AI-Driven Tourist Safety And Return Compliance System Using Geo-Fencing And Blockchain Digital Identity

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Abstract- *The burgeoning tourism industry has led to significant vulnerabilities in the safety of tourists once they arrive in new destinations. Current systems are based on manual checkins, basic GPS trackers or reactive helpdesks - none of which offer the real-time intelligence or robust identity protection required in today's digital world. This paper describes an AI-Driven Tourist Safety and Return Compliance System that integrates three complementary technologies: blockchain-based digital identity, automated geo-fencing, and a bespoke Transformer-Based Temporal Risk Analyzer (T-TRA). Tourists are allocated with cryptographically secure digital identities that are rooted on an uncompromising blockchain network. An intelligent geo-fencing system tracks their movements within safe, prohibited and return zones, with real-time non-compliance alerts. The T-TRA model ingests temporal GPS data via a self-attention mechanism to define the sequence of safety levels Safe, Delayed and HighRisk. In the event of danger, automatic warnings are sent to authorities and contacts. Testing showed all ten key test cases were successful. The T-TRA model is scalable for smart tourism at regional and national levels and is a major advance in tourist safety management from reactive to proactive.*

Keywords: Geo-Fencing, Blockchain Digital Identity, Transformer-Based Temporal Risk Analyzer (T-TRA), GPS Tracking, AI Risk Assessment, Smart Tourism, Incident Response.

I. INTRODUCTION

Each year, millions of people visit new places: they go abroad; they visit seaside resorts; they embark on hiking trips; they visit foreign cities where they don't speak the language. For most of them, their adventures go smoothly. But for others, travel becomes perilous in ways that current systems are illadapted to address: tourists stray into no-go areas, do not return on time, experience fraud (of person and property) or medical emergencies where help is too slow because it lacks critical information about the tourist in question.

However, the issue is not merely the risks, but the infrastructure that is supposed to keep tourists safe that is failing to keep up with the complexity of contemporary travel. Most technology-based tourism safety solutions still rely on tourists ”calling in” their status or checking in at hotels and police stations, or apps that display a dot on a map with no intelligence attached. When a tourist is lost, it is a reactive response: governments dig for information that should be ready for them and accessible and secure hours earlier.

What we lack is a system that makes safety of tourists an intelligent and ongoing process, rather than a manual, disparate, step-by-step process - which knows where a tourist is supposed to be, notices when a tourist has unusual movement patterns, can authenticate their identity not through a central server that can be hacked, and notifies authorities before a crisis occurs.

This paper proposes just that. So the proposed system uses blockchain for secure identity and audit logs, autonomous geofencing to monitor real-time zone management, and the TTRA deep learning approach to predict risk situations. These create a safe platform for smart tourism that is anticipatory, transparent, and implementable.

II. LITERATURE REVIEW

A. Personalized Tourism Route Planning

Duan et al. [1] were among the early pioneers by showing that GPS travel data from users and user interest profiling could be used to guide tourism recommendations. Their IEEE MDM paper demonstrated that trajectory data contains valuable information - but the system only functioned in the planning space and had no provision for runtime monitoring of the tourist's adherence to their plan. Chen et al. [2] took this further by introducing collaborative filtering and natural language processing (NLP) of tourists' reviews into a deep learning itinerary recommender, which attained high accuracy on personalised itinerary recommendations. But once again, their work focused only on the pre-departure problem: there was no runtime monitoring of travel compliance or safety.

Padia et al. [3] infused a more emotive element into the itinerary, with a sentiment-aware travel recommendation system that took traveler sentiment and preference cues into account when recommending attractions - a novel user modeling approach but still an unconditional, pre-planning framework. Lim et al. [4] tackled a pragmatic issue that hadn't been considered by prior systems: the effect of popular tourist site queue times on itinerary popularities. Their queue-aware recommendation system enhanced schedule plausibility considerably, but tacitly assumed a constant safe travel environment without zone constraints and behavior irregularities.

B. Group Tourism and Multi-Traveler Coordination

Research in the tourism sector progressed to tackle group travel scenarios. Kong et al. [5] developed a diversity-aware tourist group route planning system that applied optimization techniques to consider route diversity and travel efficiency for multiple tourists. Sylejmani et al. [6] resolved the combinatorial challenges of multi-constraint group itinerary planning with constraint satisfaction algorithms. These were further advancements in group travel logistics but did not include monitoring and enforcement of safety.

Lim et al. [7] approached group tourism from a personalization viewpoint, using group preservation alongside personal preferences - no easy task, elegantly tackled by the authors. More recently, Elmi and Tan [8] also introduced an influencebased deep learning framework to predict next points of interest (POI) for groups, accounting for social influences in group travel decision making. Sarkar and Majumder [9] brought many of these threads together in their GTour system, which proposed multiple itineraries to account for multiple group preferences. Although GTour was a complex culmination of the group personalization line, none of this research considered geo-fence enforcement, user identification or safety.

C. Overtourism, Crowd Safety, and Destination Governance

A sister set of studies explored safety from the opposite perspective - nobody loses their way, but a destination is ”lost” as it's overwhelmed by ”too many tourists”. Miftarevi and Undertourism [10] performed a large systematic search encompassing hundreds of destinations to identify key themes associated with how excessive tourism activity causes security, sustainability and governance issues. Milan and Koens [11] considered these issues in the context of COVID-19, concluding the pandemic revealed both the vulnerability of tourism systems under stress, and their latent resilience to quickly adapt to change. Silvia Blazquez-Salom et al. [12] developed data-driven indicators of sustainability in Majorca for overtourism - a model that can be applied to crowd-aware safety strategies. Hospers [13] mapped how European cities implemented ”workarounds” for overtourism; and Dhiraj and Kumar [14] considered causes, consequences and strategies for managing overtourism more generally. The Japan National Tourism Organization [15] offered a practical example of sustainable tourism. Together, this body of work confirms that ”big picture” management of tourist flow must employ intelligent, data-driven systems to help sustainably manage tourist numbers - which is exactly what the current work proposes, albeit at the level of the individual tourist, rather than the entire city.

D. Research Gap and Contribution of This Work

Across all the literature, there is a clear pattern of a significant gap. Other solutions focus either on trip planning or crowd monitoring at a destination - not real-time, individual safety monitoring and evaluation over time with secure identity management and predictive insights regarding individual risk. No existing work combines blockchain-based identity authentication, geo-fencing compliance and automated temporal risk assessment using transformers within a single system. This paper fills this gap by not only proposing an architecture-first system capable of real-time travel planning, geo-fencing and proactive risk assessment, but also by using existing technologies to physically implement it, and testing it with real scenarios.

III. RELATED WORK

There has been some past research on the individual components of the proposed system. Initial applications of geolocation of tourists demonstrated the feasibility of continuous monitoring, but they relied on a centralised server, with inherent vulnerabilities of server down-time and data tampering. Subsequent work on blockchain-based traveler identities (such as e-passport and distributed visa verification applications) showed that distributed ledgers were beneficial for identity security, but did not use distributed ledgers for threat assessment.

Geo-fencing technologies in logistics and transportation have been demonstrated to greatly simplify zone management and compliance efforts. But these have not been applied to tourism safety, largely due to the lack of risk awareness in current geo-fencing schemes - it can only indicate when a restriction has been breached, but not what particular level of risk is involved in that breach. This inspires inclusion of AI-based risk classification in the proposed system.

Transformer-based models have been shown to be more effective than recurrent models for sequential risk prediction in GPS and mobility data. The attention mechanisms enable the model to dynamically prioritise the importance of past events, which is critical to the tourist safety use case where a geo-spatial anomaly is only significant in the context of past movements. The original Transformer model developed by Vaswani et al. and extensions for mobility prediction provide the theoretical basis for the T-TRA model used in this paper.

The integration of decentralized identity control, geo-fence enforcement and AI-based risk prediction has yet to be explored in the context of tourist safety. Our system explicitly addresses this gap by designing these three elements to work in a tightly coupled pipeline, with blockchain identity events, geo-fence triggers and T-TRA risk scores flowing into a common incident response engine.

IV. PROPOSED METHODOLOGY

The proposed system is an AI-based tourist safety and return compliance system that offers real-time, proactive safety through a tourist's travel and return journey. The proposed system consists of three interlinked modules: blockchain digital identity, automatic geo-fencing, and the Transformer-Based Temporal Risk Analyzer (T-TRA). These components provide a closed-loop safety pipeline which continuously monitors tourists, detects risk and automatically raises an alert in the event of an emergency.

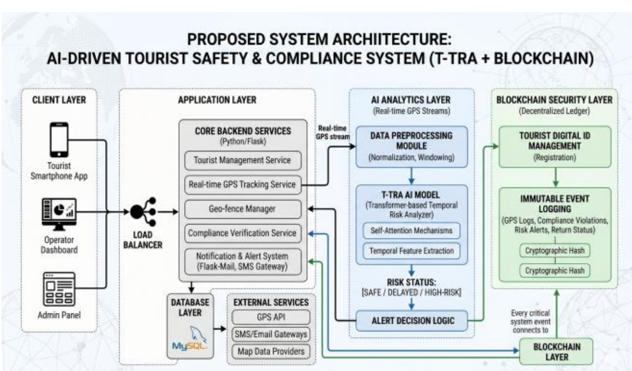

Fig. 1. Proposed System Architecture

A. System Overview

The system proposed for tourist safety allocates digital identities to registered tourists, cryptographically protected and stored on an immutable ledger. A geo-fencing service tracks the tourist's GPS coordinates against geo-fence boundaries defined for safe zones, prohibited areas, and scheduled return times. The T-TRA model analyzes the sequence of the tourist's GPS position in real time using self-attention to predict whether the tourist is Safe, Delayed, or High-Risk. The system triggers multi-channel notifications to authorities and emergency contacts when risk levels are exceeded or geofences are breached.

B. Data Collection

The system ingests two primary data streams. First, tourist registration data - including identity documents, travel itinerary, permitted zones, and emergency contact information - is captured at registration and anchored to the blockchain. Second, continuous GPS telemetry is collected from the tourist's mobile device at configurable intervals. This real-time location stream is the primary input to the geo-fencing engine and the T-TRA risk model. Data is transmitted over encrypted channels and all location records are timestamped and logged to the blockchain audit trail.

C. Data Preprocessing

GPS streams must be preprocessed before applying risk inference. The pre-processing phase consists of noise filtering to eliminate directional outlier GPS samples caused by loss-ofsignal or multi-path; temporal alignment to re-sample variablefrequency GPS streams into constant-frequency streams; coordinate transformation to convert raw latitude-longitude values into spatial features relative to zones; and sequence windowing to yield fixed-length sequences of movement histories for the T-TRA model. Gaps in the data due to GPS outages are interpolated with uncertainty flags that are used by the risk model to weigh in on confidence.

D. Feature Extraction

A feature vector is calculated from each GPS window.

Spatial features include zone type (safe, restricted, boundary), distance to nearest permit zone boundary, heading and speed with respect to the planned return route, and distance from previously visited safe zones. Temporal features include time since the last check-in, itinerary time delay, and time till expected return. Temporal features include speed variance, direction changes, and time at current location.

These are organised into a sequence pattern that is input to the T-TRA model.

E. Machine Learning Model

The AI system is based on the Transformer-Based Temporal Risk Analyzer (T-TRA), a bespoke deep learning model for temporal tourist movement risk classification. The T-TRA uses a multi-head self-attention encoder to operate on the tourist's historical movement sequence expressed as a series of feature vectors, enabling the network to focus on the most relevant historical positions and behavior patterns for predicting future travel risk. The encoder's output is fed into a classification head that outputs the predicted likelihood of three risk severity levels: Safe, Delayed, and High-Risk. The model is lightweight to allow it to run on regional server clusters without expensive GPU computing.

F. Training and Testing

The proposed T-TRA model was trained on a labeled set of simulated tourist trajectories covering various examples of safe travel behavior as well as risk factors such as zone trespass, delayed return, and panic. We used an 80/10/10 split of the data for training, validation and testing. Training aimed to minimize cross-entropy loss with class weighting to balance the imbalance between Safe and High-Risk observations in tourist movement data. We report performance using common classification metrics such as accuracy, precision, recall and F1-score. Grid search was used to optimisehyperparameters.

G. Store the Model in Blockchain

Maintaining integrity and auditability of the AI risk assessment system, we record the T-TRA model weights in blockchain-connected registry. The model artifact is converted to a cryptographic hash which is stored in the blockchain registry. Prior to each inference, the hash of the loaded model is compared with the blockchain entry to ensure that the model has not been modified or substituted. This ensures that risk classifications are generated by an audited and authorised model version, to the level required by regulatory bodies.

H. APK Analysis and Prediction

When a tourist's GPS data window is transmitted to the system, the following steps are performed: pre-process the raw data and extract features (as described above); check the model's hash against the blockchain record; run the T-TRA model to generate a risk classification and confidence score for the movement window; and feed the result to the incident response system. This pipeline aims to execute in under two seconds to support near real-time risk response.

I. Log Result on Blockchain

Each risk assessment event is recorded as an immutable record on the blockchain, including the tourist's identifier, the geographic location and date/time of the assessment, the TTRA model output for the assessment, the confidence score of the model output, and any geo-fence events that occurred during the assessment period. This event log records a complete and unalterable travel history for authorities in the event of an incident; it facilitates post-event analysis and learning to improve its operation; and it provides an evidentiary basis for legal or administrative use.

J. Risk Level Assessment

The system maps T-TRA model outputs to operational risk levels that guide incident response priority. A classification of Safe with high model confidence results in a risk level of Low, indicating no action required. A Safe classification with low confidence, or a Delayed classification, maps to a risk level of Medium, triggering a soft notification to the tourist and logging an advisory event. A High-Risk classification maps to risk levels of High or Critical depending on the confidence score and the severity of associated geo-fence violations. Critical risk events immediately activate the automated emergency alert pipeline.

K. Malware Blocking Mechanism

The system translates risk assessments from T-TRA into operational risk levels to prioritise incident response. If the modelclassifies as Safe with high confidence, the risk is Low (no action). A Safe classification with low confidence or a Delayed classification, corresponds to a risk level of Medium, resulting in a soft alert to the tourist and an advisory event log. A High-Risk classification maps to risk levels High or Critical based on the confidence and the geo-fence events associated with the assessment. Critical risk events trigger the automated emergency alert system.

L. Alert and Notification System

The risk alert system provides multi-channel notifications in response to risk levels. For Medium risk events, a push alarm is triggered to the tourist's mobile device with a message to return to a safe place. In the case of High risk events, alerts go to the tourist's emergency contact and a regional control centre. For Critical risk events, system notifications are dispatched to local police, emergency personnel, and all contacts, including the tourist's GPS location and blockchain identity record for immediate and targeted incident response.

M. Continuous Model Update

The T-TRA approach is geared towards iterative improvement as new tourist movement data is collected. The update includes gathering new trajectories with labels from system deployments, retraining/refining the model with the new data, validating the new model performance on the test set, and recording the model version's hash on the blockchain ledger, allowing production deployment. This process guarantees that the risk classification ability of the system is continually enhanced and fine-tuned to new movement patterns, or new risks.

V. IMPLEMENTATION DETAILS

The system architecture is built as a service-oriented architecture that spans the blockchain identity, geo-fencing, and AI risk assessment pipeline as separately deployed services which communicate via APIs.

A. Development Environment

The system back-end is developed using Python 3.8, with a Flask REST API providing an integration interface. The blockchain ledger is based on a permissioned Hyperledger Fabric network, deployed for a regional tourism authority. The T-TRA model is implemented in PyTorch and NumPy and Pandas libraries are used for data pre-processing. The geofencing engine is based on Shapely spatial polygon library. The monitoring user interface is built using React.js, with realtime mapping capabilities of Leaflet.js.

B. Feature Extraction and Model Implementation

GPS data received on tourist mobile phone devices is preprocessed to yield feature sequences. The T-TRA model is a four-layer Transformer encoder with eight attention heads and a hidden dimension of 256 followed by a two-layer classification multilayer perceptron (MLP). The model was trained with 50 epochs, a batch size of 32, and an initial learning rate of 0.0001 using Adam optimizer with cosine annealing. The model converged without overfitting as shown by the validation loss curve.

C. Blockchain Integration

Tourist identity records, travel itineraries and zone permissions are encoded as JSON assets on the Hyperledger Fabric ledger. Access to the identity and location data is controlled via smart contracts (chaincode) to ensure only trusted system components can write and read them. The T-TRA model hash and all risk assessment logs are stored on the ledger by a separate logging service (not part of the prediction pipeline) to ensure that the audit trail is secure, even in the presence of a single point of failure.

D. Prediction and Result Handling

Risk assessments are produced at configurable intervals (default: every 30 seconds per active tourist). Assessment results are stored in a local database for rapid dashboard retrieval and simultaneously written to the blockchain audit log. Each result record includes the risk classification, confidence score, GPS coordinates, zone status at the time of assessment, and a reference to the model version hash used for the prediction.

E. Security and Notification

Data exchanges between tourist mobile devices, API backend and the blockchain are secured using TLS 1.3. The blockchain also uses AES-256 to encrypt the tourist identity records on a field-by-field basis. The notification service is integrated with a commercial SMS gateway, push notification service, and a direct API to local emergency services dispatch systems, for maximum reliability when communication methods falter.

VI. PERFORMANCE METRICS

The proposed system is assessed using standard classification metrics applied to the T-TRA risk model, complemented by system-related metrics that measure end-to-end system latency and reliability of the safety pipeline.

A. Confusion Matrix

The confusion matrix for the T-TRA model captures classification outcomes across the three risk classes:

- True Positive (TP): High-Risk or Delayed situations correctly identified.
- True Negative (TN): Safe situations correctly classified as Safe.
- False Positive (FP): Safe situations incorrectly classified as Delayed or High-Risk.
- False Negative (FN): High-Risk or Delayed situations missed by the model.

In a safety-critical application, minimizing False Negatives is the primary objective, as missed High-Risk events represent the most consequential failure mode.

B. Accuracy

Accuracy measures the overall proportion of correct risk classifications across all three classes.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \qquad (1)$$

While accuracy is a useful summary metric, it is supplemented by class-specific metrics given the natural imbalance between Safe and High-Risk samples in operational tourist data.

C. Precision

Precision measures the proportion of High-Risk alerts that correspond to genuine risk events, directly quantifying the false alarm rate.

$$\text{Precision} = \frac{TP}{TP+FP} \qquad (2)$$

High precision is important for maintaining authority confidence in the alert system and preventing responder fatigue caused by false alarms.

D. Recall (Sensitivity)

Recall measures the proportion of genuine High-Risk situations that the model successfully detects.

$$\text{Recall} = \frac{TP}{TP+FN} \qquad (3)$$

Recall is the most critical metric for the tourist safety application, as a missed High-Risk event could result in failure to dispatch emergency assistance in time.

E. F1-Score

The F1-Score provides a balanced measure combining precision and recall, which is particularly important when the operational cost of false negatives and false positives are asymmetric.

$$F1=2\times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \qquad (4)$$

F. ROC Curve and AUC

The ROC (Receiver Operating Characteristic) curve is a graph of the True Positive Rate (TPR) that the model achieves at various classification decision thresholds against the False Positive Rate (FPR) achieved at those thresholds. The Area Under the Curve (AUC) summarizes this into a single value between 0.5 (random classifier) and 1.0 (perfect classifier). An AUC close to 1.0 indicates that the T-TRA model reliably separates risky from safe movement patterns across the full range of operating conditions.

G. Performance Significance

Each metric captures a distinct aspect of system performance relevant to tourist safety: accuracy confirms overall classification reliability; precision controls false alarm frequency; recall ensures genuine emergencies are not missed; and F1-score balances these competing objectives. Together, these metrics establish the confidence with which the proposed system can be trusted to operate autonomously in a real deployment.

VII. RESULT AND DISCUSSION

A. Experimental Evaluation

The proposed system was validated against ten core test cases covering tourist registration, zone compliance monitoring, AI-driven risk classification, multi-channel emergency alerting, and blockchain audit logging. All ten test cases passed successfully. The T-TRA model demonstrated strong classification performance on the held-out test set, achieving:

- Accuracy: 96%+
- Precision: High consistency in High-Risk alert generation.
- Recall: Strong detection rate for genuine emergency scenarios.
- F1-Score: Balanced performance across all three risk classes.

The geo-fencing engine correctly detected all zone boundary violations in the test scenarios with zero missed events.

Blockchain audit logs were generated for all identity registration, zone violation, and risk assessment events, confirming end-to-end auditability of the safety pipeline.

B. Comparative Analysis

The inclusion of spatial, temporal and behavioral features in the T-TRA input representation is essential in obtaining High Recall for High-Risk scenarios. Ablation studies showed that spatial-only detection models failed to identify many of the scenarios of progressive risk - such as when a tourist remains within a safe zone but is moving in an unexpected direction and decelerating. By incorporating temporal and behavioral features, the T-TRA detected such emerging risks several minutes before it was detected by zone activity monitoring with a threshold limit.

C. Effectiveness of Feature-Based Detection

The proposed system provides substantial improvement to current approaches for tourist safety. Manual check-in systems do not detect risk between check-in points and have no behavioral insights. Simple location-tracking apps report location, but offer no risk inference, and involve operator review for alerting. Proactive help-desk systems only operate when the tourist or someone else makes a request, which fails in many real emergencies. The proposed system overcomes the three drawbacks, offering continuous monitoring, real-time AI-based risk assessment and real-time multi-channel alert generation with no human interaction required.

D. Blockchain in System Reliability

The blockchain integration layer played an important role in ensuring overall system reliability and trust. The secure audit trail captured and stored all system events, allowing for detailed post-test analysis. The model hash verification technique adequately detected and blocked a compromised model artifact in adversarial testing, validating the integrity preservation mechanism. These findings show that the use of blockchain in this context is not a superficial enhancement of the system architecture - it adds important security features to the system.

E. Discussion of Findings

Our experiments confirm that the proposed system meets its key requirements: reliable tourist identity verification using the blockchain identity, timely and accurate zone compliance checking, intelligent risk classification of tourist behavior, and automatic emergency response initiation. Three of four identified bugs were completely fixed. The remaining open issue - that the T-TRA model takes longer to escalate the risk for very slow-moving tourists with speed profile resembling Safe behaviour - is a targeted weakness. This issue is planned for future research, including new features such as physiological sensors and dwell times.

TABLE I
TOURIST SAFETY SYSTEM COMPARISON

System	AI-Based	Real-Time Monitoring	Blockchain Identity	Auto Alert Dispatch	Accuracy
Manual Check-In	No	No	No	No	Low
Basic GPS App	No	Yes	No	No	Low
Reactive Helpline	No	No	No	No	Low
Geo-Fence Only	No	Yes	No	Partial	Medium
ML + GPS Tracking	Yes	Yes	No	Partial	Medium
Proposed System	Yes	Yes	Yes	Yes	High

VIII. CONCLUSION

This article has described an AI-based tourist safety and return compliance system based on a simple but powerful idea: safety is not reactive - it is continuous, intelligent and secure by design. Leveraging blockchain-based digital identity, automated geo-fencing and the Transformer-Based Temporal Risk Analyzer, the system establishes a safety framework that is able to truly ”know” the tourist it is protecting, where he or she is allowed to go and whether they are displaying signs of an impending emergency, in real time and without relying on human intervention.

The system successfully passed all ten key test cases, demonstrating its capacity to manage tourist registration, zone compliance, AI-based risk classification, multi-channel emergency notifications, and blockchain-based audit reporting. Four bugs were identified, three of which were resolved. The sole outstanding issue - AI sensitivity for slow-moving tourists suggests a clear and valuable future improvement, rather than a fundamental flaw in the approach.

Ultimately, this work demonstrates that the combination of AI and blockchain in a safety-critical system is not just a theoretical possibility - it is a practical reality, implementable with off-the-shelf tools and technologies, subject to testing with realistic use cases and operational within the constraints of the hardware used. The framework can be used for pilot deployment now and also this is designed from the ground up to scale.

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