 2019.

[12] E.-S. Kim, M. Sung, J. H. Lee, J. K. Lee, S.-H. Cho, and J. Kim, "Coverage extension of indoor 5G network using RoF-based distributed antenna system," *IEEE Access*, vol. 8, pp. 194992–194999, 2020.

[13] G. Yammine, M. Alawieh, G. Ilin, M. Momani, M. Elkhouly, P. Karbownik, N. Franke, and E. Eberlein, "Experimental investigation of 5G positioning performance using a mmWave measurement setup," in *Proc. Int. Conf. Indoor Positioning Indoor Navigat. (IPIN)*, Nov. 2021, pp. 1–8.

[14] *Study on Channel Model for Frequencies From 0.5 to 100 GHz*, document TR 38.855, 3GPP, 2019.

[15] C. Sudhamani, M. Roslee, L. L. Chuan, A. Waseem, A. F. Osman, and M. H. Jusoh, "Enhanced indoor path loss and RSRP of 5G mmWave communication system with multi-objective genetic algorithm," *Wireless Pers. Commun.*, vol. 138, no. 1, pp. 603–621, Sep. 2024.

[16] S. Fortes, J. A. Santoyo-Ramón, D. Palacios, E. Baena, R. Mora-García, M. Medina, P. Mora, and R. Barco, "The campus as a smart city: University of Málaga environmental, learning, and research approaches," *Sensors*, vol. 19, no. 6, p. 1349, Mar. 2019.

[17] G. Fokin and D. Volgushev, "Model for interference evaluation in 5G millimeter-wave ultra-dense network with location-aware beamforming," *Information*, vol. 14, no. 1, p. 40, Jan. 2023.

[18] S. Dargaoui, M. Azrour, A. E. Allaoui, A. Guezzaz, A. Alabdulatif, and A. Alnajim, "Internet of Things authentication protocols: Comparative study," *Comput., Mater. Continua*, vol. 79, no. 1, pp. 65–91, 2024.

[19] S. Fiore, L. Dekkar, and K. Aseda, "Eduroam in Africa," in *Proc. IST-Africa Conf. (IST-Africa)*, May 2023, pp. 1–11.

[20] L. Florio and K. Wierenga, "Eduroam, providing mobility for roaming users," in *Proc. EUNIS Conf.*, 2005.

[21] T. Perković, A. Dagelić, M. Bugarić, and M. Čagalj, "On WPA2-enterprise privacy in high education and science," *Secur. Commun. Netw.*, vol. 2020, pp. 1–11, Sep. 2020.

[22] O. Hashem, K. A. Harras, and M. Youssef, "Accurate indoor positioning using IEEE 802.11mc round trip time," *Pervas. Mobile Comput.*, vol. 75, Aug. 2021, Art. no. 101416.

[23] C. Gentner, M. Ulmschneider, I. Kuehner, and A. Dammann, "WiFi-RTT indoor positioning," in *Proc. IEEE/ION Position, Location Navigat. Symp. (PLANS)*, Apr. 2020, pp. 1029–1035.

[24] N. R. Khatiwoda, B. R. Dawadi, and S. R. Joshi, "Capacity and coverage dimensioning for 5G standalone mixed-cell architecture: An impact of using existing 4G infrastructure," *Future Internet*, vol. 16, no. 11, p. 423, Nov. 2024.

[25] I. Martin-Escalona and E. Zola, "Passive round-trip-time positioning in dense IEEE 802.11 networks," *Electronics*, vol. 9, no. 8, p. 1193, Jul. 2020.

[26] S. Jin and D. Kim, "WiFi fingerprint indoor localization employing AdaBoost and probability-one access point selection for multi-floor campus buildings," *Future Internet*, vol. 16, no. 12, p. 466, Dec. 2024.

[27] L. Fen, J. Liu, Y. Yin, W. Wang, H. Dong-hai, P. Chen, and Q. Niu, "Survey on WiFi-based indoor positioning techniques," *IET Commun.*, vol. 14, no. 9, pp. 1372–1383, Feb. 2020.

[28] L. Schuhmacher, S. Pollin, and H. Sallouha, "EcoBLE: A low-computation energy consumption prediction framework for Bluetooth low energy," 2023, *arXiv:2309.16686*.

[29] M. N. Amr, H. M. Elattar, M. H. A. E. Azeem, and H. E. Badawy, "An enhanced indoor positioning technique based on a novel received signal strength indicator distance prediction and correction model," *Sensors*, vol. 21, no. 3, p. 719, Jan. 2021.

[30] T. Kluge, C. Groba, and T. Springer, "Trilateration, fingerprinting, and centroid: Taking indoor positioning with Bluetooth LE to the wild," in *Proc. IEEE 21st Int. Symp. World Wireless, Mobile Multimedia Netw. (WoWMoM)*, Aug. 2020, pp. 264–272.

[31] Z. Wei, Q. Wei, Y. Geng, and Y. Yang, "A survey on IoT security: Vulnerability detection and protection," in *Proc. Int. Conf. Artif. Intell. Things Comput.*, Aug. 2024, pp. 1–8.

[32] A. Puckdeevongs, N. K. Tripathi, A. Witayangkurn, and P. Saengudomlert, "Classroom attendance systems based on Bluetooth low energy indoor positioning technology for smart campus," *Information*, vol. 11, no. 6, p. 329, Jun. 2020.

[33] A. Barua, M. A. A. Alamin, M. S. Hossain, and E. Hossain, "Security and privacy threats for Bluetooth low energy in IoT and wearable devices: A comprehensive survey," *IEEE Open J. Commun. Soc.*, vol. 3, pp. 251–281, 2022.

[34] T. Sutjarittham, H. Habibi Gharakheili, S. S. Kanhere, and V. Sivaraman, "Experiences with IoT and AI in a smart campus for optimizing classroom usage," *IEEE Internet Things J.*, vol. 6, no. 5, pp. 7595–7607, Oct. 2019.

[35] S. Azizi, G. Nair, R. Rabiee, and T. Olofsson, "Application of Internet of Things in academic buildings for space use efficiency using occupancy and booking data," *Building Environ.*, vol. 186, Dec. 2020, Art. no. 107355.

[36] T. Anagnostopoulos, P. Kostakos, A. Zaslavsky, I. Kantzavelou, N. Tsotsolas, I. Salmon, J. Morley, and R. Harle, "Challenges and solutions of surveillance systems in IoT-enabled smart campus: A survey," *IEEE Access*, vol. 9, pp. 131926–131954, 2021.

[37] I. Martínez, B. Zalba, R. Trillo-Lado, T. Blanco, D. Cambra, and R. Casas, "Internet of Things (IoT) as sustainable development goals (SDG) enabling technology towards smart readiness indicators (SRI) for university buildings," *Sustainability*, vol. 13, no. 14, p. 7647, Jul. 2021.

[38] F. M. Pérez, J. V. B. Martínez, and I. L. Fonseca, "Modelling and implementing smart universities: An IT conceptual framework," *Sustainability*, vol. 13, no. 6, p. 3397, Mar. 2021.

[39] A. S. Olagoke, H. Ibrahim, and S. S. Teoh, "Literature survey on multi-camera system and its application," *IEEE Access*, vol. 8, pp. 172892–172922, 2020.

[40] A. Das, K. Jens, and M. B. Kjærgaard, "Space utilization and activity recognition using 3D stereo vision camera inside an educational building," in *Proc. ACM Int. Joint Conf. Pervasive Ubiquitous Comput. Proc. ACM Int. Symp. Wearable Comput.*, Sep. 2020, pp. 629–637.

[41] A. Morar, A. Moldoveanu, I. Mocanu, F. Moldoveanu, I. E. Radoi, V. Asavei, A. Gradinaru, and A. Butean, "A comprehensive survey of indoor localization methods based on computer vision," *Sensors*, vol. 20, no. 9, p. 2641, May 2020.

[42] M. Sun, L. Zhang, Y. Liu, X. Miao, and X. Ding, "See-your-room: Indoor localization with camera vision," in *Proc. ACM Turing Celebration Conf.-China*, May 2019, pp. 1–5.

[43] F. Ashiq, M. Asif, M. B. Ahmad, S. Zafar, K. Masood, T. Mahmood, M. T. Mahmood, and I. H. Lee, "CNN-based object recognition and tracking system to assist visually impaired people," *IEEE Access*, vol. 10, pp. 14819–14834, 2022.

[44] S. Saponara, A. Elhanashi, and A. Gagliardi, "Implementing a real-time, AI-based, people detection and social distancing measuring system for COVID-19," *J. Real-Time Image Process.*, vol. 18, no. 6, pp. 1937–1947, Dec. 2021.

[45] M. Heydariaan, H. Dabirian, and O. Gnawali, "AnguLoc: Concurrent angle of arrival estimation for indoor localization with UWB radios," in *Proc. 16th Int. Conf. Distrib. Comput. Sensor Syst. (DCOSS)*, May 2020, pp. 112–119.

[46] S. Zheng, Z. Li, Y. Yin, Y. Liu, H. Zhang, P. Zheng, and X. Zou, "Multi-robot relative positioning and orientation system based on UWB range and graph optimization," *Measurement*, vol. 195, May 2022, Art. no. 111068.

[47] A. Elsharkawy, K. Naheem, D. Koo, and M. S. Kim, "A UWB-driven self-actuated projector platform for interactive augmented reality applications," *Appl. Sci.*, vol. 11, no. 6, p. 2871, Mar. 2021.

[48] A. Arun, S. Saruwatari, S. Shah, and D. Bharadia, "XRLoc: Accurate UWB localization to realize XR deployments," in *Proc. 21st ACM Conf. Embedded Networked Sensor Syst.*, Nov. 2023, pp. 459–473.

[49] M. Elsanhoury, P. Mäkelä, J. Koljonen, P. Välisuo, A. Shamsuzzoha, T. Mantere, M. Elmusrati, and H. Kuusniemi, "Precision positioning for smart logistics using ultra-wideband technology-based indoor navigation: A review," *IEEE Access*, vol. 10, pp. 44413–44445, 2022.

[50] O. C. Daniel, V. Ramsurrun, and A. K. Seeam, "Smart library seat, occupant and occupancy information system, using pressure and RFID sensors," in *Proc. Conf. Next Gener. Comput. Appl. (NextComp)*, Sep. 2019, pp. 1–5.

[51] H. El Mrabet and A. Ait Moussa, "IoT-school attendance system using RFID technology," *Int. J. Interact. Mobile Technol.*, vol. 14, no. 14, p. 95, Aug. 2020.

[52] J. Joshi, A. Patil, M. Yogesh, and A. Karwa, "GNL: GeoFencing based smart outdoor navigation and localization," *ADBU J. Eng. Technol.*, vol. 11, no. 1, 2022.

[53] R. Want, *RFID Explained: A Primer on Radio Frequency Identification Technologies*. Cham, Switzerland: Springer, 2022.

[54] S. Cortesi, M. Dreher, and M. Magno, "Design and implementation of an RSSI-based Bluetooth low energy indoor localization system," in *Proc. 17th Int. Conf. Wireless Mobile Comput., Netw. Commun. (WiMob)*, Oct. 2021, pp. 163–168.

[55] P. Teunissen and O. Montenbruck, *Springer Handbook of Global Navigation Satellite Systems*. Cham, Switzerland: Springer, 2017.

[56] Y. V. Yasyukevich, B. Zhang, and V. R. Devanaboyina, "Advances in GNSS positioning and GNSS remote sensing," *Sensors*, vol. 24, no. 4, p. 1200, Feb. 2024.

[57] Y. You, "Channel estimation for millimeter wave massive MIMO communication," Ph.D. dissertation, Univ. Leeds, Leeds, U.K., 2020.

[58] J. H. Lee, B. Shin, D. Shin, J. Kim, J. Park, and T. Lee, "Precise indoor localization: Rapidly-converging 2D surface correlation-based fingerprinting technology using LTE signal," *IEEE Access*, vol. 8, pp. 172829–172838, 2020.

[59] K. Maneerat and K. Kaemarungsi, "RoC: Robust and low-complexity wireless indoor positioning systems for multifloor buildings using location fingerprinting techniques," *Mobile Inf. Syst.*, vol. 2019, pp. 1–22, Feb. 2019.

[60] Y.-X. Ye, A.-N. Lu, M.-Y. You, K. Huang, and B. Jiang, "Wireless localization based on deep learning: State of art and challenges," *Math. Problems Eng.*, vol. 2020, pp. 1–8, Oct. 2020.

[61] S. J. Hayward, K. van Lopik, C. Hinde, and A. A. West, "A survey of indoor location technologies, techniques and applications in industry," *Internet Things*, vol. 20, Nov. 2022, Art. no. 100608.

[62] R. Kawecki, S. Hausman, and P. Korbel, "Performance of fingerprinting-based indoor positioning with measured and simulated RSSI reference maps," *Remote Sens.*, vol. 14, no. 9, p. 1992, Apr. 2022.

[63] R. M. M. R. Rathnayake, M. W. P. Maduranga, V. Tilwari, and M. B. Dissanayake, "RSSI and machine learning-based indoor localization systems for smart cities," *Eng*, vol. 4, no. 2, pp. 1468–1494, May 2023.

[64] M. I. AlHajri, N. T. Ali, and R. M. Shubair, "Indoor localization for IoT using adaptive feature selection: A cascaded machine learning approach," *IEEE Antennas Wireless Propag. Lett.*, vol. 18, pp. 2306–2310, 2019.

[65] J. Yang, Y. Sun, R. Lin, and H. Zhu, "Strategic framework and global trends of national smart education policies," *Humanities Social Sci. Commun.*, vol. 11, no. 1, pp. 1–13, Sep. 2024.

[66] K. W. Kosko, R. E. Ferdig, and L. Roche, "Conceptualizing a shared definition and future directions for extended reality (XR) in teacher education," *J. Technol. Teacher Educ.*, vol. 29, no. 3, pp. 267–277, 2021.

[67] L. Shi, B. Li, C. Kim, P. Kellnhofer, and W. Matusik, "Towards real-time photorealistic 3D holography with deep neural networks," *Nature*, vol. 591, no. 7849, pp. 234–239, Mar. 2021.

[68] A. Khaleghi, Z. Aghaei, and M. A. Mahdavi, "A gamification framework for cognitive assessment and cognitive training: Qualitative study," *JMIR Serious Games*, vol. 9, no. 2, May 2021, Art. no. e21900.

[69] P. Jagoda, *Experimental Games: Critique, Play, and Design in the Age of Gamification*. Chicago, IL, USA: University of Chicago Press, 2020.

[70] A. L. Imoize, O. Adedeji, N. Tandiya, and S. Shetty, "6G enabled smart infrastructure for sustainable society: Opportunities, challenges, and research roadmap," *Sensors*, vol. 21, no. 5, p. 1709, Mar. 2021.

[71] X. Huang, Y. Xue, S. Ren, and F. Wang, "Sensor-based wearable systems for monitoring human motion and posture: A review," *Sensors*, vol. 23, no. 22, p. 9047, Nov. 2023.

[72] M. Eswaran and M. V. A. R. Bahubalendruni, "Challenges and opportunities on AR/VR technologies for manufacturing systems in the context of industry 4.0: A state of the art review," *J. Manuf. Syst.*, vol. 65, pp. 260–278, Oct. 2022.

[73] G. C. Alexandropoulos, N. Shlezinger, I. Alamzadeh, M. F. Imani, H. Zhang, and Y. C. Eldar, "Hybrid reconfigurable intelligent metasurfaces: Enabling simultaneous tunable reflections and sensing for 6G wireless communications," 2021, *arXiv:2104.04690*.

[74] F. Alriksson, D. H. Kang, C. Phillips, J. L. Pradas, and A. Zaidi, "XR and 5G: Extended reality at scale with time-critical communication," *Ericsson Technol. Rev.*, vol. 2021, no. 8, pp. 2–13, Aug. 2021.

[75] S. Dargan, S. Bansal, M. Kumar, A. Mittal, and K. Kumar, "Augmented reality: A comprehensive review," *Arch. Comput. Methods Eng.*, vol. 30, no. 2, pp. 1057–1080, Oct. 2022.

[76] A. Elzanaty, A. Guerra, F. Guidi, D. Dardari, and M.-S. Alouini, "Towards 6G holographic localization: Enabling technologies and perspectives," *IEEE Internet Things Mag.*, pp. 1–7, 2023.

[77] J. V. D. Hooft, M. T. Vega, S. Petrangeli, T. Wauters, and F. D. Turck, "Tile-based adaptive streaming for virtual reality video," *ACM Trans. Multimedia Comput., Commun., Appl.*, vol. 15, no. 4, pp. 1–24, Nov. 2019.

[78] D. Fox and I. G. Thornton, *Extended Reality (XR) Ethics and Diversity, Inclusion and Accesibility*, Standard, 2022.

[79] X. H. Ng and W. N. Lim, "Design of a mobile augmented reality-based indoor navigation system," in *Proc. 4th Int. Symp. Multidisciplinary Stud. Innov. Technol. (ISMSIT)*, Oct. 2020, pp. 1–6.

[80] N. El-Sheimy and Y. Li, "Indoor navigation: State of the art and future trends," *Satell. Navigat.*, vol. 2, no. 1, pp. 1–23, Dec. 2021.

[81] Z. Huang, G. Ye, P. Yang, and W. Yu, "Application of multi-sensor fusion localization algorithm based on recurrent neural networks," *Sci. Rep.*, vol. 15, no. 1, p. 8195, Mar. 2025.

[82] D. Tian and Q. Xiang, "Research on indoor positioning system based on UWB technology," in *Proc. IEEE 5th Inf. Technol. Mechatronics Eng. Conf. (ITOEC)*, Jun. 2020, pp. 662–665.

[83] F. J. Aranda, F. Parralejo, F. J. Álvarez, and J. A. Paredes, "Performance analysis of fingerprinting indoor positioning methods with BLE," *Expert Syst. Appl.*, vol. 202, Sep. 2022, Art. no. 117095.

[84] J. M. Rocamora, I. Wang-Hei Ho, W.-M. Mak, and A. P.-T. Lau, "Survey of CSI fingerprinting-based indoor positioning and mobility tracking systems," *IET Signal Process.*, vol. 14, no. 7, pp. 407–419, Sep. 2020.

[85] M. S. Soyer, A. Abdel-Qader, and M. C. Onbasli, "An efficient and low-latency deep inertial odometer for smartphone positioning," *IEEE Sensors J.*, vol. 21, no. 24, pp. 27676–27685, Dec. 2021.

[86] M. O. Wong and S. Lee, "Indoor navigation and information sharing for collaborative fire emergency response with BIM and multi-user networking," *Autom. Construct.*, vol. 148, Apr. 2023, Art. no. 104781.

[87] G. Anthony, T. Gjøsæter, J. Radianti, and C. Paupini, "Universally designed beacon-assisted indoor navigation for emergency evacuations," in *Proc. Int. Conf. Inf. Technol. Disaster Risk Reduction*, Poznan, Poland. Cham, Switzerland: Springer, Jan. 2019, pp. 120–129.

[88] H. Singh and S. J. Miah, "Smart education literature: A theoretical analysis," *Educ. Inf. Technol.*, vol. 25, no. 4, pp. 3299–3328, Jul. 2020.

[89] K. Ngamakeur, S. Yongchareon, J. Yu, and S. U. Rehman, "A survey on device-free indoor localization and tracking in the multi-resident environment," *ACM Comput. Surv.*, vol. 53, no. 4, pp. 1–29, Jul. 2021.

[90] J. Xue, J. Zhang, Z. Gao, and W. Xiao, "Enhanced WiFi CSI fingerprints for device-free localization with deep learning representations," *IEEE Sensors J.*, vol. 23, no. 3, pp. 2750–2759, Feb. 2023.

[91] Q. Li, X. Liao, M. Liu, and S. Valaee, "Indoor localization based on CSI fingerprint by Siamese convolution neural network," *IEEE Trans. Veh. Technol.*, vol. 70, no. 11, pp. 12168–12173, Nov. 2021.

[92] Y. Sasiwat, N. Jindapetch, D. Buranapanichkit, and A. Booranawong, "An experimental study of human movement effects on RSSI levels in an indoor wireless network," in *Proc. 12th Biomed. Eng. Int. Conf. (BMEiCON)*, Nov. 2019, pp. 1–5.

[93] S. S. Kolahi and A. A. Almatrook, "The impact of human shadowing/movement on performance of 802.11 ac client-to-server WLAN," *Int. J. Comput. Digit. Syst.*, vol. 8, no. 3, pp. 243–251, 2019.

[94] A. S. A. Sukor, L. M. Kamarudin, A. Zakaria, N. A. Rahim, S. Sudin, and H. Nishizaki, "RSSI-based for device-free localization using deep learning technique," *Smart Cities*, vol. 3, no. 2, pp. 444–455, Jun. 2020.

[95] D. Konings, F. Alam, F. Noble, and E. M-K. Lai, "SpringLoc: A device-free localization technique for indoor positioning and tracking using adaptive RSSI spring relaxation," *IEEE Access*, vol. 7, pp. 56960–56973, 2019.

[96] X. Yang, J. Cheng, X. Tang, and L. Xie, "CSI-based human behavior segmentation and recognition using commodity Wi-Fi," *EURASIP J. Wireless Commun. Netw.*, vol. 2023, no. 1, p. 46, Jun. 2023.

[97] B. Mager, P. Lundrigan, and N. Patwari, "Fingerprint-based device-free localization performance in changing environments," *IEEE J. Sel. Areas Commun.*, vol. 33, no. 11, pp. 2429–2438, Nov. 2015.

[98] M. Hazas and A. Ward, "A novel broadband ultrasonic location system," in *Proc. Int. Conf. Ubiquitous Comput.*, Göteborg, Sweden. Cham, Switzerland: Springer, Sep. 2002, pp. 264–280.

[99] D. T. Delaney, G. M. P. O'Hare, and A. G. Ruzzelli, "Evaluation of energy-efficiency in lighting systems using sensor networks," in *Proc. 1st ACM Workshop Embedded Sens. Syst. Energy-Efficiency Buildings*, Nov. 2009, pp. 61–66.

[100] T. Leephakpreeda, R. Thitipatanapong, T. Grittiyachot, and V. Yungchareon, "Occupancy-based control of indoor air ventilation: A theoretical and experimental study," *Sci. Asia*, vol. 27, no. 4, pp. 279–284, 2001.

[101] B. Bartanen, "Principal quality and Student attendance," *Educ. Researcher*, vol. 49, no. 2, pp. 101–113, Mar. 2020.

[102] M. Yousef and V. Dattana, "Auto attendance smartphones application based on the global positioning system (GPS)," in *Proc. Future Inf. Commun. Conf.*, vol. 1, Jan. 2021, pp. 917–934.

[103] M. Abdel-Basset, G. Manogaran, M. Mohamed, and E. Rushdy, "Internet of Things in smart education environment: Supportive framework in the decision-making process," *Concurrency Comput., Pract. Exper.*, vol. 31, no. 10, p. 4515, May 2019.

[104] A. Y. Strueva and E. V. Ivanova, "Student attendance control system with face recognition based on neural network," in *Proc. Int. Russian Autom. Conf. (RusAutoCon)*, Sep. 2021, pp. 929–933.

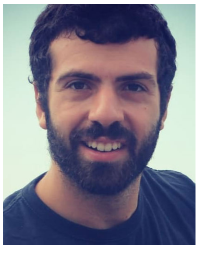
[105] K. N. Qureshi, A. Naveed, Y. Kashif, and G. Jeon, "Internet of Things for education: A smart and secure system for schools monitoring and alerting," *Comput. Electr. Eng.*, vol. 93, Jul. 2021, Art. no. 107275.

[106] A. Y. Mustafa and L. M. Jawad, "Electronic student attendance management system based on ID-card," *Sumer J. Pure Sci.*, vol. 1, no. 1, pp. 56–66, 2022.

[107] M. Ula, A. Pratama, Y. Asbar, W. Fuadi, R. Fajri, and R. Hardi, "A new model of the Student attendance monitoring system using RFID technology," *J. Phys., Conf. Ser.*, vol. 1807, no. 1, Apr. 2021, Art. no. 012026.

[108] G. Singh, R. Dwivedi, and A. Anand, "Attendance monitoring and management using QR code based sensing with cloud based processing," *Int. J. Sci. Res. Comput. Sci. Appl. Manage. Stud.*, vol. 8, no. 5, pp. 1–10, 2019.

[109] A. Varadannanavar, A. Nair, A. Kumar, and A. R. Choudhury, "Automatic attendance system using biometric authentication and varying QR code," in *Proc. 4th Int. Conf. Adv. Comput., Commun. Control Netw. (ICAC3N)*, Dec. 2022, pp. 2425–2429.
[110] W. Ji, K. Zhao, Z. Zheng, C. Yu, and S. Huang, "Multivariable fingerprints with random forest variable selection for indoor positioning system," *IEEE Sensors J.*, vol. 22, no. 6, pp. 5398–5406, Mar. 2022.
[111] J. S. Yoo, M. Y. Hong, J. W. Heo, K. H. Lee, and J. W. Yoon, "Fast private location-based information retrieval over the torus," in *Proc. IEEE Int. Conf. Adv. Video Signal Based Surveill. (AVSS)*, Jul. 2024, pp. 1–7.
[112] Official document of the European Union. (2016). *Regulation (EU) 2016/679 of the European Parliament and of the Council*. Accessed: Feb. 17, 2025. [Online]. Available: https://eur-lex.europa.eu/eli/reg/2016/679/oj/eng
[113] T. Linden, R. Khandelwal, H. Harkous, and K. Fawaz, "The privacy policy landscape after the GDPR," *Proc. Privacy Enhancing Technol.*, vol. 2020, no. 1, pp. 47–64, Jan. 2020.
[114] J. M. Blanke, "Protection for 'inferences drawn': A comparison between the general data protection regulation and the California consumer privacy act," *Global Privacy Law Rev.*, vol. 1, no. 2, pp. 81–92, Jun. 2020.
[115] L. Determann and J. Tam, "The California privacy rights act of 2020: A broad and complex data processing regulation that applies to businesses worldwide," *J. Data Protection Privacy*, vol. 4, no. 1, p. 7, 2020.
[116] Dept. Justice. (2000). *Personal Information Protection and Electronic Documents Act*. Accessed: Feb. 17, 2025. [Online]. Available: https://laws-lois.justice.gc.ca/pdf/p-8.6.pdf
[117] B. K. Swargam, R. N. Yadav, and M. Chaturvedi, "Two level Wi-Fi fingerprinting based indoor localization using machine learning," in *Proc. 24th Int. Conf. Distrib. Comput. Netw.*, Jan. 2023, pp. 324–329.
[118] J. Hatwell, M. M. Gaber, and R. M. A. Azad, "CHIRPS: Explaining random forest classification," *Artif. Intell. Rev.*, vol. 53, no. 8, pp. 5747–5788, Dec. 2020.
[119] M.-H. Roy and D. Larocque, "Robustness of random forests for regression," *J. Nonparametric Statist.*, vol. 24, no. 4, pp. 993–1006, Dec. 2012.
[120] J. Sen, S. Mehtab, and A. Engelbrecht, *Machine Learning: Algorithms, Models and Applications*. Books on Demand, 2021.
[121] C. S. A. Merino, 2024, "Automatic attendance control system for indoor localization in smart education," doi: 10.21227/y7a5-6e40.



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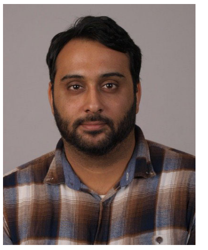

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