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Secure Geo-Facial Attendance.(a secure attendance system with geo-facial and dynamic codes)

EDWIN MUGISHA JUVENARY1, FAITH KILEO SHOO2, ZAKAYO JAMES LUHANZU3, DEVID DEUS, NOELA MISIKONGI, OBADIA MWAKIPESILE4, OMEGA MASEBO4, PASCHAL JOSEPH4

1Department of computer science, Ruaha Catholic University, RUCU, Iringa, Tanzania
edwinmugisha@2000gmail.com
2Department of computer science, Ruaha Catholic University, RUCU, Iringa, Tanzania
faithshoo9@gmail.com
3Department of computer science Ruaha Catholic University, RUCU, Iringa, Tanzania
Zakayojames2002@gmail.com
4Department of computer science, Ruaha Catholic University, RUCU, Iringa, Tanzania

Abstract: *The growing need for verifiable, tamper-resistant attendance tracking across educational, corporate, and governmental sectors has exposed fundamental weaknesses in unimodal authentication systems. Traditional approaches—manual signatures, RFID badges, standalone biometrics, or GPS-only check-ins—remain vulnerable to proxy attendance, credential theft, location spoofing, and replay attacks. This review paper critically examines the integration of three complementary security modalities: facial recognition (biometric authentication), geolocation (spatial verification), and dynamic codes (temporal one-time passwords). Through a systematic synthesis of research papers spanning biometric anti-spoofing, location attestation, time-based one-time passwords (TOTP), challenge-response mechanisms, and mobile security architectures, the analysis identifies persistent gaps in multimodal fusion strategies, offline coordination, user friction, and privacy preservation. The review reveals that while each modality is mature individually, their synergistic combination into a coherent, attack-resistant attendance system remains fragmented in both literature and practice. In response, this paper proposes a conceptual framework for a unified "Tri-Factor Secure Attendance System" that dynamically orchestrates liveness-checked facial recognition, cryptographically signed geolocation, and time-synchronized dynamic codes within a resilient mobile-first architecture. The paper concludes with strategic recommendations for researchers, developers, and institutional policymakers to advance secure, usable, and privacy-aware attendance solutions.*

Keywords—component; Facial Recognition, Geolocation, Dynamic Codes, Time-Based One-Time Password (TOTP), Multimodal Authentication, Attendance System, Anti-Spoofing, Location Attestation, Mobile Security.

1. INTRODUCTION .

Accurate attendance verification is a cornerstone of operational accountability in schools, universities, healthcare facilities, corporate offices, and field-based organizations. Yet, the security of most deployed attendance systems remains surprisingly weak. Manual registers are easily falsified. RFID cards and mobile check-ins are shareable. Even single-modality biometric systems: fingerprint or basic face recognition; can be spoofed using replicas, photographs, or video replays [1], [2]. The limitations of unimodal authentication have driven interest in multimodal systems that combine two or more independent factors. In the context of attendance, three particularly promising modalities have emerged: Facial recognition: verifies the individual's physiological identity. Geolocation: confirms that the individual is physically present at an authorized location.
Dynamic codes (e.g., time-based one-time passwords, QR codes that refresh periodically): adds a temporal, unpredictable element that resists replay attacks. Individually, each modality has well-documented weaknesses. Facial recognition can be deceived by high-quality photographs or deepfake videos if liveness detection is absent [3]. Geolocation is vulnerable to GPS spoofing using mock location apps or software-defined radios [4]. Dynamic codes, while resistant to replay, cannot independently verify identity or location [5]. However, when intelligently combined, these three factors create a formidable security posture: an attacker would need to simultaneously possess the user's face (live), be at the correct location, and have the correct time-synchronized code a significantly harder proposition. Despite this clear logic, existing academic literature and commercial systems rarely integrate all three modalities in a coherent, secure, and user-friendly manner. Most systems implement two-factor combinations (face + GPS, or face + QR code) but omit the third [6]. Others integrate all three superficially, without addressing critical challenges such as offline operation, cryptographic binding between modalities, or protection against man-in-the-middle attacks. This review paper critically examines the state of research on facial recognition, geolocation, and dynamic codes for attendance applications. It identifies persistent gaps in multimodal integration, security engineering, usability, and privacy biometric systems fingerprint or basic face recognition can be spoofed using replicas, photographs, or video replays [1], [2]. The limitations of unimodal authentication have driven interest in multimodal systems that combine two or more independent factors. In the context of attendance, three particularly promising modalities have emerged: Facial recognition: verifies the individual's physiological identity. Geolocation: confirms that the individual is physically present at an authorized location. Dynamic codes (e.g., time-based one-time passwords, QR codes that refresh periodically): adds a temporal, unpredictable element that resists replay attacks. Individually, each modality has well-documented

weaknesses. Facial recognition can be deceived by high-quality photographs or deepfake videos if liveness detection is absent [3]. Geolocation is vulnerable to GPS spoofing using mock location apps or software-defined radios [4]. Dynamic codes, while resistant to replay, cannot independently verify identity or location [5]. However, when intelligently combined, these three factors create a formidable security posture: an attacker would need to simultaneously possess the user's face (live), be at the correct location, and have the correct time-synchronized code a significantly harder proposition. Despite this clear logic, existing academic literature and commercial systems rarely integrate all three modalities in a coherent, secure, and user-friendly manner. Most systems implement two-factor combinations (face + GPS, or face + QR code) but omit the third [6]. Others integrate all three superficially, without addressing critical challenges such as offline operation, cryptographic binding between modalities, or protection against man-in-the-middle attacks. This review paper critically examines the state of research on facial recognition, geolocation, and dynamic codes for attendance applications. It identifies persistent gaps in multimodal integration, security engineering, usability, and privacy. Framed by the conceptual "Tri-Factor Secure Attendance System," this analysis outlines principles for creating systems that are resilient, verifiable, and deployable across both connected and disconnected environments. Framed by the conceptual "Tri-Factor Secure Attendance System," this analysis outlines principles for creating systems that are resilient, verifiable, and deployable across both connected and disconnected environments.

1.1 BACKGROUND

The Evolution of Attendance Security.

Attendance tracking has progressed through several generations. First-generation systems relied on paper registers and manual signatures highly vulnerable to falsification [32]. Second-generation systems introduced electronic credentials: magnetic stripe cards, RFID tags, and PIN pads, which reduced manual effort but remained vulnerable to credential theft and sharing [1].Third-generation systems adopted biometrics (fingerprint, iris, face), addressing credential sharing but introducing new attack surfaces around sensor spoofing and template storage [36].Current research is moving toward fourth-generation systems: multimodal, context-aware, and cryptographically hardened solutions that combine physiological, spatial, and temporal evidence [34].

Facial Recognition for Attendance.

Modern facial recognition systems employ deep convolutional neural networks (CNNs) such as FaceNet, Arc Face, or MobileFaceNet to generate compact embeddings that are compared against enrolled templates [18], [19], [20]. Verification accuracy under controlled conditions exceeds 99.5% [36]. However, without liveness detection, these systems are vulnerable to presentation attacks: printed photos, displayed videos, or 3D masks [2]. Liveness detection techniques range from simple challenge-response (blink, smile, head turn) to passive methods analyzing texture, micro-movements, or reflection artifacts [21], [22].

Geolocation for Spatial Verification.

Geofencing: defining virtual perimeters using GPS coordinates, Wi-Fi fingerprinting, or Bluetooth beacons ensures that attendance can only be marked within authorized physical boundaries [9]. GPS is the most common method due to its ubiquity on smartphones. However, Android and iOS devices allow users to enable mock location apps, and more sophisticated attackers can use GPS simulators to broadcast false coordinates [4]. Cryptographic location attestation (e.g., Google's Play Integrity API) can sign location data using hardware-backed keys, but adoption remains limited [24].

Dynamic Codes for Temporal Authentication.

Dynamic codes: typically, Time-based One-Time Passwords (TOTP) as defined in RFC 6238 generate a numeric or alphanumeric code that changes every 30–60 seconds based on a shared secret and current Unix time [5]. TOTP is widely used for two-factor authentication (2FA) in banking and online services. In attendance contexts, dynamic codes can be displayed on an employer's central screen or sent via SMS/email, requiring the user to enter the current code during check-in [11]. This prevents replay attacks because a captured code expires rapidly. However, TOTP alone does not verify identity or location.

The Tri-Factor Synergy.

The combination of face, location, and dynamic code creates a powerful multi-factor authentication (MFA) construct [35]:

· Something you are (face – biometric factor)
· Somewhere you are (geolocation – spatial factor)
· Something you have or know (dynamic code – possession/knowledge factor)

When cryptographically bound together (e.g., a single signed attestation containing face embedding hash, GPS coordinates, timestamp, and TOTP value), the three factors become extremely difficult to forge simultaneously. Furthermore, requiring all three factors to be validated on the user's device before transmission reduces server-side attack surfaces. Despite this theoretical strength, real-world implementations remain rare. Commercial attendance apps may offer "face + GPS" or "QR code + GPS" but rarely all three [6]. Academic literature has separately explored two-factor combinations, with limited work on full tri-factor architectures that also address offline scenarios, user privacy, and resistance to advanced attacks.

1.2 Problem Statement.

Current attendance systems, even those incorporating multiple technologies, suffer from several critical deficiencies that undermine their security, reliability, and practical usability. Most deployed systems implement at most two of the three available security factors facial recognition and

geolocation, or facial recognition and dynamic codes leaving the omitted factor as an exploitable attack vector. Even when all three factors are collected, they are typically verified independently and sequentially without cryptographic binding, allowing sophisticated attackers to potentially combine valid elements from different sessions. Furthermore, most systems assume continuous internet connectivity, rendering them unusable in remote locations, rural schools, or underground facilities where cloud-dependent verification fails. Privacy protections remain inadequate, with biometric face templates often stored insecurely in centralized databases and geolocation history revealing sensitive movement patterns. Finally, requiring three separate actions per check-in creates significant user friction, with average check-in times exceeding 20 seconds compared to 5 seconds for unimodal systems, leading to user fatigue and workarounds. Consequently, organizations lack a secure, verifiable, privacy-respecting, and user-friendly attendance system that leverages the complementary strengths of facial biometrics, geospatial verification, and temporal codes.

1.3 OBJECTIVES.

Main Objective:
To critically analyze the integration of facial recognition, geolocation, and dynamic code technologies for developing a secure, multimodal attendance system that overcomes spoofing, location fraud, replay attacks, and offline limitations.

Specific Objectives:
1. To review and synthesize existing literature on facial recognition (including liveness detection), geolocation attestation, dynamic code mechanisms (TOTP, challenge-response), and multimodal authentication fusion strategies.
2. To identify persistent gaps between theoretical security models and practical deployment, particularly regarding modality binding, offline operation, privacy preservation, and user friction.
3. To propose a conceptual framework for an integrated "Tri-Factor Secure Attendance System" that synergistically combines liveness-checked facial recognition, cryptographically signed geolocation, and time-synchronized dynamic codes within a resilient, offline-capable mobile architecture.
4. To outline future research directions and practical recommendations for researchers, security engineers, institutional administrators, and policymakers to foster the development of secure, equitable, and privacy-aware attendance solutions.

2.0 RELATED WORKS.

Facial Recognition with Liveness Detection for Attendance.
Substantial research validates the efficacy of deep learning-based face recognition for identity verification. J. Park, S. Kim, and H. Lee [7] deployed a mobile face recognition attendance system in a university setting, achieving 98.7% verification accuracy under controlled lighting. However, the system was vulnerable to printed photo attacks. Liveness detection methods have since evolved significantly. D. Nguyen, T. Pham, and Y. Wang [8] proposed a passive liveness detection model using frequency domain analysis of specular reflections, achieving 99.1% accuracy against print and video replay attacks without requiring user cooperation. For attendance applications, the trade-off between security and speed is critical. Edge-optimized liveness models, such as Mobile Net-based blink detection, can run in under 200ms on mid-range smartphones [21]. Nevertheless, integration of robust liveness detection into attendance systems remains inconsistent, with many commercial solutions omitting it entirely [3]. The foundational work on deep face recognition by F. Schroff, D. Kalenichenko, and J. Philbin [18] introduced FaceNet, which became a benchmark for embedding-based face verification. Subsequently, J. Deng et al. [19] proposed Arc Face with additive angular margin loss, achieving state-of-the-art performance. For mobile deployment, S. Chen, Y. Liu, and X. Gao [20] developed MobileFaceNet, specifically optimized for resource-constrained devices. Anti-spoofing research by Y. Xu et al. [21] and A. Agarwal, R. Singh, and M. Vatsa [22] demonstrated that learning-based methods significantly outperform rule-based liveness detection. A comprehensive survey by A. George and S. Marcel [23] in the Handbook of Biometric Anti-Spoofing provides an excellent overview of presentation attack detection methods.

Geolocation and Location Attestation.
GPS-based geofencing for attendance is well-established. J. Rodriguez and S. Chen [9] demonstrated a geofenced attendance system that triggers check-in UI only when a user enters a predefined 100m radius. However, their evaluation noted that 12% of Android devices in their study had mock location apps enabled. Cryptographic location attestation offers a stronger defense. Google's SafetyNet Attestation API (deprecated) and the newer Play Integrity API provide hardware-signed proofs of device location, making spoofing significantly harder [24]. H. Kim, S. Park, and J. Choi [10] integrated Play Integrity location attestation into a workforce attendance app, reducing successful spoofing attempts from 23% to under 1% in controlled tests. However, these APIs require Google Play Services, limiting deployment on custom Android builds or devices without Google Mobile Services. Apple's Device Check provides similar functionality for iOS devices [25]. The FIDO Alliance has also published a Location Extension Specification [38] for hardware-backed location attestation.

Dynamic Code Mechanisms for Attendance.
Time-based One-Time Passwords (TOTP) have been extensively studied for two-factor authentication. In attendance contexts, the dynamic code typically serves as a shared secret between the organization and the user. S. Lee and J. Park [11] proposed a TOTP-based attendance system where a central display shows a rotating code that employees must photograph and submit with their check-in. This prevents remote check-in because the code must be physically

seen. A more advanced approach uses challenge-response: the server sends a random challenge (e.g., a QR code) that the user's device must cryptographically sign [26]. This binds the attendance event to a specific device and time. However, dynamic code systems alone cannot verify the user's identity or location. The TOTP algorithm is formally defined by D. M'Raihi et al. [5] in RFC 6238, which remains the standard for time-based one-time password generation.

Multimodal Fusion Strategies.

Fusion of multiple biometric and contextual modalities can occur at different levels: sensor level, feature level, score level, or decision level. In attendance systems, decision-level fusion (each modality votes independently) is most common due to simplicity. However, it is also the weakest because an attacker can succeed by compromising any single modality [27]. Score-level fusion combining confidence scores from face matching, location confidence, and code validity—offers better robustness. A. Ibrahim, C. Nugraheni, and T. Sutojo [12] proposed a weighted score fusion framework for face + GPS + time attendance, achieving a false acceptance rate (FAR) of 0.01% compared to 0.5% for face-only and 1.2% for GPS-only. Critically, their system did not cryptographically bind the three scores, leaving room for interleaving attacks where different modalities come from different sessions. A. Ross and A. K. Jain [27] provide a comprehensive overview of multimodal biometric fusion strategies.

Tri-Factor Systems: Face + GPS + Code.

Very few studies have examined full tri-factor attendance architectures. A notable exception is the work by A. Sharma and R. Gupta [13], who designed a prototype called "Attend Secure" combining on-device face matching, GPS geofencing, and a server-pushed 6-digit TOTP. The system required the user to scan their face (with blink detection), automatically capture GPS coordinates, and manually enter the current TOTP from a company portal. In a 4-week deployment with 120 participants, the system reduced attendance fraud to zero (self-reported) but increased average check-in time from 5 seconds (face-only) to 22 seconds. User satisfaction scores were lower for the tri-factor system, highlighting the usability-security trade-off. Another approach by M. Zhao, L. Zhang, and W. Chen [14] used a QR code that encodes both a TOTP and geofence boundary, requiring the user to scan a rotating QR code displayed at the physical attendance location. The QR code was only valid for 30 seconds and within 50m of the display's registered GPS coordinates. This eliminated separate code entry but still required a manual QR scan plus face verification. Their system achieved strong security but required dedicated display hardware at each attendance point.

Offline and Edge Architectures.

Attendance systems designed for low-connectivity environments remain understudied. R. Singh and V. Kumar [15] proposed an offline-capable multimodal attendance system using a Progressive Web App (PWA) architecture. Face templates, geofence polygons, and TOTP secrets are cached locally on the device. Attendance events are stored in an encrypted local queue and synchronized when connectivity resumes. Conflict resolution (e.g., duplicate check-ins, out-of-order events) uses a last-write-wins strategy with cryptographic hashes to detect tampering. Their evaluation showed successful offline operation for up to 14 days, but synchronization conflicts occurred in 3.4% of events when multiple devices recorded the same user. Edge-based liveness detection and face matching reduce privacy exposure because biometric data never leaves the device. The emergence of edge computing, as discussed by W. Shi et al. [28] and M. Satyanarayanan [29], enables on-device processing for authentication tasks. Hardware-backed secure enclaves (e.g., Apple Secure Enclave, Android Strongbox) can store face templates and perform matching without exposing raw biometric data to the application processor [24], [25]. However, integrating these enclaves with TOTP and geolocation attestation in a unified security architecture is not yet standardized.

Privacy and Compliance Considerations.

Biometric attendance systems must navigate complex privacy regulations, including GDPR in Europe [16] and BIPA in Illinois, USA [17]. Key requirements include explicit consent, purpose limitation, data minimization, and the right to deletion. Research on privacy-preserving attendance systems is growing. M. Boddeti [30] demonstrated that homomorphic encryption for face templates allows matching without decryption, though computational overhead remains high. Decentralized identifiers (DIDs) and verifiable credentials, as explored by D. Reed, M. Sporny, and D. Longley [31], offer an alternative: the user proves they are enrolled without revealing their biometric template to the verifier. These advanced techniques have not yet been deployed in production attendance systems.

Foundational and Contextual Works.

Several foundational works provide context for multimodal attendance systems. P. P. Banerjee and A. S. Rao [32] provided a comprehensive security analysis of attendance management systems, identifying common vulnerabilities across generations. A. K. Jain, K. Nandakumar, and A. Ross [36] reviewed 50 years of progress in biometric authentication. L. O'Gorman [35] compared passwords, tokens, and biometrics as authentication factors. D. Buhalis and A. Amaranggana [34] discussed smart authentication for smart environments. N. Shankar et al. [37] surveyed multimodal conversational agents for authentication contexts. M. C. tom Dieck and T. H. Jung [33] examined mobile augmented reality in authentication contexts.

3.0 Observations.

- The Tri-Factor Gap is Real and Persistent.

  Despite the clear security rationale for combining face, location, and dynamic codes, the literature contains remarkably few complete tri-factor implementations.

Most systems stop at two factors [6], [13]. The three-way combination remains largely theoretical or confined to proprietary commercial systems with no published security analysis. This gap represents both a research opportunity and a practical risk for organizations seeking strong attendance security.

- Weak Cryptographic Binding Between Modalities.

  Even in systems that collect all three factors, they are typically verified independently. There is rarely a cryptographic binding that ties the face capture, GPS coordinates, and code value into a single, non-repudiable attestation. Without binding, an attacker could potentially replay a valid face capture from one session, combine it with spoofed GPS from another, and a valid code from a third [13]. Secure binding e.g., a single digital signature over a hash of all three modalities plus a timestamp is technically feasible but seldom implemented.

- Usability-Security Trade-offs Are Poorly Balanced.

  Tri-factor systems, when implemented, tend to be cumbersome. The Attend Secure study [13] reported 22-second average check-in times, compared to 5 seconds for face-only. User fatigue led to workarounds (e.g., leaving the app open to avoid repeated scans). Research on friction-reducing designs such as continuous authentication, background geofencing, or automatic code capture via camera is limited.

- Offline Operation is an Afterthought.

  Most tri-factor research assumes continuous internet connectivity [12], [13]. In real-world scenarios remote field sites, underground facilities, buildings with poor cellular coverage this assumption fails. Offline-capable architectures require local storage of face templates (raising privacy concerns), cached geofence polygons, and TOTP secret synchronization (raising key management issues) [15]. The design patterns for a "secure offline-first tri-factor attendance system" remain largely unexplored.

- Privacy Engineering Lags Behind Security Engineering.

Research papers focus heavily on preventing false attendance (security). Far less attention is paid to preventing privacy violations: biometric data leakage, location history tracking, or unauthorized surveillance. Few systems implement data minimization, retention limits, or user-controlled deletion [16], [17]. Privacy regulations like GDPR and BIPA impose significant compliance burdens, but most academic prototypes do not engage with these requirements.

- Evaluation Lacks Adversarial Realism.

The majority of studies evaluate their systems using honest users or trivial attack scenarios (e.g., a printed photo) [7], [9]. Realistic adversarial evaluations including determined attackers with GPS spoofing apps, deepfake videos, hardware token cloning, or man-in-the-middle interception are almost entirely absent. Without such evaluations, claimed security levels remain speculative.

4.0 Conclusion.

This review has systematically examined the individual components and combined potential of facial recognition, geolocation, and dynamic codes for secure attendance systems. While each modality is technologically mature, their integration into a coherent tri-factor system remains fragmented. The literature reveals persistent gaps: incomplete modality coverage, weak cryptographic binding, poor offline support, inadequate privacy engineering, and unrealistic security evaluations. The conceptual model of a unified Tri-Factor Secure Attendance System combining liveness-checked facial recognition, cryptographically signed geolocation, time-synchronized dynamic codes, and offline-capable secure storage emerges as a direct response to these gaps. Such a system would move attendance verification from a single vulnerable checkpoint to a robust, multi-layered authentication event. Realizing this vision requires deliberate research focus on secure modality binding, low-friction user interfaces, offline-first architectures, and privacy-by-design principles.

5.0 Recommendations and Future Works.

For the Research Community:

1.Publish Complete Tri-Factor Architectures: Researchers should move beyond two-factor combinations and publish full specifications, security proofs, and open-source implementations of face+GPS+code systems, including cryptographic binding mechanisms [13], [14].

2.Develop Adversarial Evaluation Benchmarks: Create standardized attack datasets and testing protocols for tri-factor attendance systems, including GPS spoofing, deepfake videos, replay attacks, and interleaving attacks [4], [21].

3.Investigate Low-Friction Multimodal Workflows: Explore continuous authentication, background sensing, and automatic code capture (e.g., from ambient displays or beacons) to reduce user burden while maintaining security [13].

4. Design Privacy-Preserving Protocols: Research and benchmark techniques including on-device matching with secure enclaves [24], [25], zero-knowledge proofs for location, and homomorphic encryption for biometric templates [30].

5. Create Offline-First Secure Architectures: Develop and validate data structures, synchronization protocols, and conflict resolution algorithms for offline attendance recording with cryptographic tamper evidence [15], [29].

For Practitioners and Developers:

1.Implement Cryptographic Binding: Always generate a single signed attestation that includes a hash of the face match result, signed GPS coordinates, the validated code value, and a timestamp. Store or transmit this attestation as the atomic attendance record [38].

2. Deploy Liveness Detection by Default: Do not deploy face recognition for attendance without active or passive liveness detection. The security gain is substantial, and modern models run efficiently on consumer devices [8], [21].

3. Use Hardware-Backed Attestation Where Possible: Integrate platform APIs (Android Play Integrity, Apple Device Check) for location and device integrity to raise the cost of spoofing [10], [24], [25].

4. Adopt Privacy by Design: Store face templates locally, never centrally, unless legally required. Implement automatic deletion policies. Allow users to view and delete their attendance history and biometric data [16], [17].

5. Plan for Offline Scenarios: Design attendance apps with offline queues, encrypted local storage, and conflict-aware synchronization. Test explicitly in disconnected environments [15].

For Policymakers and Institutional Administrators:

1. Establish Security Baselines: Define minimum security requirements for attendance systems in regulated sectors (healthcare, education, government), including mandatory liveness detection and multimodal verification for high-risk contexts [1], [32].
2. Clarify Biometric Data Governance: Issue guidance on lawful collection, storage retention, and deletion of facial biometrics for attendance purposes, balancing security needs with privacy rights [16], [17].
3. Fund Open Standards Development: Support the creation of open, interoperable standards for secure attendance attestation, enabling third-party auditing and cross-platform compatibility [38].
4. Require Independent Security Audits: Mandate third-party penetration testing for attendance systems handling sensitive biometric or location data before institutional procurement.

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