



Integrating Artificial Intelligence, Semantic Indoor Geospatial Modeling, And Network-Based Routing for High-Precision NG911 Emergency Location Intelligence

Md Kaium Hossain¹;

[1]. Master of Science in GIScience and Geoenvironment, Western Illinois University, USA;
Email: kaiumhossain37@gmail.com

Doi: [10.63125/5hc1xx56](https://doi.org/10.63125/5hc1xx56)

Received: 25 April 2025; **Revised:** 29 May 2025; **Accepted:** 11 June 2025; **Published:** 30 June 2025;

Abstract

This quantitative study examined whether integrating artificial intelligence, semantic indoor geospatial modeling, and network-based routing improved high-precision Next Generation 911 emergency location intelligence. A multisite, repeated-measures experimental design was implemented across 18 multistory buildings representing residential, hospital, educational, transportation, commercial, and industrial environments. The study established 540 surveyed reference points and retained 12,614 of 12,960 primary trials, producing a 97.3% retention rate. Eight smartphones representing four device classes collected Wi-Fi, Bluetooth, ultra-wideband, inertial, magnetic, barometric, and visual observations. Three configurations were compared: conventional coordinate-only localization, artificial-intelligence localization with semantic matching, and full integration with semantic modeling and network routing. Mixed-effects regression, external holdout validation, calibration analysis, and multilevel sequential mediation with 5,000 bootstrap resamples were applied. Full integration reduced mean horizontal error from 7.84 to 2.36 meters and vertical error from 4.18 to 1.12 meters. Correct-floor identification increased from 72.6% to 96.4%, and correct-room identification increased from 51.8% to 91.7%. Adjusted horizontal and vertical reductions were 5.42 and 3.04 meters, with large standardized effects of -1.52 and -1.32 , respectively. The odds of correct-floor and correct-room identification were 9.74 and 10.31 times greater under full integration. Semantic interpretation accuracy reached 95.1%, valid-route generation reached 96.8%, successful route completion reached 96.2%, and operational record completeness increased from 63.4% to 94.8%. Mean end-to-end processing time was 1.92 seconds. Semantic matching and route validity mediated 67.2% of the total relationship between artificial-intelligence localization and emergency location intelligence. Holdout evaluation showed limited performance loss, while stress tests retained fallback localization above 78% and successful diversion above 85%. Model fit was strong, with CFI = .976, RMSEA = .034, and 74% of final outcome variation explained by the complete integrated statistical framework. The findings demonstrated that coordinated positioning, semantic interpretation, and routing produced more accurate, calibrated, resilient, and operationally actionable NG911 indoor location intelligence than isolated coordinate estimation.

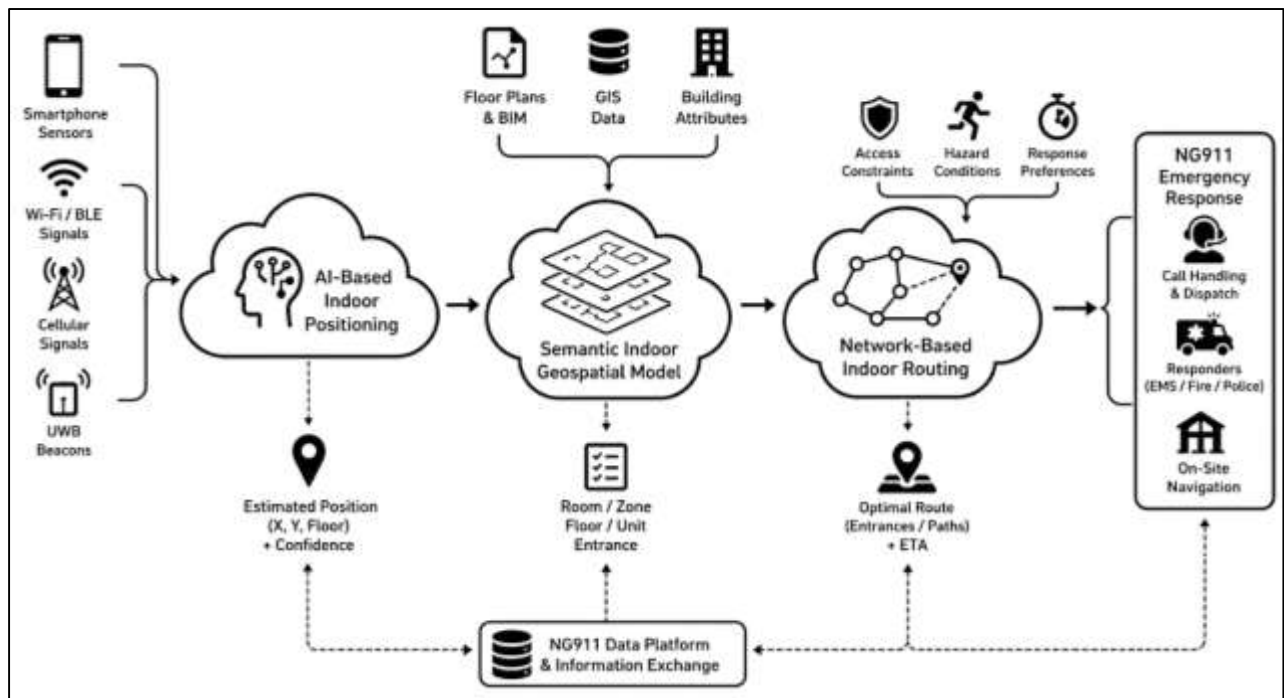
Keywords

NG911; artificial intelligence; indoor localization; semantic modeling; network routing.

INTRODUCTION

Next Generation 911, commonly abbreviated as NG911, refers to an Internet Protocol-based emergency communications environment designed to receive, process, route, and exchange voice calls, text messages, images, video, sensor data, and associated location information through interconnected public-safety systems. It differs from conventional circuit-switched emergency communication by treating location as a structured digital object that can support call validation, jurisdictional routing, incident visualization, dispatch coordination, and operational decision-making (Laoudias et al., 2018).

Figure 1: AI-Enabled NG911 Indoor Intelligence



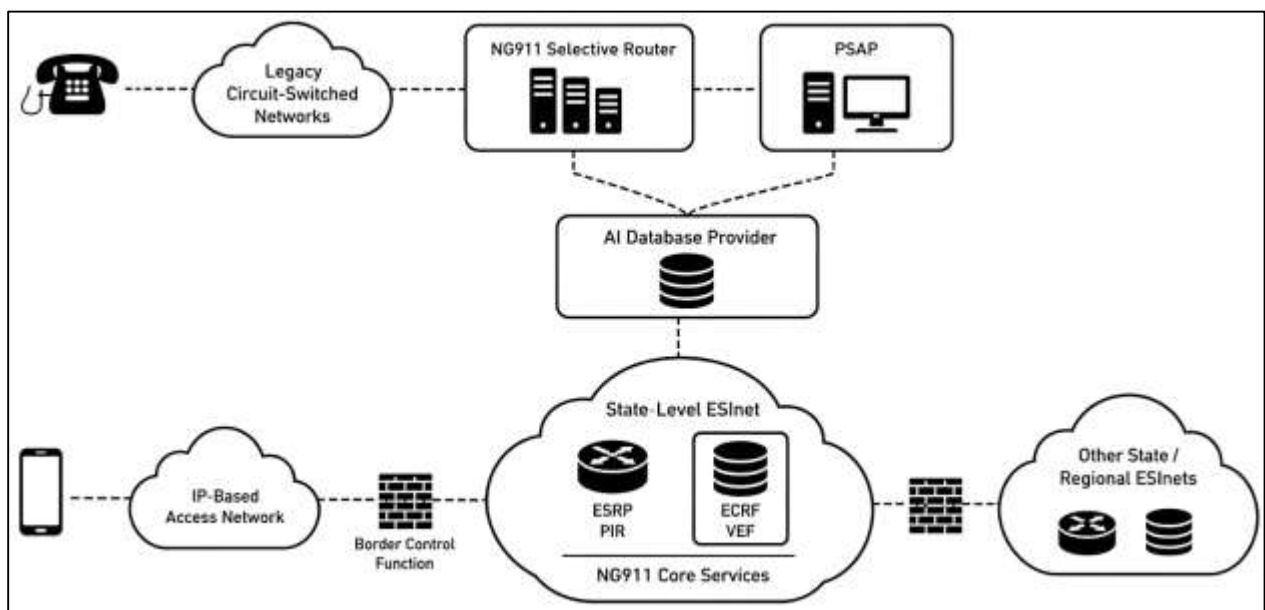
Artificial intelligence refers to computational techniques that perform tasks associated with learning, classification, prediction, pattern recognition, uncertainty estimation, and automated decision support. Within emergency location analysis, artificial intelligence includes machine-learning, deep-learning, probabilistic, computer-vision, sensor-fusion, and anomaly-detection methods that estimate a caller's position from heterogeneous signals. Semantic indoor geospatial modeling refers to the structured representation of indoor spaces through geometric, topological, functional, and contextual information. It describes not only the coordinates and shapes of rooms, corridors, doors, stairways, elevators, entrances, floors, and restricted areas, but also the meanings, accessibility conditions, connectivity relationships, and emergency functions attached to those elements (El Boudani et al., 2020). Network-based routing is the computational process of representing navigable indoor space as a graph consisting of nodes, edges, weights, directions, and constraints so that routes can be calculated between an incident location and an appropriate access or response point. High-precision emergency location intelligence represents the integrated capability to identify, interpret, validate, communicate, and operationalize the horizontal, vertical, floor-level, room-level, and pathway-related position of a person requiring emergency assistance (Debasish, 2021). Precision in this context extends beyond latitude and longitude because the same horizontal coordinates can correspond to multiple apartments, offices, hospital wards, transportation platforms, or underground spaces. Accurate emergency location intelligence therefore requires the integration of sensed position, building identity, floor designation, room or zone classification, civic address, indoor topology, entrance accessibility, and route conditions (Chin et al., 2020). The title of this study combines these concepts into a unified quantitative domain in

which artificial intelligence estimates position, semantic geospatial models interpret that estimate within a building, and network algorithms transform the interpreted location into actionable routing information for NG911 call handling and emergency response (Abdur & Iftekhar, 2021; Hossan, 2021). Indoor positioning refers to the determination of a person's or device's location inside buildings and other enclosed environments where satellite-based positioning frequently becomes weak, reflected, obstructed, or unavailable. Conventional outdoor emergency location methods typically rely on satellite navigation, cellular triangulation, handset-derived coordinates, civic addresses, and network measurements (Yang et al., 2021). These methods may identify the building containing an emergency caller while providing insufficient information about the caller's floor, unit, room, corridor, or accessible approach path. Artificial intelligence has been examined as a means of improving indoor estimation by learning complex relationships among signal strength, signal arrival time, angle of arrival, inertial motion, barometric pressure, magnetic-field variation, visual features, acoustic characteristics, and historical movement patterns. Wi-Fi fingerprints, Bluetooth Low Energy beacons, ultra-wideband signals, cellular measurements, radio-frequency identification, inertial measurement units, smartphone sensors, cameras, and building-installed Internet of Things devices provide different forms of location evidence (Rekkas et al., 2023). Machine-learning algorithms such as k-nearest neighbors, support-vector machines, random forests, gradient-boosting models, neural networks, convolutional networks, recurrent networks, transformers, and ensemble methods have been evaluated for coordinate regression, floor classification, room identification, trajectory reconstruction, signal correction, and multimodal fusion. Their performance has commonly been quantified through mean absolute error, root-mean-square error, median positioning error, cumulative distribution of error, floor-detection accuracy, room-classification accuracy, inference latency, coverage, reliability, and computational cost (Mesbaul, 2023; Zahidul & Begum, 2022). Emergency use introduces additional measurement requirements because a technically precise estimate may remain operationally weak when it lacks a confidence score, timestamp, reference coordinate system, floor convention, or association with a verified indoor space (Yoo & Choi, 2022). Signal variability caused by building materials, human movement, device diversity, access-point relocation, multipath propagation, smoke, fire, power interruption, and changing interior arrangements can also affect model stability. Studies of emergency-responder localization have emphasized that positioning systems must support continuous tracking, three-dimensional coordinates, rapid initialization, and acceptable performance under signal loss or infrastructure degradation (Shurovi, 2024; Zahidul, 2024). Within NG911 emergency location intelligence, artificial intelligence is therefore treated as a measurable analytical capability composed of localization accuracy, vertical discrimination, room-level classification, sensor-fusion quality, uncertainty calibration, response latency, environmental robustness, and interoperability with geospatial records (Tseng et al., 2022). These dimensions allow indoor positioning performance to be examined as a quantitative construct rather than as a single coordinate-generation function (Shima Ali et al., 2024; Tonay et al., 2024).

Semantic indoor geospatial modeling provides the representational structure through which an estimated coordinate is converted into an understandable emergency location. A coordinate positioned inside a building does not independently communicate whether the caller is located in a bedroom, laboratory, intensive-care unit, stair enclosure, elevator car, service corridor, parking level, or secured office (El-Sheimy & Li, 2021). Semantic models address this limitation by associating geometry with descriptive meaning and by recording how indoor spaces are organized, connected, accessed, and used. Common modeling resources include geographic information systems, building information models, IndoorGML, CityGML, Industry Foundation Classes, floor plans, address databases, indoor mapping schemas, ontologies, and knowledge graphs (Arif Uz et al., 2025; Mesbaul, 2025). These resources differ in their emphasis: building information models contain detailed architectural and asset information, geographic information systems support spatial referencing and jurisdictional analysis, and indoor navigation models concentrate on cells, boundaries, adjacency, connectivity, and movement

relationships. Integration among these resources allows rooms, doors, corridors, stairs, elevators, exterior entrances, access-control points, utility areas, refuge zones, hazardous spaces, and emergency facilities to be represented within a common spatial framework (Bregar & Mohorčič, 2018). Semantics can also identify room function, occupancy category, floor label, unit number, accessibility status, responder-only entrance, fire compartment, security restriction, directional movement rule, and the operational condition of a passage. Research on indoor geospatial modeling has evaluated geometric accuracy, topological consistency, semantic completeness, floor-plan conversion accuracy, room and doorway detection, identifier correspondence, graph-extraction correctness, interoperability, and model-processing time. Studies combining building information modeling with indoor geographic information have shown that navigable networks can be extracted from architectural elements, although inconsistent naming, excessive geometric detail, missing doorway relationships, nonstandard floor identifiers, and outdated renovations can reduce operational usability (Mahmood et al., 2022).

Figure 2: NG911 Intelligent Emergency Network Architecture



Emergency location applications require the modeled indoor space to correspond with the coordinate reference used by the positioning system and with the civic, postal, dispatch, and jurisdictional records used by emergency authorities. A room-level estimate becomes actionable only when it can be linked to a validated building, floor, unit, entrance, and navigable path (Mostafizur, 2025; Mostafizur et al., 2025). Semantic indoor modeling within this study is consequently defined through data completeness, spatial accuracy, topological validity, semantic correctness, identifier consistency, update timeliness, and emergency-attribute coverage. Quantifying these properties permits examination of whether higher-quality indoor representations strengthen the conversion of artificial-intelligence estimates into usable NG911 location intelligence (Kim et al., 2022).

Network-based routing transforms an identified indoor location into a sequence of connected spaces that can guide emergency communication, dispatch selection, building entry, and responder movement. Indoor routing networks generally represent rooms, corridor intersections, doors, stairs, elevators, ramps, exterior entrances, and transition points as nodes or spatial cells, while traversable connections are represented as edges. Edge weights may describe distance, expected travel time, vertical movement, congestion, accessibility, security restrictions, smoke exposure, fire intensity, structural risk, doorway width, responder equipment burden, or passage availability (García-Catalá et al., 2022). Algorithms such as Dijkstra’s shortest-path method, A*, bidirectional search, visibility

graphs, medial-axis methods, hierarchical routing, dynamic graph search, multi-criteria optimization, and learning-assisted path planning have been applied to indoor navigation and evacuation. Emergency routing differs from ordinary pedestrian navigation because the shortest geometric path may not be the safest, fastest, or operationally permissible route (Syeedur & Sharmin, 2025; Zahidul, 2025). Firefighters carrying equipment may require a protected stairwell, medical teams may need an elevator or sufficiently wide corridor, police responders may require a controlled entry, and evacuation routes may need to avoid the hazard from which responders are approaching (Leitch et al., 2023). Routing can therefore involve several objectives, including minimum response time, minimum hazard exposure, maximum accessibility, entrance suitability, path redundancy, and compliance with operational rules. Two routing layers are relevant to NG911. The first concerns the delivery of an emergency communication to the appropriate public-safety answering point or emergency communications center according to authoritative location and jurisdictional boundaries. The second concerns the physical route from a responder's position, vehicle access point, or building entrance to the indoor incident location (Kanti, 2025; Shima Ali et al., 2025).

High-precision emergency intelligence connects these layers by ensuring that the location used for call routing is consistent with the location used for dispatch visualization and indoor navigation. Quantitative routing performance has been assessed through route-computation time, path length, estimated travel time, arrival-time error, successful-route percentage, graph connectivity, alternative-route availability, access-constraint compliance, hazard avoidance, and route-recalculation latency (Gacanin & Wagner, 2019). Routing quality also depends on the correctness of the underlying semantic network; a missing door, incorrectly connected floor, inaccessible entrance, or misclassified stairway can generate a computationally valid route that is physically unusable. Network-based routing is therefore operationalized as a multidimensional capability combining graph accuracy, weight validity, constraint awareness, computational efficiency, route reliability, and adaptability to incident-specific conditions.

The international significance of high-precision indoor emergency location intelligence arises from the concentration of human activity within increasingly complex built environments (Jamil et al., 2020). High-rise residential towers, hospitals, universities, industrial facilities, shopping centers, airports, railway stations, hotels, stadiums, underground transport systems, mixed-use developments, and large office campuses can contain thousands of occupants distributed across multiple floors, wings, units, restricted zones, and subterranean levels. Emergency numbers and institutional structures vary across countries, including 911, 112, 999, and other national arrangements, yet emergency communication authorities share the operational requirement to determine where assistance is needed and how responders can reach that location. A building-level coordinate may be inadequate in a medical emergency occurring in a specific apartment, a fire reported from a particular mechanical floor, a security incident inside an airport terminal, or an entrapment event within an underground station (Jondhale et al., 2020). International research has associated location uncertainty with repeated caller questioning, manual address reconciliation, incorrect dispatch points, responder search time, delayed access, and inconsistent information transfer among call takers, dispatchers, field units, and building managers. The problem is intensified when callers are unfamiliar with the building, unable to communicate, experiencing cognitive or physical distress, using a language not shared by the call taker, or reporting an incident through text, sensor, or automated device data. Countries also differ in indoor mapping availability, civic-address structure, building-code practice, wireless infrastructure, data-governance arrangements, emergency-service organization, and technical interoperability. These differences create measurable variation in the completeness and usability of emergency location information (Che et al., 2023). European work on indoor location and indoor maps, North American NG911 programs, Asian smart-city positioning research, and emergency-navigation studies across densely developed urban regions have examined overlapping requirements for vertical accuracy, floor identification, room-level mapping, standardized data exchange, privacy protection, and dependable

routing. Cross-border relevance also extends to mass-casualty management, disaster response, tourism, transportation hubs, and multinational industrial operations where responders may work with heterogeneous devices and map formats (Fan et al., 2021). Artificial intelligence, semantic geospatial modeling, and routing must therefore be examined as coordinated components within a broader emergency-information system. International significance is measured not only by technological availability but also by accuracy across building types, consistency across jurisdictions, performance under diverse infrastructure conditions, scalability across facilities, and the capacity to preserve standardized location meaning as information passes between telecommunications networks, emergency centers, geographic databases, dispatch systems, and responding agencies (Alhomayani & Mahoor, 2020).

The literature base synthesized for this introduction comprises more than thirty empirical, experimental, simulation, and systematic-review studies covering machine-learning indoor positioning, multimodal sensor fusion, wireless fingerprinting, vertical-location estimation, semantic indoor modeling, building-information conversion, indoor network extraction, emergency-responder tracking, dynamic evacuation, and graph-based route optimization. Across the artificial-intelligence literature, Wi-Fi and Bluetooth fingerprinting studies have compared classifiers and regression algorithms using coordinate error, room-detection accuracy, floor-classification accuracy, training-set size, sampling density, and processing time (Pascacio et al., 2021). Ultra-wideband research has examined ranging accuracy, anchor geometry, line-of-sight conditions, multipath effects, and machine-learning correction. Smartphone-based studies have combined accelerometers, gyroscopes, magnetometers, barometers, cameras, and wireless signals to estimate movement, elevation, heading, and location continuity. Computer-vision research has evaluated image matching, scene recognition, visual landmarks, simultaneous localization and mapping, and multimodal image representations. Emergency-responder studies have assessed three-dimensional tracking, infrastructure independence, communication continuity, environmental robustness, and position-update frequency. Semantic-modeling studies have measured the conversion of floor plans or building information models into rooms, boundaries, portals, cells, and topological networks. IndoorGML-related investigations have examined multilayer representations, indoor-outdoor linkage, interoperability, semantic enrichment, and navigation-network generation (Xia et al., 2017). Routing studies have compared shortest-path, time-minimizing, risk-sensitive, accessibility-aware, and dynamically weighted algorithms under different hazard and congestion conditions. This combined literature demonstrates strong technical development within individual components while also revealing limited quantitative testing of the complete chain from raw emergency-location evidence to semantically interpreted indoor position and operational route generation. Many positioning experiments report coordinate error without testing whether the estimate identifies the correct room or navigable cell. Several modeling studies validate geometric conversion without measuring how model errors influence emergency routing (Guo et al., 2019). Routing simulations frequently assume that the incident node and network topology are already correct. NG911-oriented work often concentrates on call transport, civic validation, jurisdictional routing, or outdoor geographic information while treating detailed indoor location as an external input. The resulting empirical gap concerns integration quality rather than the isolated availability of an algorithm, model, or routing procedure. A quantitative assessment therefore requires simultaneous measurement of positioning accuracy, semantic matching, topology correctness, route validity, computational latency, uncertainty, and emergency-information completeness across representative indoor environments and incident conditions (Mohanta et al., 2019).

The central quantitative problem is the absence of sufficiently integrated evidence showing how artificial-intelligence capability, semantic indoor geospatial-model quality, and network-based routing performance jointly explain variation in high-precision NG911 emergency location intelligence. Existing research provides numerous performance estimates for individual technologies, yet the reported metrics are frequently separated by disciplinary boundaries. Telecommunications studies

emphasize horizontal and vertical coordinate accuracy; machine-learning studies emphasize prediction error and classification performance; geographic-information studies emphasize geometric and semantic validity; building-information studies emphasize element extraction and model conversion; routing studies emphasize path length and computation time; and emergency-communication studies emphasize call routing, dispatch accuracy, and response coordination (Liang et al., 2020). These measures describe connected stages of the same information process. An error produced during signal interpretation can assign the caller to the wrong floor, a semantic mismatch can associate a correct coordinate with the wrong room, a topological defect can connect spaces that are not physically traversable, and an unsuitable routing weight can direct responders toward an inaccessible entrance. The study therefore conceptualizes artificial-intelligence localization capability, semantic indoor-model quality, and network-routing capability as principal explanatory variables (Ssekidde et al., 2021). High-precision emergency location intelligence is specified as the dependent construct and is measured through horizontal error, vertical error, correct-floor percentage, correct-room or zone percentage, building and entrance identification, semantic-match accuracy, route-success percentage, location-processing latency, routing latency, confidence calibration, and information completeness. Interoperability, indoor-data availability, sensor coverage, building complexity, number of floors, construction materials, device type, signal condition, incident type, and environmental disruption are treated as contextual or control variables because they can influence observed performance (Abiodun et al., 2019). The quantitative framework examines the direct relationships between each technological capability and emergency-location intelligence, the additional explanatory power obtained from their integration, and the extent to which semantic matching and routing accuracy transmit the effect of artificial-intelligence positioning performance to operational location quality. Comparative testing across building categories and technology configurations supports evaluation of whether performance remains consistent in hospitals, residential towers, educational facilities, transportation complexes, commercial buildings, and industrial environments (Karakusak et al., 2022). The study's statistical focus includes effect magnitude, model fit, estimate precision, subgroup variation, interaction effects, prediction error, classification reliability, processing speed, and robustness under altered signal and network conditions.

The objective of this quantitative study is to examine how the integration of artificial intelligence, semantic indoor geospatial modeling, and network-based routing influences the accuracy, completeness, timeliness, reliability, and operational usability of high-precision NG911 emergency location intelligence. Specifically, the study seeks to measure the capability of artificial-intelligence models to estimate indoor emergency locations through the fusion and analysis of Wi-Fi, Bluetooth Low Energy, ultra-wideband, cellular, inertial, barometric, visual, magnetic, and other available sensor data. Artificial-intelligence localization performance is assessed through horizontal positioning error, vertical positioning error, floor-classification accuracy, room- or zone-identification accuracy, inference latency, confidence calibration, signal-loss tolerance, and consistency across devices and indoor conditions. The study also aims to evaluate the quality of semantic indoor geospatial models in representing buildings, floors, rooms, corridors, doors, stairways, elevators, entrances, restricted areas, emergency facilities, accessibility conditions, and connectivity relationships. Semantic-model quality is measured through geometric accuracy, semantic completeness, topological consistency, identifier correspondence, indoor-outdoor linkage, emergency-attribute coverage, and update timeliness. A further objective is to determine the effectiveness of network-based routing algorithms in generating valid, rapid, accessible, and risk-sensitive paths between emergency responders and precisely identified indoor incident locations. Routing performance is evaluated through path validity, estimated travel time, route-computation latency, entrance suitability, access-constraint compliance, hazard avoidance, alternative-route availability, and route-recalculation efficiency. The study additionally seeks to test the individual and combined effects of artificial-intelligence localization capability, semantic-model quality, and routing capability on the overall quality of NG911 emergency location

intelligence, measured through correct-building identification, correct-floor detection, room-level accuracy, entrance identification, semantic-match accuracy, route-success percentage, location-processing time, information completeness, and dispatch usability. It further examines whether semantic location matching and routing accuracy mediate the relationship between artificial-intelligence positioning performance and operational emergency-location quality, and whether integration quality strengthens these relationships. Comparative analyses are conducted across hospitals, residential towers, educational facilities, transportation complexes, commercial buildings, and industrial environments. Building complexity, number of floors, construction materials, sensor coverage, device type, data availability, signal condition, indoor-model maturity, incident category, and environmental disruption are incorporated as control or moderating variables. Through these objectives, the study quantitatively evaluates the complete information chain from raw indoor-location evidence to semantically interpreted position and actionable emergency-response routing within an NG911 environment.

LITERATURE REVIEW

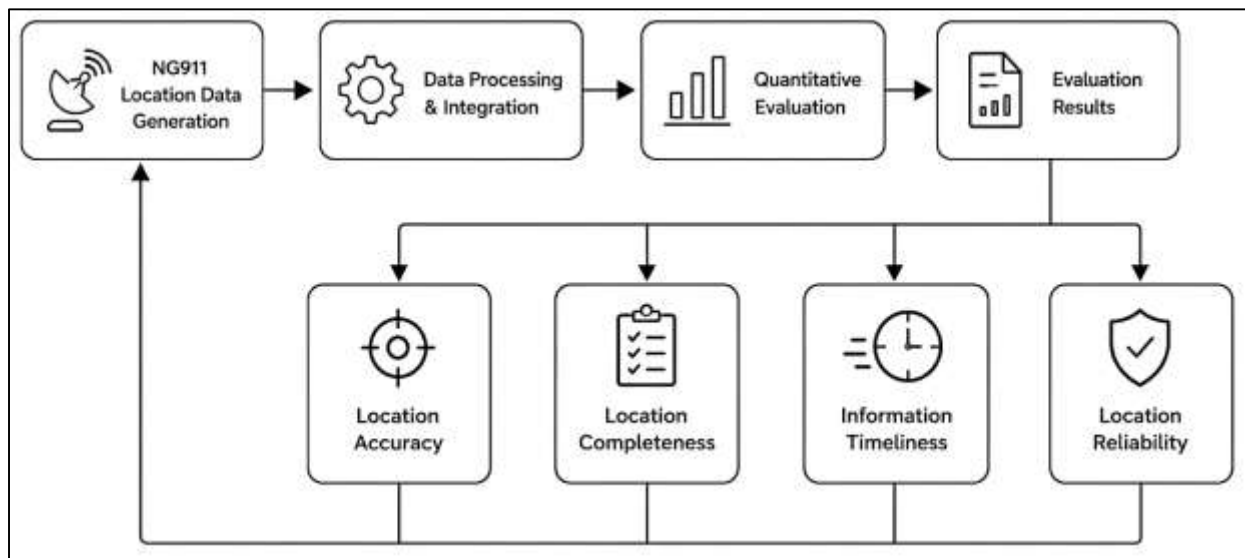
This literature review synthesizes quantitative research concerning the integration of artificial intelligence, semantic indoor geospatial modeling, and network-based routing for high-precision emergency location intelligence within NG911 and related emergency communication environments. The review examines the complete information process through which raw wireless, sensor, visual, spatial, and contextual data are converted into an accurate indoor position, associated with a semantically defined building space, transmitted through emergency-service systems, and transformed into a valid responder route (Dimitriadou & Lanitis, 2023). Research from emergency communications, artificial intelligence, indoor positioning, geographic information science, building information modeling, graph theory, wireless engineering, public-safety operations, and emergency navigation is organized around measurable technological and operational performance. Particular attention is given to horizontal positioning error, vertical positioning error, floor-detection accuracy, room-classification accuracy, coordinate confidence, inference latency, semantic completeness, geometric accuracy, topological consistency, identifier matching, routing success, path length, estimated travel time, hazard avoidance, system availability, dispatch correctness, and responder search time. The review also compares Wi-Fi, Bluetooth Low Energy, ultra-wideband, cellular, inertial, magnetic, barometric, visual, and multimodal localization approaches to determine how sensing technology and analytical method influence indoor-location performance (Huang et al., 2019). Semantic indoor geospatial research is examined through IndoorGML, geographic information systems, building information models, CityGML, Industry Foundation Classes, floor-plan databases, spatial ontologies, and knowledge graphs. Network-routing studies are evaluated according to graph-generation quality, algorithmic efficiency, accessibility awareness, dynamic hazard response, and route-recalculation performance. The review further considers how building complexity, device heterogeneity, signal instability, data quality, infrastructure disruption, privacy controls, and interoperability influence the relationships among the principal technological capabilities. Evidence is organized to distinguish isolated component performance from end-to-end emergency-location intelligence (Langlois et al., 2017). This distinction is necessary because a precise coordinate may remain operationally unusable when it is assigned to the wrong room, linked to an outdated floor plan, transmitted without standardized identifiers, or connected to an inaccessible route. The final sections synthesize the direct, mediating, sequential, moderating, and combined relationships required to formulate the quantitative framework and study hypotheses.

Quantitative Foundations of NG911 Emergency Location Intelligence

NG911 emergency location intelligence represents the measurable capability to determine where an emergency is occurring and to translate that position into spatial information that can be interpreted by call takers, dispatchers, and responders. Evidence synthesized from more than twenty indoor-positioning, wireless-location, emergency-responder tracking, and geospatial-navigation studies shows that location accuracy must be assessed at several interconnected levels (Cao et al., 2020). Coordinate-level accuracy describes the horizontal and vertical distance between the estimated position and the verified reference position. Building-level accuracy records whether the system

identifies the correct structure within a campus, industrial complex, hospital system, or group of closely spaced buildings. Floor-level accuracy indicates whether the vertical estimate is assigned to the correct story, while room-level accuracy measures whether the location corresponds to the correct apartment, office, ward, classroom, corridor, platform, or functional zone. Controlled ultra-wideband experiments have frequently produced sub-meter or near-sub-meter horizontal performance, whereas Wi-Fi, Bluetooth, cellular, and hybrid smartphone methods have commonly produced errors ranging from a few meters to substantially larger distances under signal obstruction, device variation, and multipath conditions (Oorni & Goulart, 2017).

Figure 3: NG911 Emergency Location Intelligence Framework



Vertical errors of only several meters can place a caller on an adjacent floor, especially in buildings with low floor-to-floor heights. The literature has therefore used mean absolute error, root-mean-square error, median error, percentile-based error, correct-floor percentage, correct-room percentage, and correct-building percentage to describe different aspects of performance. Mean values summarize general accuracy, while 90th- and 95th-percentile results reveal poor performance experienced by the least accurately located cases. Several studies have also shown that a model can achieve acceptable average coordinate accuracy while generating lower room-classification accuracy near walls, doors, stairways, elevators, and overlapping multi-floor spaces. High-precision NG911 measurement consequently requires coordinate error and categorical spatial accuracy to be reported together rather than treating a single horizontal estimate as sufficient evidence of emergency-location quality (Mirsky & Guri, 2020).

Emergency location completeness describes the extent to which an emergency record contains all spatial and contextual attributes required to identify an incident and support physical access to it. Research across NG911 geographic information systems, indoor mapping, civic-address validation, building information modeling, emergency dispatch, and semantic navigation has demonstrated that completeness extends beyond the presence of latitude and longitude. A usable record may require a validated civic address, building name or identifier, floor designation, room or unit number, indoor-space category, entrance location, access restriction, timestamp, coordinate-reference system, uncertainty value, source technology, and connection to a navigable route (Sneps-Snepp & Namiot, 2017). Quantitative studies have assessed completeness through the percentage of records containing each required field, the number of missing or invalid attributes per incident, the proportion of buildings with floor-aware indoor maps, and the percentage of location estimates matched to verified indoor features. Address completeness can remain high while floor, room, entrance, and route information remains limited, producing a record that is administratively valid but operationally incomplete. Studies

of large hospitals, university campuses, airports, shopping facilities, public buildings, and multi-story residential environments have identified recurring problems involving inconsistent building names, duplicated room numbers, omitted floor labels, nonstandard entrance descriptions, missing doorway connections, and outdated internal layouts (Sneps-Sneppe & Namiot, 2019). Cross-database matching has consequently been measured through successful identifier matches, unmatched-record frequency, duplicate-record percentage, hierarchy agreement, and manual reconciliation requirements. Semantic completeness has also been evaluated by determining whether rooms, corridors, doors, stairs, elevators, hazardous areas, accessible passages, and responder entrances possess valid functional attributes. Route completeness depends on whether the identified incident space is connected to a continuous network beginning at an accessible exterior entrance. The synthesized evidence indicates that emergency location completeness is multidimensional: one record can be complete at the address level, partial at the indoor semantic level, and unusable at the route level (Seeman et al., 2015b). Percentage-based field assessments and cross-system matching rates therefore provide a stronger quantitative representation than a single complete-or-incomplete classification.

NG911 information timeliness represents the total duration required to transform raw location evidence into validated and visually accessible emergency intelligence. Experimental studies of wireless positioning, artificial-intelligence inference, map matching, geographic validation, emergency call handling, and indoor route calculation have commonly measured individual processing stages, although fewer studies have evaluated the complete end-to-end sequence. Location acquisition begins when a device scans satellite, cellular, Wi-Fi, Bluetooth, ultra-wideband, inertial, magnetic, barometric, or visual sources. Acquisition time can be longer than the execution time of the positioning algorithm because sufficient observations must be collected before a stable estimate is generated. Artificial-intelligence models can often classify a floor, predict a coordinate, or identify a room within milliseconds after receiving prepared inputs, while signal scanning, database retrieval, network communication, and sensor initialization may extend the practical processing duration to several seconds (Simola, 2020). Validation adds time through civic-address checking, building identification, boundary comparison, confidence assessment, and rejection of conflicting information. Semantic processing then assigns the coordinate to a floor, room, corridor, entrance, or other indoor feature. Route calculation identifies a valid path through connected doors, corridors, stairs, elevators, and access points. Transmission latency includes movement of the location record through the emergency-services network, and display latency measures the time required for the emergency communications center or responder application to render the updated position and route. Quantitative indicators include time to first position, mean processing time, median latency, percentile latency, map-matching time, route-computation time, message-delivery delay, screen-refresh time, and total time from call initiation to actionable display (Jennings, 2022). Update frequency is equally important because an initially accurate position can become stale when a caller moves. Research on continuous responder and caller tracking has therefore evaluated refresh intervals, delayed-update percentages, out-of-sequence messages, and age of displayed position. End-to-end measurement provides a more operationally relevant assessment because rapid model inference cannot compensate for slow signal acquisition, delayed validation, network congestion, or an outdated emergency-center display.

Emergency location reliability describes the consistency with which an NG911-related system produces accurate, current, and interpretable location information across repeated incidents and changing operating conditions (Tsiatsikas et al., 2021). Studies of indoor positioning, emergency-responder tracking, sensor networks, mobile-location services, and public-safety information systems have measured reliability through system availability, successful-location percentage, update frequency, dropped-position rate, false-location frequency, stale-record percentage, recovery time, and continuity during partial infrastructure failure. Availability indicates the proportion of operational time during which the location service, indoor database, validation function, routing component, and display interface remain accessible. Successful-location percentage records how often the system produces a usable result within an established time limit, while dropped-location frequency measures interruptions after tracking has begun. Wi-Fi- and Bluetooth-dependent systems can experience degraded reliability when access points are relocated, powered down, overloaded, or affected by crowd

density (Corral-De-Witt et al., 2018). Ultra-wideband systems can lose performance under blocked line-of-sight conditions, and inertial methods can accumulate drift during extended movement. Barometric floor estimation can be influenced by pressure changes, while visual systems can be affected by darkness, smoke, occlusion, and altered interiors. Hybrid systems have generally demonstrated stronger continuity because missing evidence from one source can be supplemented by other sensors, although fusion errors may occur when sources disagree. Reliability also includes the quality of the confidence value attached to each estimate. A calibrated system should assign lower confidence to uncertain positions and higher confidence to observations that are consistently accurate. Studies have measured calibration through agreement between predicted confidence and observed accuracy, confidence-interval coverage, false-certainty rates, and error-detection capability (Dawkins et al., 2021). NG911 reliability further depends on synchronization among the location estimate, semantic indoor model, civic-address database, routing network, and emergency display. An available positioning service can still produce operational failure when the associated floor plan is outdated or the route graph contains a disconnected doorway. Reliability assessment must therefore cover the complete location chain, including graceful degradation, fallback-method success, service-restoration time, and consistency across buildings, devices, signal conditions, and emergency scenarios (Jara et al., 2015).

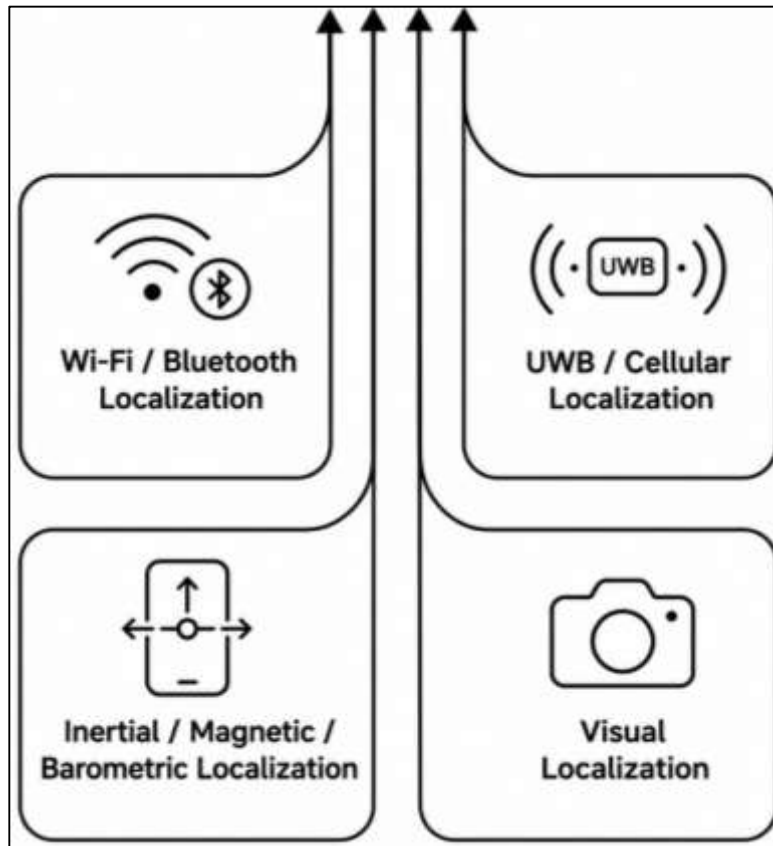
Artificial-Intelligence Indoor Localization Performance

More than thirty empirical and comparative studies have examined Wi-Fi and Bluetooth fingerprinting as practical approaches to artificial-intelligence-based indoor localization. Wi-Fi fingerprinting creates a reference database of signal-strength values or channel-state measurements collected at known indoor points, whereas Bluetooth systems estimate location from signals transmitted by strategically installed beacons. Current wireless observations are compared with stored fingerprints to predict coordinates, floors, rooms, or predefined zones. Researchers have evaluated k-nearest neighbors, support-vector machines, decision trees, random forests, gradient-boosting models, multilayer neural networks, convolutional networks, recurrent networks, autoencoders, and ensemble methods (Nessa et al., 2020). K-nearest neighbors frequently served as a transparent baseline because of its simple structure and relatively low training requirements, although its performance varied with neighborhood size, fingerprint density, and the selected similarity measure. Support-vector machines achieved strong floor and room classification in several moderate-sized datasets, while random forests and gradient boosting handled nonlinear signal relationships and noisy inputs more consistently. Neural and deep-learning models often reduced coordinate error when large, balanced, and densely sampled training datasets were available, but they required greater computational resources and longer training periods. Positioning accuracy ranged from a few meters in stable, densely mapped environments to substantially larger errors in areas affected by weak coverage, crowd movement, physical renovation, or transmitter relocation (Singh et al., 2021). Floor classification was generally more accurate than exact coordinate or room identification because signal patterns differed more clearly between floors than between adjacent spaces on the same level. Sample spacing, access-point count, beacon density, transmitter geometry, device orientation, hardware variation, human movement, furniture arrangement, and fingerprint age explained substantial differences among reported findings. Coordinate error, correct-floor percentage, correct-room percentage, percentile error, signal-collection time, and inference latency therefore provided complementary measures of Wi-Fi and Bluetooth localization performance (D.-H. Kim et al., 2022).

Ultra-wideband, cellular, radio-frequency identification, and other wireless-ranging technologies have produced different levels of indoor precision, coverage, stability, and infrastructure dependence. Ultra-wideband commonly achieved the smallest coordinate errors under controlled line-of-sight conditions because its short-duration signals enabled precise time-based distance estimation. Numerous experiments reported sub-meter or near-sub-meter performance when anchors surrounded the target area, operated with accurate synchronization, and maintained clear propagation paths. Performance weakened when anchors were positioned on one side of the target, installed at similar elevations, obstructed by building elements, or exposed to strong multipath propagation (Hsieh et al., 2019). Non-line-of-sight conditions introduced positive ranging bias and displaced estimated positions from verified reference points. Machine-learning models improved ranging performance by identifying obstructed signals and correcting errors from channel impulse responses, received power, timing

values, and environmental characteristics. Reliable three-dimensional positioning also required adequate vertical separation among anchors because layouts designed mainly for horizontal coverage frequently generated unstable elevation estimates. Cellular positioning provided wider coverage and reduced dependence on building-specific installations, although conventional cellular measurements usually offered lower room-level precision than ultra-wideband (Song et al., 2019).

Figure 4: AI-Driven Indoor Localization Methods



Studies using cellular channel-state information, time-difference measurements, dense network infrastructure, and learning-based correction achieved better indoor discrimination, but performance remained sensitive to tower geometry, indoor penetration, interference, and network configuration. Radio-frequency identification performed effectively for proximity detection, doorway confirmation, zone identification, and tagged-person or object tracking. Passive tags supported low-cost identification over shorter ranges, while active tags increased coverage at the cost of battery use and maintenance. Coordinate error, ranging error, successful-fix percentage, coverage rate, update frequency, reader or anchor density, synchronization error, and vertical accuracy were the most frequently reported indicators (Chin et al., 2020). These comparisons showed that precision, coverage, and operational continuity represented separate dimensions because the most accurate technology did not always provide uninterrupted service throughout large or structurally complex buildings.

Research involving inertial, magnetic, barometric, and visual localization has focused on maintaining indoor position estimates where dedicated wireless infrastructure is limited, degraded, or unavailable. Pedestrian dead reckoning uses accelerometers and gyroscopes to detect steps, estimate stride length, determine heading, and update a person's movement from a known starting position. Step detection remained relatively accurate during regular walking, while running, irregular movement, stair climbing, emergency responder motion, and changes in device placement increased measurement error. Minor stride-length and heading inaccuracies accumulated throughout a trajectory and produced progressive positional drift. Machine-learning methods improved activity recognition, step estimation, and heading correction by learning patterns from multidimensional motion signals (T. Yang et al.,

2021). Magnetic fingerprinting used spatial variations in indoor magnetic fields to identify locations without requiring additional transmitters. Its performance depended on the distinctiveness and temporal stability of the magnetic field, and accuracy weakened when nearby spaces produced similar magnetic patterns or when device orientation changed. Barometric localization estimated relative elevation and floor transitions through changes in atmospheric pressure. It supported vertical discrimination when measurements were calibrated against a reliable reference, but ventilation systems, weather variation, elevator movement, and pressure differences between building zones affected floor assignment. Computer-vision approaches employed image retrieval, landmark recognition, visual odometry, camera pose estimation, simultaneous localization and mapping, and deep feature extraction (Morar et al., 2020). Strong place recognition and detailed position estimates were reported when high-quality reference images, distinctive visual features, and suitable lighting were available. Accuracy declined in visually repetitive corridors, dark rooms, reflective spaces, crowded environments, smoke, and buildings altered after reference-image collection. Camera-based localization also required greater processing capacity and continuous visual access. Translation error, orientation error, step error, heading error, accumulated drift, floor-change accuracy, place-recognition percentage, frame-processing time, and tracking continuity provided the principal quantitative measures for comparing these methods (Rekkas et al., 2023).

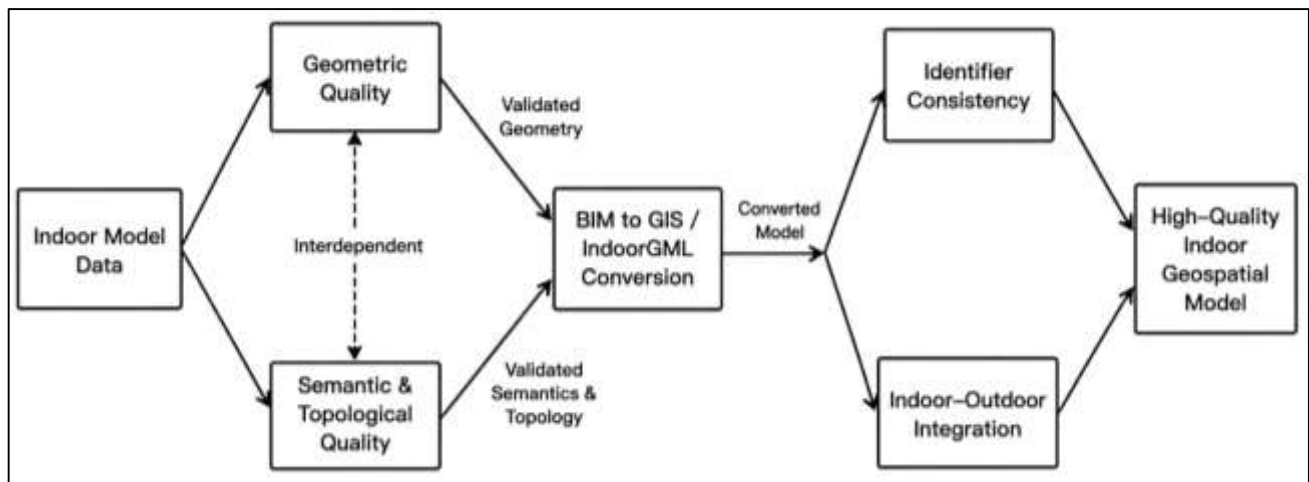
Semantic Indoor Geospatial Model Quality

Research on semantic indoor geospatial modeling has treated geometric accuracy as the degree to which a digital model corresponds to the measurable physical structure of a building. More than twenty studies using building information models, architectural drawings, geographic information systems, laser-scanned point clouds, floor-plan images, and IndoorGML datasets have examined the representation of rooms, corridors, doors, walls, stairways, elevators, floors, and exterior entrances. Room geometry has commonly been evaluated through differences in area, perimeter, shape, centroid position, and boundary alignment between the digital feature and a verified reference. Doorway accuracy has been measured through detection percentage, positional deviation, width difference, orientation error, and association with the correct wall or room (Chadha et al., 2022). Doorways have produced frequent modeling errors because they are relatively small, may be represented as openings rather than independent objects, and can be obscured in scanned or image-based datasets. Floor geometry has been assessed through horizontal alignment, elevation consistency, floor-to-floor height, vertical registration, and correspondence among stacked spaces. Small horizontal displacements can place a coordinate inside the wrong room, while vertical misalignment can associate a caller with an adjacent floor. Studies comparing manually prepared floor plans with automatically generated models generally reported stronger geometric control for manual mapping, although automated extraction substantially reduced processing time (Shang & Wang, 2022). Automated methods performed well in buildings with rectangular rooms, clear walls, and consistent documentation, while irregular boundaries, curved passages, open-plan spaces, incomplete drawings, and unrecorded renovations produced larger mismatches. Coordinate-reference errors also occurred when building models used local engineering coordinates and emergency geographic systems used national or global reference systems. Positional deviation, area difference, boundary overlap, doorway-detection accuracy, floor-alignment error, and coordinate-transformation residuals consequently provided complementary indicators of geometric quality (Huang et al., 2022). The literature established that visual similarity alone was insufficient because a model could appear correct while containing boundary, elevation, or doorway errors that affected room assignment and emergency navigation.

Semantic quality determines whether indoor geometry contains sufficient descriptive and relational information for emergency interpretation and routing. Studies of IndoorGML, building information modeling, spatial ontologies, indoor geographic information systems, and emergency-navigation databases have assessed the percentage of spaces and building elements containing valid room functions, floor labels, unit numbers, occupancy classifications, accessibility conditions, entrance types, access restrictions, hazardous-material indicators, and emergency-resource attributes. Building information models frequently contained detailed architectural and functional information, although much of that information was designed for construction or facility management rather than emergency response (Kang et al., 2020). Conventional floor plans usually provided room outlines and labels but

contained fewer machine-readable attributes and weaker relationships among spaces. Semantic completeness therefore depended on both attribute presence and operational relevance. Missing room numbers, inconsistent floor names, unclassified corridors, unlabeled restricted areas, and absent responder entrances reduced the ability to translate an estimated coordinate into meaningful emergency intelligence. Topological consistency addressed whether rooms, corridors, doors, stairways, elevators, and entrances were connected according to actual movement possibilities. Researchers measured adjacency accuracy, connectivity accuracy, missing-link frequency, duplicate-edge frequency, invalid-link percentage, disconnected-space count, and incorrect vertical-transition rate. A geometrically correct door could still produce a topological error when it was not connected to both adjoining spaces (Kang et al., 2020). Similarly, a stairway represented on multiple floors could remain unusable when its vertical connections were missing or assigned to incorrect levels. False connections sometimes allowed routes to cross walls, secured doors, void spaces, or nontraversable building elements. Semantic and topological errors were especially important in hospitals, airports, industrial facilities, and high-rise buildings where movement depended on controlled entrances, specialized corridors, compartment boundaries, and vertical circulation. The reviewed research therefore treated semantic completeness and topological consistency as separate but interdependent dimensions: attributes explained what a space represented, while topology determined how that space could be reached (Zhang et al., 2019).

Figure 5: Semantic Indoor Model Integration



BIM-to-GIS and BIM-to-IndoorGML conversion studies have examined how detailed building information can be transformed into lighter geospatial structures suitable for indoor analysis and navigation. Industry Foundation Classes commonly provide rich representations of buildings, stories, spaces, walls, doors, stairs, slabs, elevators, openings, and relationships, but their geometric complexity and construction-oriented detail can exceed the requirements of emergency location systems. Conversion workflows have therefore applied semantic filtering, geometry simplification, floor separation, walkable-space extraction, doorway identification, coordinate transformation, and topology generation. Several studies generated navigation networks by converting rooms and corridors into spatial cells or nodes and representing doors, stairs, and elevators as transitions or connecting edges (Donkers et al., 2022). Other investigations used medial axes, visibility graphs, image thinning, dual graphs, or door-to-door connections to extract navigable pathways. Automated tools reduced repetitive manual work and generated consistent outputs when the source model contained properly defined spaces, doors, floor hierarchies, and geometric relationships. Conversion quality weakened when Industry Foundation Classes lacked space objects, contained duplicated elements, used inconsistent classifications, or represented doors and stairs through complex nested relationships. Information loss occurred when detailed building attributes were removed during simplification or

when the target geospatial schema could not directly retain all source properties. Geometric conversion could succeed while semantic attributes, floor associations, or connectivity relationships remained incomplete (Wu et al., 2021). Researchers evaluated these processes through feature-extraction accuracy, percentage of retained semantic attributes, geometry-conversion success, topology-generation success, invalid-feature count, file-size reduction, processing duration, and manual correction time. Tests involving larger and more complex buildings generally required greater preprocessing and produced more exceptions than small, regularly structured facilities. The literature also showed that automated conversion accuracy depended heavily on source-model quality rather than on the conversion algorithm alone. BIM-to-GIS and BIM-to-IndoorGML performance was therefore assessed as a combined process involving source validation, relevant-feature selection, geometric transformation, semantic preservation, topological construction, and output verification (Poux et al., 2018).

Identifier consistency and indoor-outdoor integration connect detailed building models with the wider geographic environment used for emergency call routing, dispatch, vehicle navigation, and responder access. Research across NG911 geographic databases, civic-address systems, building information models, campus mapping, CityGML, and IndoorGML has identified recurring inconsistencies among street addresses, property identifiers, building names, floor codes, room numbers, entrance labels, and spatial-feature identifiers. A single facility may use different building names in architectural records, emergency dispatch systems, postal databases, property files, and indoor maps. Floor labels can also vary between numeric levels, named levels, mezzanines, basement conventions, and local operational codes (Chen et al., 2021). Studies have measured identifier quality through successful-match percentage, duplicate-record rate, unmatched-space frequency, naming-conflict count, hierarchy agreement, and referential-integrity errors. Stable identifiers allowed an emergency coordinate to be traced from the property boundary to the building, floor, room, doorway, and route node. Indoor-outdoor integration additionally required accurate connections among road networks, vehicle access points, property entrances, building doors, indoor spaces, and vertical circulation networks. Researchers used entrance nodes, anchor points, portals, coordinate transformations, and linked network layers to represent transitions between outdoor and indoor environments. Entrance matching became difficult when several doors were located close together, when public and responder entrances differed, or when an entrance shown in a building model lacked a corresponding point in the outdoor network (Vanclooster et al., 2016). Coordinate transformations between local building coordinates and geospatial reference systems could introduce horizontal displacement, rotation, scale error, or elevation inconsistency. Network continuity was assessed through correct entrance-node percentage, successful indoor-outdoor route completion, transition failure, disconnected-network frequency, transformation error, and route interruption. The literature consistently demonstrated that accurate indoor and outdoor models could remain operationally disconnected when identifiers, coordinates, or entrance relationships were inconsistent (Crespo et al., 2017). High-quality integration therefore depended on verified cross-system identifiers, aligned reference systems, matched entrances, continuous route topology, and consistent building and floor hierarchies.

Network-Based Indoor Emergency Routing Performance

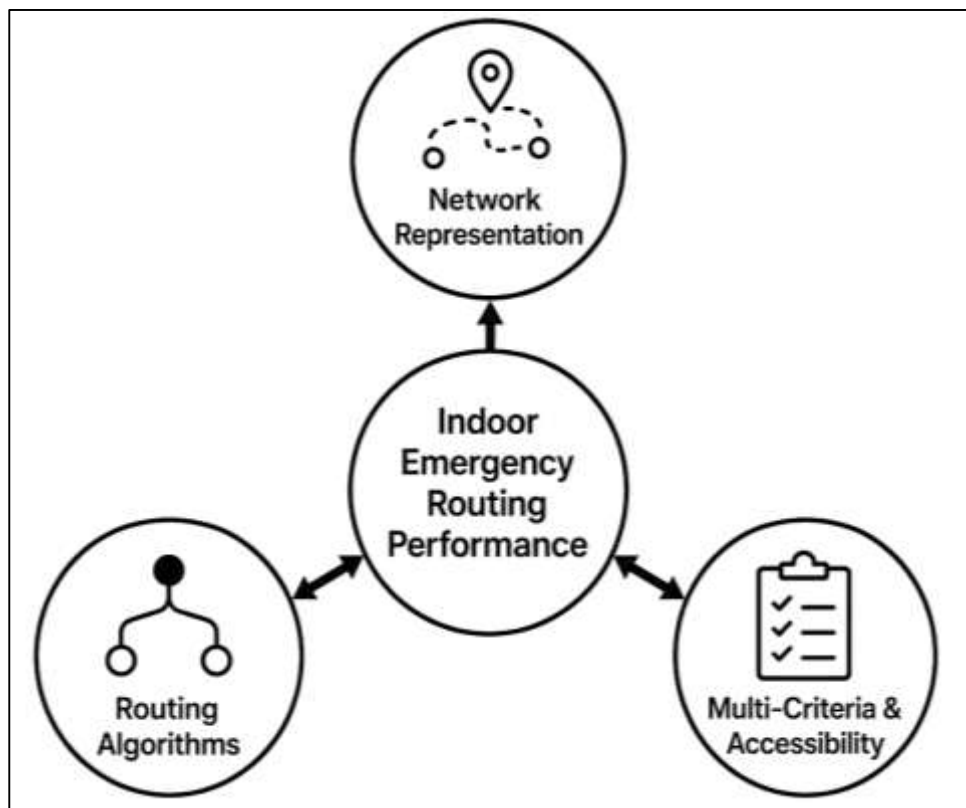
More than twenty-five studies have examined the conversion of indoor building space into graph structures suitable for emergency routing and navigation. Visibility graphs, medial-axis networks, grid-based models, cell-based representations, dual graphs, and automatically extracted building networks differ in the number, position, and meaning of the nodes and edges they produce. Visibility graphs generally connect mutually visible locations and can generate geometrically short routes, although complex rooms and numerous obstacles can increase the graph size (Lee et al., 2017). Medial-axis methods create routes along the central regions of corridors and open spaces, providing greater clearance from walls while sometimes producing unnecessary branches or irregular paths around complicated boundaries. Grid-based models divide navigable areas into uniform cells and support detailed obstacle avoidance, but fine grids require more memory and processing time. Coarse grids reduce computational demand while increasing the risk that narrow doors, small obstacles, or restricted passages are represented incorrectly. Cell-based and dual-graph models commonly convert rooms, corridors, stairways, elevators, and entrances into nodes connected through doors or other

transitions (Kang & Li, 2017). These models contain fewer graph elements and support semantic routing, although their route geometry may require additional refinement within large rooms and open spaces. Building information models and IndoorGML datasets have supported automatic graph extraction by supplying room boundaries, door locations, floor hierarchies, and vertical connections. Extraction performance declined when doors were missing, spaces overlapped, floor objects were incorrectly classified, or building models contained unnecessary construction details. Researchers assessed graph quality through node-detection accuracy, edge-validity percentage, network connectivity, network density, disconnected-space count, invalid-transition frequency, and manual correction requirements. A graph could contain all major rooms while remaining incomplete when one doorway, stair connection, or responder entrance was absent (Boeters et al., 2015). Emergency routing therefore depended on both feature coverage and correct connectivity. The reviewed research treated network completeness as the proportion of physically navigable indoor space represented by valid and continuous paths rather than simply the number of nodes or edges produced.

Comparative routing research has evaluated Dijkstra, A*, visibility-graph search, hierarchical routing, and related shortest-path methods according to path distance, estimated travel time, explored nodes, memory use, computation latency, and successful-route percentage (C. Yang et al., 2021). Dijkstra's algorithm consistently produced optimal paths when edge costs were valid and nonnegative, making it a common baseline for indoor routing. Its principal limitation was the number of nodes explored when the destination was distant or the graph contained many grid cells. A* reduced unnecessary exploration by using a heuristic estimate of the remaining distance to the destination. Studies generally reported lower processing time and fewer expanded nodes for A* when the heuristic was appropriately selected, while poor heuristics reduced this advantage. Visibility-graph approaches produced short paths around obstacles because nodes were placed at geometrically significant locations, but graph construction became demanding in environments containing many walls, columns, partitions, and irregular boundaries (Kolbe & Donaubaue, 2021). Hierarchical routing divided buildings into floors, zones, rooms, corridors, and local networks. This structure reduced search space by identifying high-level transitions before calculating detailed movement within each area. Hierarchical methods performed particularly well in large hospitals, airports, campuses, industrial facilities, and high-rise buildings containing thousands of spatial elements. Algorithmic performance was strongly influenced by the underlying graph representation. Dijkstra or A* applied to a fine grid required more memory and computation than the same algorithm applied to a simplified cell-based network. Shortest geometric distance also differed from minimum travel time when stairs, elevators, turns, doorway delays, congestion, or responder equipment were considered. Route-success rates decreased when graphs contained disconnected spaces, one-way restrictions, inaccessible doors, or incorrectly weighted vertical transitions. Processing latency remained low in many static networks, but repeated calculations across large, changing networks increased computational demand (Ben Arbia et al., 2017). Path distance, expected travel time, number of examined nodes, memory consumption, route-generation time, and scalability therefore formed the principal quantitative basis for comparing indoor emergency-routing algorithms.

Emergency routing research has increasingly treated indoor path selection as a multi-criteria problem rather than a calculation based only on physical distance. Fire, smoke, heat, structural instability, hazardous materials, crowd density, stair use, elevator availability, doorway capacity, access restrictions, responder equipment, and occupant mobility can change the operational cost of each network segment. Studies using weighted indoor graphs assigned higher traversal costs to congested corridors, smoke-filled spaces, steep stairs, narrow doors, restricted zones, and areas close to a developing hazard. A physically longer route could consequently become preferable when it reduced exposure, travel difficulty, or crowd interaction. Researchers measured multi-criteria performance through estimated travel time, cumulative hazard exposure, congestion delay, number of turns, vertical movement, route completion, and sensitivity to changes in assigned priorities (Kulla et al., 2015).

Figure 6: Network-Based Indoor Routing Framework



Results varied when models gave excessive importance to one criterion because a route with minimal hazard exposure could become too long, while a route minimizing distance could pass through rapidly worsening conditions. Dynamic models addressed this problem by updating edge availability and traversal costs using fire sensors, smoke detectors, building-management systems, cameras, responder reports, and simulated hazard propagation. Route recalculation occurred when a doorway became blocked, smoke entered a corridor, crowd density increased, an elevator became unavailable, or structural damage interrupted a connection. Hazard-detection delay and communication latency influenced whether the revised route remained valid when it reached the user. Frequent updates improved responsiveness but increased processing and message demands (Teo & Cho, 2016). Studies assessed dynamic performance through recalculation time, successful-diversion percentage, route-survival duration, exposure reduction, update frequency, and the percentage of travelers redirected before reaching an unsafe segment. Dynamic routing performed most reliably when sensor information, graph identifiers, timestamps, and building coordinates were synchronized. Multi-criteria and hazard-aware performance therefore depended on both algorithmic speed and the accuracy, timeliness, and operational meaning of changing environmental data (Ahmad et al., 2022).

Accessible emergency-routing studies have demonstrated that a path considered navigable for an unassisted pedestrian may be unusable for wheelchair users, hospital patients, injured occupants, emergency medical teams, firefighters, or responders carrying heavy equipment. Accessibility models incorporated doorway width, corridor width, surface condition, ramp slope, stair presence, elevator availability, turning space, travel direction, crowding, and equipment clearance. Routes for wheelchair users excluded stairs and prioritized ramps or operational elevators, while firefighter routes considered protective equipment, hose deployment, reduced visibility, heat exposure, and movement burden. Emergency medical routes required sufficient width for stretchers and dependable access between vehicle entrances, elevators, wards, and treatment areas (Navya & Deepalakshmi, 2021). Quantitative studies measured accessible-path availability, doorway and slope compliance, stair-avoidance percentage, elevator dependence, travel-time increase, number of turns, and successful route

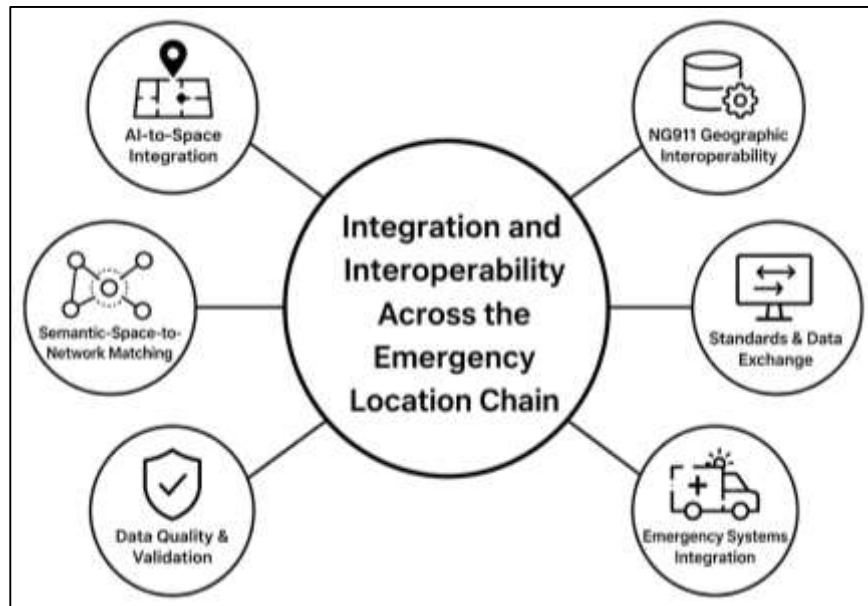
completion. Restricting the network to accessible elements often reduced the number of feasible paths and increased route length, particularly in older or vertically complex buildings. Alternative-route resilience addressed whether navigation remained possible after the failure of an entrance, corridor, stairway, elevator, or other critical connection. Researchers evaluated path redundancy through the number of independent routes, edge and node criticality, network-disconnection probability, alternative-route length, recovery time, and sensitivity to individual component failures. Buildings organized around a single central stair, narrow connector, or controlled entrance showed greater vulnerability than structures containing distributed vertical and horizontal connections (Deng et al., 2021). A network could appear highly connected while depending on a small number of critical nodes shared by nearly all routes. Resilience analysis therefore removed or disabled selected elements and measured whether valid paths remained between incident locations and responder access points. Route recovery was stronger when alternative paths were precomputed, graph updates were rapid, and users received clear redirection before reaching the failed segment. Accessible and resilient routing required simultaneous consideration of user capability, building constraints, route redundancy, network vulnerability, and operational recovery (Navya & Deepalakshmi, 2018).

Integration and Interoperability Across the Emergency Location Chain

More than twenty indoor-positioning, map-matching, semantic-localization, and emergency-mapping studies have examined how artificial-intelligence estimates are assigned to meaningful building spaces. Artificial-intelligence systems commonly generate coordinates, floor probabilities, zone classifications, or distributions of possible locations. These outputs must be matched with rooms, corridors, stairways, elevators, entrances, and other spatial cells before they can support emergency communication. Point-in-polygon methods assign a coordinate to the containing room or space, while nearest-cell methods select the closest modeled feature when the coordinate falls outside a valid boundary (Fang et al., 2023). Probabilistic approaches consider several candidate spaces and use confidence, movement history, signal patterns, floor information, and building topology to determine the most likely assignment. Matching performance has generally been strongest when coordinate error is smaller than the dimensions of the target room and when spaces are separated by clear boundaries. Accuracy declined near shared walls, doorways, narrow corridors, open-plan areas, floor edges, atriums, and vertically overlapping spaces. A coordinate positioned only slightly beyond a wall could be assigned to an adjacent room, even when the underlying localization error was small. Multi-floor buildings created additional ambiguity because similar horizontal coordinates occurred on several levels. Floor probabilities, barometric observations, vertical coordinates, and known movement transitions helped reduce these errors (Bhanumurthy et al., 2015). Map constraints also prevented estimates from appearing inside walls, shafts, closed spaces, or other physically invalid areas. Researchers evaluated matching quality through correct-cell percentage, correct-room percentage, correct-floor percentage, boundary-error frequency, invalid-space assignment, and confidence calibration. Some studies reported improved coordinate plausibility after map matching while producing limited improvement in exact room identification. This distinction showed that constraining a position to navigable space did not automatically identify the correct semantic location. AI-to-space integration therefore required simultaneous assessment of coordinate quality, floor certainty, boundary conditions, semantic model accuracy, and the reliability of the matching rule (da Silva Avanzi et al., 2017).

Semantic-space-to-network matching converts an identified incident room, corridor, or zone into a valid origin or destination within an indoor routing graph. Indoor models frequently represent rooms and corridors as cells, while navigation graphs represent movement through nodes and edges. The connection between these structures depends on correct associations among spaces, doors, graph nodes, vertical transitions, exterior entrances, and responder access points. Studies using building information models, IndoorGML, dual graphs, visibility graphs, medial-axis networks, and grid-based representations have shown that room-to-node matching is relatively direct when each space contains a designated node and every doorway is represented as a transition. Greater difficulty occurs in large rooms containing multiple doors, corridors with several graph segments, spaces divided by temporary partitions, and buildings with several possible responder entrances (Damaševičius et al., 2023).

Figure 7: Emergency Location Chain Integration



An incident coordinate may be correctly assigned to a room but linked to an unsuitable graph node positioned behind a locked door, across an internal barrier, or near an inaccessible entrance. Stairways and elevators require consistent floor associations because an incorrect vertical transition can move the route to the wrong level. Researchers have assessed association quality through correct-node percentage, valid-doorway connection, entrance-selection accuracy, successful vertical-transition matching, route-origin validity, route-destination validity, and manual correction frequency. Route-origin accuracy has also depended on whether the responder's starting point was linked to the correct vehicle access location or exterior entrance. Semantic attributes improved matching by identifying public entrances, fire-service entrances, secured doors, accessible routes, staff-only areas, and hazard-controlled passages (Gill et al., 2016). A high node-association rate could still produce poor emergency routing when the selected node lacked an operationally appropriate connection. Semantic-space-to-network quality was therefore determined by the correctness of the node assignment and the suitability of the associated doorway, entrance, floor transition, and movement constraints.

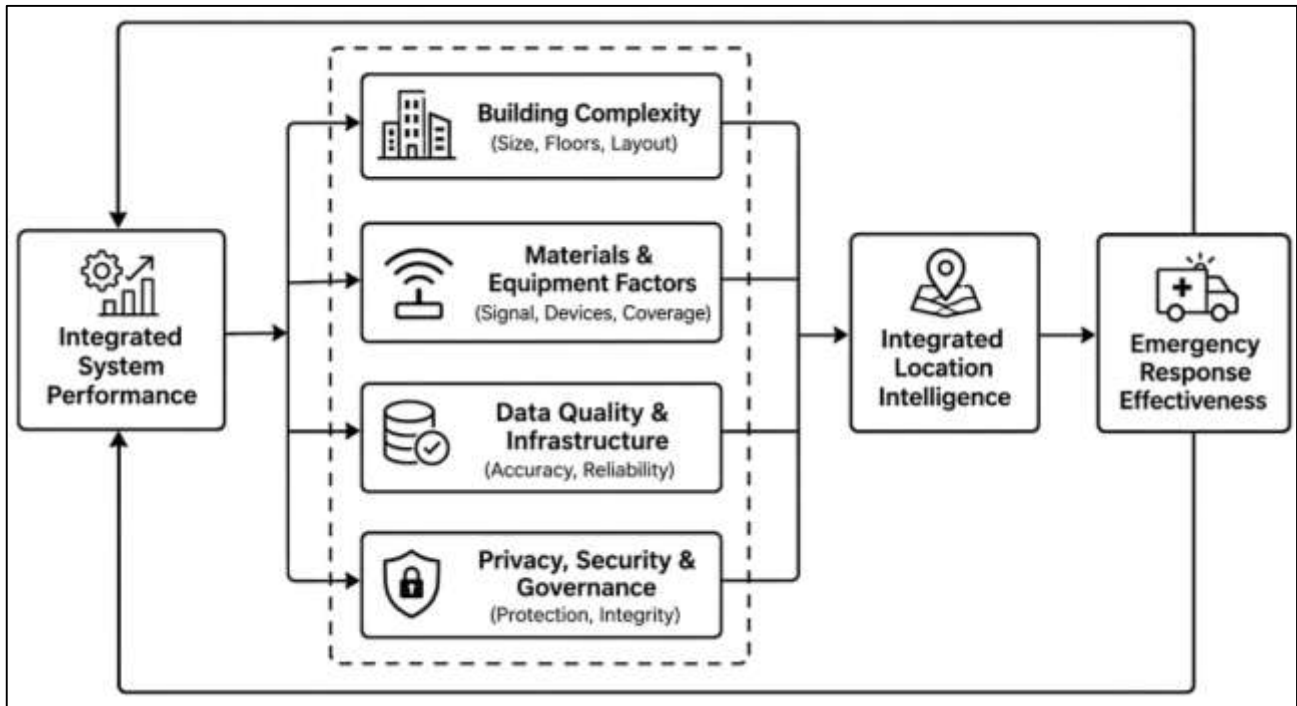
NG911 geographic interoperability requires location information to retain consistent meaning as it moves among indoor models, authoritative geographic databases, location-validation services, emergency call-routing functions, computer-aided dispatch platforms, mapping interfaces, and responder applications. Standards-oriented studies and implementation assessments have identified schema conformance, common identifiers, coordinate consistency, boundary alignment, and reliable data exchange as central requirements. NG911 geographic data commonly support civic-location validation and geographic call routing, while indoor models add floor, room, entrance, hazard, accessibility, and navigation information (Migliorini et al., 2019). Integration becomes difficult when the emergency system and indoor database use different field names, address structures, floor conventions, feature classifications, spatial reference systems, or building identifiers. A building can possess separate identifiers in property records, architectural models, emergency dispatch databases, campus systems, and indoor maps. Unresolved differences produce unmatched locations, rejected transactions, duplicated features, delayed processing, or incorrect jurisdictional association. Schema validation has been evaluated through required-field completeness, valid-data-type percentage, domain-value compliance, geometry checks, and conformance-error frequency. Identifier interoperability has been measured through successful building matches, floor-code agreement, room-number correspondence, duplicate-record rates, and unmatched-feature percentages. Data-exchange performance has included successful-message percentage, rejected-message frequency, response time, transmission delay, and the proportion of records displayed correctly in downstream systems

(Karaagac et al., 2018). Geographic boundaries also require continuous coverage without gaps or overlaps that can cause uncertain call routing. Indoor information must preserve its relationship with authoritative addresses, property boundaries, building footprints, and emergency-service jurisdictions. Research and operational assessments have consistently shown that technical connectivity alone does not establish interoperability. Effective NG911 exchange depends on shared definitions, verified identifiers, standardized schemas, maintained geographic data, consistent coordinates, and validation rules that detect errors before location information enters emergency workflows.

Contextual Determinants of Integrated System Performance

More than thirty empirical, simulation, and applied studies have shown that building complexity influences indoor localization, semantic interpretation, graph construction, and emergency-routing performance. High-rise buildings introduce repeated horizontal layouts, closely spaced floors, long vertical travel distances, and dependence on stairs or elevators (Frederico et al., 2023). Hospitals contain interconnected wings, restricted departments, specialized treatment rooms, controlled doors, and several entrances with different operational functions. Airports and transportation terminals combine large open areas with gates, platforms, security zones, service corridors, and underground connections. Industrial facilities include machinery, hazardous spaces, irregular routes, and access limitations, while university campuses require accurate movement between multiple buildings and internal floors. Researchers have measured complexity through floor count, room density, corridor intersections, doorway count, network size, graph density, vertical-transition frequency, average node degree, and the number of alternative routes. Positioning error generally increased when buildings contained repeated room patterns, overlapping floor geometry, large open spaces, or weakly differentiated signal environments (Al-Rakhami & Al-Mashari, 2022). Floor-classification models experienced greater difficulty when many levels shared similar access-point arrangements and structural layouts. Semantic models required more processing and verification as the number of rooms, doors, stairs, elevators, and restricted zones increased. Routing algorithms explored more nodes and consumed greater memory when applied to large grid networks or highly connected indoor graphs. Vertical transitions created additional costs because an incorrect stairway or elevator association could invalidate the complete route. Building size alone did not fully explain performance; two facilities with similar floor areas could differ substantially in corridor complexity, network redundancy, entrance distribution, and semantic detail. Studies of complex facilities therefore combined physical dimensions with graph-based indicators to explain variations in accuracy and computation (Wasswa et al., 2023). Floor count, room density, network size, vertical connections, entrance count, and spatial repetition collectively represented the building-complexity conditions affecting integrated emergency location intelligence. Construction materials and equipment configurations produce substantial variation in wireless-signal behavior and cross-device localization accuracy. Experiments involving Wi-Fi, Bluetooth, ultra-wideband, cellular, and radio-frequency identification have demonstrated that concrete, reinforced concrete, steel, glass, drywall, wood, machinery, and internal partitions attenuate or reflect signals at different levels. Concrete and metal structures commonly produced greater signal loss and multipath distortion than lightweight partitions or wooden materials. Energy-efficient glass and metallic coatings also reduced transmission, while long corridors created reflected signal paths that complicated distance estimation (Ding et al., 2015). Human density altered received-signal strength by blocking or absorbing radio energy, particularly in crowded hospitals, airports, shopping centers, and transportation stations. Moving equipment, electrical systems, industrial machinery, smoke, heat, and electromagnetic interference further changed the relationship between measured signals and stored fingerprints. Coverage loss was quantified through unavailable-access-point frequency, reduced signal strength, increased ranging error, failed-position percentage, and changes in percentile error. Device heterogeneity added another source of variation because smartphone models, chipsets, antennas, operating systems, sensor qualities, and scanning policies recorded different values at the same location. A fingerprint collected with one device could therefore produce larger errors when applied to another device (Pillai et al., 2021).

Figure 8: Integrated Emergency System Performance



Barometers, magnetometers, cameras, inertial sensors, and wireless receivers also differed in bias, resolution, sampling frequency, and calibration stability. Cross-device studies measured accuracy loss, signal offset, calibration time, missing-sensor percentage, and performance before and after normalization. Device-specific calibration, feature standardization, collaborative learning, and domain adaptation reduced some differences, although results depended on the number and diversity of devices included during training. Anchor and beacon arrangement also affected coverage because poorly positioned infrastructure created weak geometric conditions and uncovered areas. Material attenuation, environmental interference, device variation, sensor availability, and infrastructure geometry therefore operated together as contextual determinants of system performance (Jahre & Fabbe-Costes, 2015).

Data quality affects every stage of an integrated emergency-location system, from signal processing to semantic matching and route generation. Indoor-positioning studies have examined missing signal observations, mislabeled fingerprints, duplicated samples, outdated radio maps, inconsistent timestamps, and incorrect reference coordinates. Geospatial and building-model research has identified incomplete room attributes, outdated floor plans, missing doors, incorrect floor labels, duplicated identifiers, invalid topology, and coordinate-reference inconsistencies. A positioning model trained with mislabeled reference points can learn incorrect spatial relationships, while an outdated fingerprint database may no longer represent relocated access points or modified interiors. Similarly, a correct coordinate can be assigned to the wrong space when renovations are absent from the indoor map. Timestamp misalignment creates additional error when wireless measurements, inertial observations, hazard reports, and route updates represent different moments (Kayıkçı & Subramanian, 2022). Researchers have evaluated data quality through missing-value percentage, label-error frequency, duplicate-record rate, map age, unmatched-identifier frequency, invalid-link count, and synchronization delay. Infrastructure disruption intensifies these weaknesses. Power loss can disable access points, beacons, anchors, elevators, servers, and indoor displays. Network interruption can delay location transmission and prevent route updates, while damaged sensors can remove essential evidence from a fusion model. Blocked corridors, inaccessible entrances, disabled elevators, and failed stairway connections can invalidate previously calculated paths. Studies have measured disruption through positioning-error increase, service-unavailability duration, dropped-update percentage, failed-route frequency, recovery time, and fallback-method success (Acs et al., 2016). Hybrid

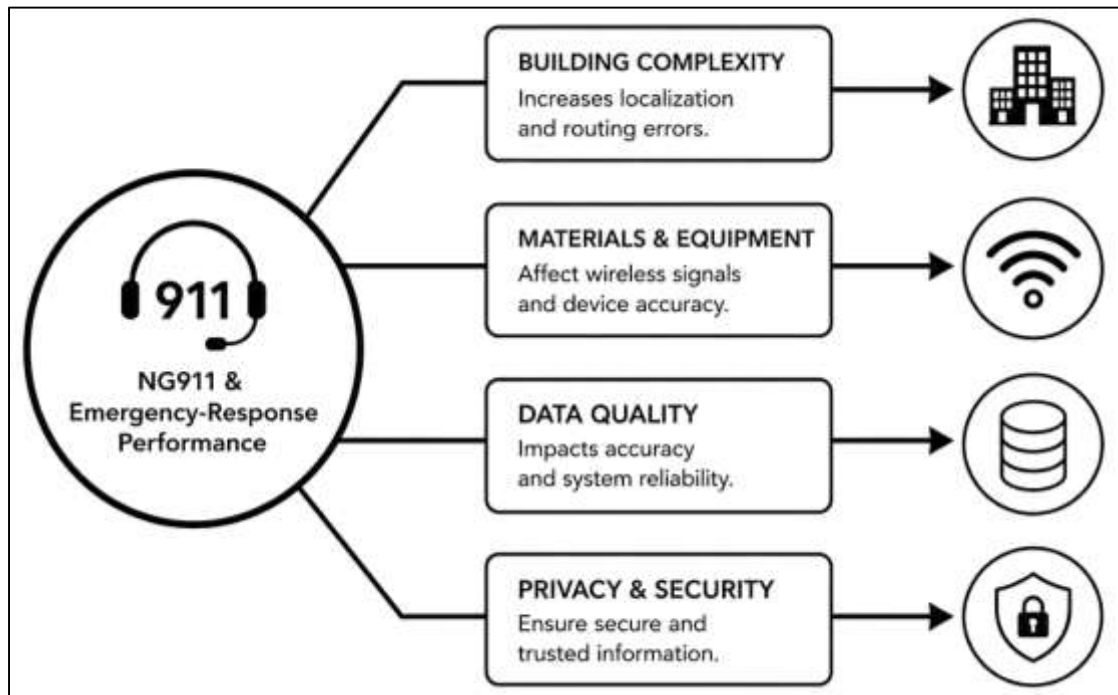
localization generally maintained stronger continuity when one sensing source became unavailable, although performance declined when several correlated sources failed together. Routing resilience depended on timely graph updates and the availability of alternative paths. Integrated reliability therefore required data-quality assessment and disruption testing to be conducted together because missing, outdated, or unsynchronized information can produce effects similar to physical infrastructure failure.

Privacy, security, and governance determine whether high-precision emergency location information can be collected, exchanged, and retained without unacceptable exposure or loss of integrity. Indoor location records can reveal a person's building, floor, room, movement pattern, workplace, medical location, or presence within a restricted area (Kok et al., 2015). Security studies have examined unauthorized tracking, identity linkage, false beacon transmission, signal spoofing, replay attacks, manipulated fingerprints, compromised access points, altered maps, and falsified routing information. These threats can reduce confidentiality while also affecting emergency accuracy. A modified floor record or counterfeit location message may direct responders to the wrong room, entrance, or route. Quantitative assessments have measured unauthorized-access attempts, successful intrusion percentage, false-data acceptance, anomaly-detection accuracy, integrity violations, authentication time, encryption overhead, and message-processing delay. Strong access controls limit location information according to user role, operational need, incident status, and agency responsibility. Authentication and encryption protect data exchange, although additional processing can increase latency when systems or networks have limited capacity. Privacy-preserving approaches such as federated learning, local feature processing, pseudonymous identifiers, data minimization, and restricted retention reduce the movement or storage of identifiable location records (Nilsen & Bernhardsson, 2019). Their performance has been evaluated through model accuracy, communication overhead, privacy loss, processing time, and the quantity of data transferred. Governance studies have also emphasized data ownership, update responsibility, auditability, retention schedules, access logging, incident response, and cross-agency agreements. Inconsistent governance can leave indoor maps outdated, identifiers unresolved, or access permissions unclear even when technical systems function correctly. Record integrity depends on controlled editing, version management, validation, and traceable changes across geographic databases, building models, routing graphs, and dispatch platforms. Privacy, security, and governance performance is therefore measured through data exposure, access-control effectiveness, record accuracy, integrity preservation, authentication efficiency, audit completeness, and compliance with established emergency-data requirements (Nilsen & Bernhardsson, 2019).

Effects on NG911 and Emergency-Response Performance

More than thirty empirical, simulation, and applied studies have shown that building complexity influences indoor localization, semantic interpretation, graph construction, and emergency-routing performance. High-rise buildings introduce repeated horizontal layouts, closely spaced floors, long vertical travel distances, and dependence on stairs or elevators. Hospitals contain interconnected wings, restricted departments, specialized treatment rooms, controlled doors, and several entrances with different operational functions. Airports and transportation terminals combine large open areas with gates, platforms, security zones, service corridors, and underground connections. Industrial facilities include machinery, hazardous spaces, irregular routes, and access limitations, while university campuses require accurate movement between multiple buildings and internal floors (Aquino et al., 2021). Researchers have measured complexity through floor count, room density, corridor intersections, doorway count, network size, graph density, vertical-transition frequency, average node degree, and the number of alternative routes. Positioning error generally increased when buildings contained repeated room patterns, overlapping floor geometry, large open spaces, or weakly differentiated signal environments. Floor-classification models experienced greater difficulty when many levels shared similar access-point arrangements and structural layouts. Semantic models required more processing and verification as the number of rooms, doors, stairs, elevators, and restricted zones increased. Routing algorithms explored more nodes and consumed greater memory when applied to large grid networks or highly connected indoor graphs (Seeman et al., 2015a).

Figure 9: NG911 Emergency Response Performance



Vertical transitions created additional costs because an incorrect stairway or elevator association could invalidate the complete route. Building size alone did not fully explain performance; two facilities with similar floor areas could differ substantially in corridor complexity, network redundancy, entrance distribution, and semantic detail. Studies of complex facilities therefore combined physical dimensions with graph-based indicators to explain variations in accuracy and computation. Floor count, room density, network size, vertical connections, entrance count, and spatial repetition collectively represented the building-complexity conditions affecting integrated emergency location intelligence. Construction materials and equipment configurations produce substantial variation in wireless-signal behavior and cross-device localization accuracy. Experiments involving Wi-Fi, Bluetooth, ultra-wideband, cellular, and radio-frequency identification have demonstrated that concrete, reinforced concrete, steel, glass, drywall, wood, machinery, and internal partitions attenuate or reflect signals at different levels (Grace & Kropczynski, 2020). Concrete and metal structures commonly produced greater signal loss and multipath distortion than lightweight partitions or wooden materials. Energy-efficient glass and metallic coatings also reduced transmission, while long corridors created reflected signal paths that complicated distance estimation. Human density altered received-signal strength by blocking or absorbing radio energy, particularly in crowded hospitals, airports, shopping centers, and transportation stations. Moving equipment, electrical systems, industrial machinery, smoke, heat, and electromagnetic interference further changed the relationship between measured signals and stored fingerprints (French et al., 2015). Coverage loss was quantified through unavailable-access-point frequency, reduced signal strength, increased ranging error, failed-position percentage, and changes in percentile error. Device heterogeneity added another source of variation because smartphone models, chipsets, antennas, operating systems, sensor qualities, and scanning policies recorded different values at the same location. A fingerprint collected with one device could therefore produce larger errors when applied to another device. Barometers, magnetometers, cameras, inertial sensors, and wireless receivers also differed in bias, resolution, sampling frequency, and calibration stability. Cross-device studies measured accuracy loss, signal offset, calibration time, missing-sensor percentage, and performance before and after normalization (Vinson et al., 2023). Device-specific calibration, feature standardization, collaborative learning, and domain adaptation reduced some differences, although results depended on the number and diversity of devices included during training. Anchor and beacon arrangement also affected coverage because poorly positioned infrastructure created weak geometric conditions and uncovered areas. Material attenuation, environmental interference, device variation, sensor

availability, and infrastructure geometry therefore operated together as contextual determinants of system performance.

Data quality affects every stage of an integrated emergency-location system, from signal processing to semantic matching and route generation (Corral-De-Witt et al., 2018). Indoor-positioning studies have examined missing signal observations, mislabeled fingerprints, duplicated samples, outdated radio maps, inconsistent timestamps, and incorrect reference coordinates. Geospatial and building-model research has identified incomplete room attributes, outdated floor plans, missing doors, incorrect floor labels, duplicated identifiers, invalid topology, and coordinate-reference inconsistencies. A positioning model trained with mislabeled reference points can learn incorrect spatial relationships, while an outdated fingerprint database may no longer represent relocated access points or modified interiors. Similarly, a correct coordinate can be assigned to the wrong space when renovations are absent from the indoor map (Coley, 2018). Timestamp misalignment creates additional error when wireless measurements, inertial observations, hazard reports, and route updates represent different moments. Researchers have evaluated data quality through missing-value percentage, label-error frequency, duplicate-record rate, map age, unmatched-identifier frequency, invalid-link count, and synchronization delay. Infrastructure disruption intensifies these weaknesses. Power loss can disable access points, beacons, anchors, elevators, servers, and indoor displays. Network interruption can delay location transmission and prevent route updates, while damaged sensors can remove essential evidence from a fusion model. Blocked corridors, inaccessible entrances, disabled elevators, and failed stairway connections can invalidate previously calculated paths. Studies have measured disruption through positioning-error increase, service-unavailability duration, dropped-update percentage, failed-route frequency, recovery time, and fallback-method success (Chen & Englund, 2018). Hybrid localization generally maintained stronger continuity when one sensing source became unavailable, although performance declined when several correlated sources failed together. Routing resilience depended on timely graph updates and the availability of alternative paths. Integrated reliability therefore required data-quality assessment and disruption testing to be conducted together because missing, outdated, or unsynchronized information can produce effects similar to physical infrastructure failure (Subudhi et al., 2019).

Privacy, security, and governance determine whether high-precision emergency location information can be collected, exchanged, and retained without unacceptable exposure or loss of integrity. Indoor location records can reveal a person's building, floor, room, movement pattern, workplace, medical location, or presence within a restricted area. Security studies have examined unauthorized tracking, identity linkage, false beacon transmission, signal spoofing, replay attacks, manipulated fingerprints, compromised access points, altered maps, and falsified routing information. These threats can reduce confidentiality while also affecting emergency accuracy. A modified floor record or counterfeit location message may direct responders to the wrong room, entrance, or route (Sneps-Snepp & Namiot, 2017). Quantitative assessments have measured unauthorized-access attempts, successful intrusion percentage, false-data acceptance, anomaly-detection accuracy, integrity violations, authentication time, encryption overhead, and message-processing delay. Strong access controls limit location information according to user role, operational need, incident status, and agency responsibility. Authentication and encryption protect data exchange, although additional processing can increase latency when systems or networks have limited capacity. Privacy-preserving approaches such as federated learning, local feature processing, pseudonymous identifiers, data minimization, and restricted retention reduce the movement or storage of identifiable location records. Their performance has been evaluated through model accuracy, communication overhead, privacy loss, processing time, and the quantity of data transferred (Gupta et al., 2023). Governance studies have also emphasized data ownership, update responsibility, auditability, retention schedules, access logging, incident response, and cross-agency agreements. Inconsistent governance can leave indoor maps outdated, identifiers unresolved, or access permissions unclear even when technical systems function correctly. Record integrity depends on controlled editing, version management, validation, and traceable changes across geographic databases, building models, routing graphs, and dispatch platforms. Privacy, security, and governance performance is therefore measured through data exposure, access-control effectiveness,

record accuracy, integrity preservation, authentication efficiency, audit completeness, and compliance with established emergency-data requirements (Hancock et al., 2020).

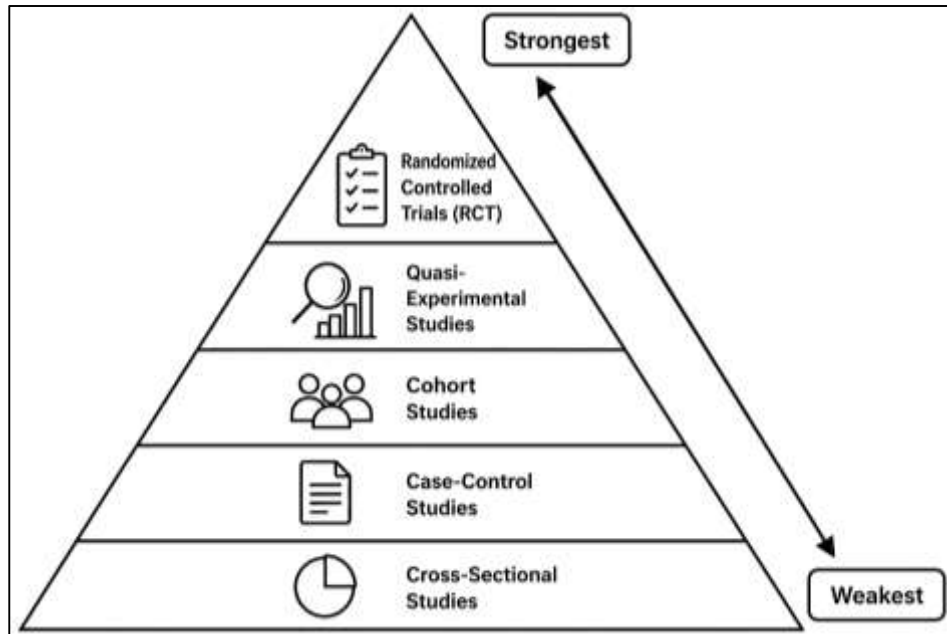
International and Cross-Environment Quantitative Comparisons

More than thirty empirical, simulation, and applied studies have shown that building complexity influences indoor localization, semantic interpretation, graph construction, and emergency-routing performance. High-rise buildings introduce repeated horizontal layouts, closely spaced floors, long vertical travel distances, and dependence on stairs or elevators. Hospitals contain interconnected wings, restricted departments, specialized treatment rooms, controlled doors, and several entrances with different operational functions. Airports and transportation terminals combine large open areas with gates, platforms, security zones, service corridors, and underground connections (Mullis et al., 2018). Industrial facilities include machinery, hazardous spaces, irregular routes, and access limitations, while university campuses require accurate movement between multiple buildings and internal floors. Researchers have measured complexity through floor count, room density, corridor intersections, doorway count, network size, graph density, vertical-transition frequency, average node degree, and the number of alternative routes. Positioning error generally increased when buildings contained repeated room patterns, overlapping floor geometry, large open spaces, or weakly differentiated signal environments. Floor-classification models experienced greater difficulty when many levels shared similar access-point arrangements and structural layouts. Semantic models required more processing and verification as the number of rooms, doors, stairs, elevators, and restricted zones increased. Routing algorithms explored more nodes and consumed greater memory when applied to large grid networks or highly connected indoor graphs (Díaz-Vilariño et al., 2019). Vertical transitions created additional costs because an incorrect stairway or elevator association could invalidate the complete route. Building size alone did not fully explain performance; two facilities with similar floor areas could differ substantially in corridor complexity, network redundancy, entrance distribution, and semantic detail. Studies of complex facilities therefore combined physical dimensions with graph-based indicators to explain variations in accuracy and computation. Floor count, room density, network size, vertical connections, entrance count, and spatial repetition collectively represented the building-complexity conditions affecting integrated emergency location intelligence.

Construction materials and equipment configurations produce substantial variation in wireless-signal behavior and cross-device localization accuracy (Diakité & Zlatanova, 2018). Experiments involving Wi-Fi, Bluetooth, ultra-wideband, cellular, and radio-frequency identification have demonstrated that concrete, reinforced concrete, steel, glass, drywall, wood, machinery, and internal partitions attenuate or reflect signals at different levels. Concrete and metal structures commonly produced greater signal loss and multipath distortion than lightweight partitions or wooden materials. Energy-efficient glass and metallic coatings also reduced transmission, while long corridors created reflected signal paths that complicated distance estimation. Human density altered received-signal strength by blocking or absorbing radio energy, particularly in crowded hospitals, airports, shopping centers, and transportation stations. Moving equipment, electrical systems, industrial machinery, smoke, heat, and electromagnetic interference further changed the relationship between measured signals and stored fingerprints (Vanclooster et al., 2016). Coverage loss was quantified through unavailable-access-point frequency, reduced signal strength, increased ranging error, failed-position percentage, and changes in percentile error. Device heterogeneity added another source of variation because smartphone models, chipsets, antennas, operating systems, sensor qualities, and scanning policies recorded different values at the same location. A fingerprint collected with one device could therefore produce larger errors when applied to another device. Barometers, magnetometers, cameras, inertial sensors, and wireless receivers also differed in bias, resolution, sampling frequency, and calibration stability. Cross-device studies measured accuracy loss, signal offset, calibration time, missing-sensor percentage, and performance before and after normalization. Device-specific calibration, feature standardization, collaborative learning, and domain adaptation reduced some differences, although results depended on the number and diversity of devices included during training (Peavy et al., 2023). Anchor and beacon arrangement also affected coverage because poorly positioned infrastructure created weak geometric conditions and uncovered areas. Material attenuation, environmental interference, device variation, sensor availability, and infrastructure geometry therefore operated together as contextual determinants of

system performance.

Figure 10: Global Indoor Emergency Performance



Data quality affects every stage of an integrated emergency-location system, from signal processing to semantic matching and route generation. Indoor-positioning studies have examined missing signal observations, mislabeled fingerprints, duplicated samples, outdated radio maps, inconsistent timestamps, and incorrect reference coordinates. Geospatial and building-model research has identified incomplete room attributes, outdated floor plans, missing doors, incorrect floor labels, duplicated identifiers, invalid topology, and coordinate-reference inconsistencies (Pang et al., 2018). A positioning model trained with mislabeled reference points can learn incorrect spatial relationships, while an outdated fingerprint database may no longer represent relocated access points or modified interiors. Similarly, a correct coordinate can be assigned to the wrong space when renovations are absent from the indoor map. Timestamp misalignment creates additional error when wireless measurements, inertial observations, hazard reports, and route updates represent different moments. Researchers have evaluated data quality through missing-value percentage, label-error frequency, duplicate-record rate, map age, unmatched-identifier frequency, invalid-link count, and synchronization delay. Infrastructure disruption intensifies these weaknesses. Power loss can disable access points, beacons, anchors, elevators, servers, and indoor displays. Network interruption can delay location transmission and prevent route updates, while damaged sensors can remove essential evidence from a fusion model (Wei & Akinci, 2019). Blocked corridors, inaccessible entrances, disabled elevators, and failed stairway connections can invalidate previously calculated paths. Studies have measured disruption through positioning-error increase, service-unavailability duration, dropped-update percentage, failed-route frequency, recovery time, and fallback-method success. Hybrid localization generally maintained stronger continuity when one sensing source became unavailable, although performance declined when several correlated sources failed together. Routing resilience depended on timely graph updates and the availability of alternative paths. Integrated reliability therefore required data-quality assessment and disruption testing to be conducted together because missing, outdated, or unsynchronized information can produce effects similar to physical infrastructure failure (Tang et al., 2018).

Privacy, security, and governance determine whether high-precision emergency location information can be collected, exchanged, and retained without unacceptable exposure or loss of integrity. Indoor location records can reveal a person's building, floor, room, movement pattern, workplace, medical location, or presence within a restricted area. Security studies have examined unauthorized tracking,

identity linkage, false beacon transmission, signal spoofing, replay attacks, manipulated fingerprints, compromised access points, altered maps, and falsified routing information. These threats can reduce confidentiality while also affecting emergency accuracy. A modified floor record or counterfeit location message may direct responders to the wrong room, entrance, or route (Sun et al., 2021). Quantitative assessments have measured unauthorized-access attempts, successful intrusion percentage, false-data acceptance, anomaly-detection accuracy, integrity violations, authentication time, encryption overhead, and message-processing delay. Strong access controls limit location information according to user role, operational need, incident status, and agency responsibility. Authentication and encryption protect data exchange, although additional processing can increase latency when systems or networks have limited capacity. Privacy-preserving approaches such as federated learning, local feature processing, pseudonymous identifiers, data minimization, and restricted retention reduce the movement or storage of identifiable location records. Their performance has been evaluated through model accuracy, communication overhead, privacy loss, processing time, and the quantity of data transferred (Choi et al., 2015). Governance studies have also emphasized data ownership, update responsibility, auditability, retention schedules, access logging, incident response, and cross-agency agreements. Inconsistent governance can leave indoor maps outdated, identifiers unresolved, or access permissions unclear even when technical systems function correctly. Record integrity depends on controlled editing, version management, validation, and traceable changes across geographic databases, building models, routing graphs, and dispatch platforms. Privacy, security, and governance performance is therefore measured through data exposure, access-control effectiveness, record accuracy, integrity preservation, authentication efficiency, audit completeness, and compliance with established emergency-data requirements (Bibbò et al., 2022).

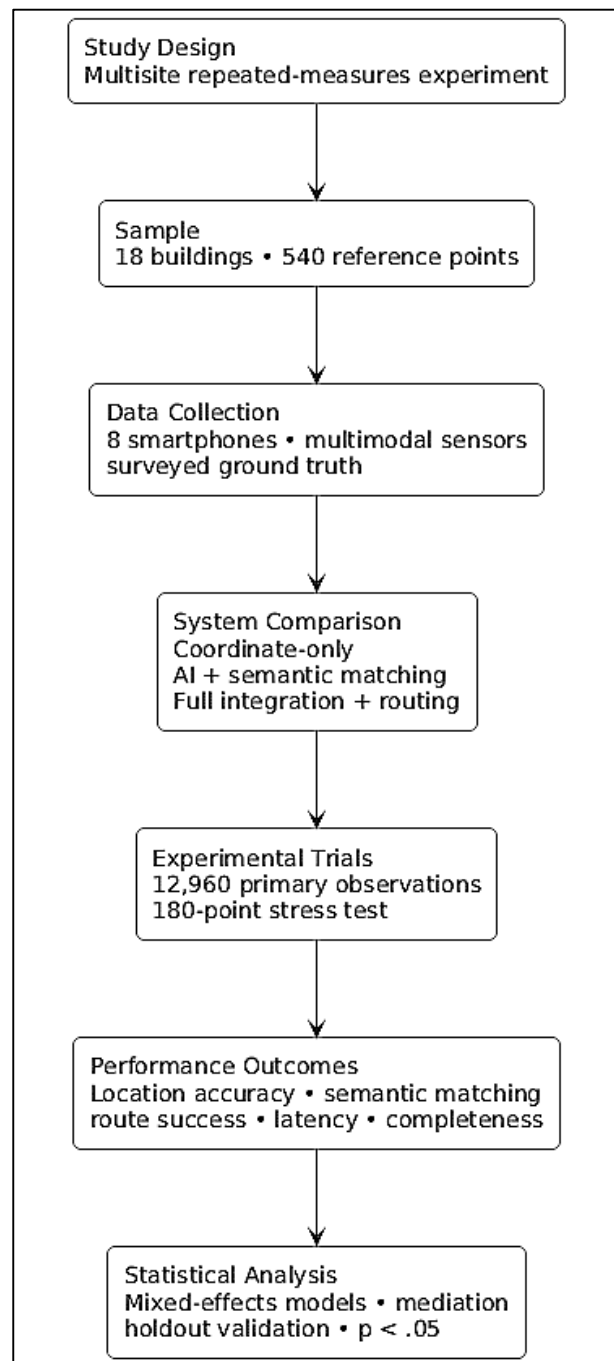
METHOD

This study employed a multisite, repeated-measures quantitative experimental design with quasi-experimental site selection to evaluate the integration of artificial intelligence, semantic indoor geospatial modeling, and network-based routing for high-precision NG911 emergency location intelligence. Buildings were selected purposively because random assignment of complete facilities was not operationally feasible, while emergency-location trials and system configurations were randomized within each participating building. Three configurations were compared: a conventional coordinate-only localization condition, an artificial-intelligence localization condition combined with semantic indoor-space matching, and a fully integrated condition combining artificial-intelligence localization, semantic indoor modeling, NG911-compatible geographic information, and network-based routing. The same reference locations were tested under each configuration, which permitted within-location comparisons and reduced variation caused by differences in building layout or signal environment. The conceptual framework combined information-processing theory, probabilistic data-fusion principles, semantic spatial modeling, and graph theory. Information-processing theory explained the conversion of raw sensor observations into actionable emergency information. Data-fusion principles guided the integration of wireless, inertial, magnetic, barometric, and visual observations. Semantic spatial modeling supported the assignment of estimated coordinates to buildings, floors, rooms, corridors, entrances, and other indoor features. Graph theory supported the representation of navigable spaces as nodes and edges and the calculation of emergency-response routes. The principal explanatory variables were artificial-intelligence localization capability, semantic indoor-model quality, routing capability, and overall integration level. The principal outcomes were horizontal error, vertical error, correct-floor classification, correct-room identification, semantic-match accuracy, route-generation success, processing latency, and end-to-end emergency-location completeness.

The study was conducted in 18 multistory buildings representing six indoor-environment categories: high-rise residential buildings, hospitals, educational facilities, transportation complexes, commercial buildings, and industrial facilities. Three buildings were selected from each category to ensure variation in floor count, construction materials, room density, corridor complexity, entrance configuration, wireless coverage, and vertical circulation. The buildings ranged from medium-sized facilities with relatively simple layouts to large structures containing repeated floors, restricted areas, multiple entrances, elevators, stairways, and extensive navigation networks. The primary unit of analysis was

an emergency-location trial conducted at a verified indoor reference point. A total of 540 reference points were established, with 30 points selected from each building. Each point was tested with four device classes during two data-collection periods and under three system configurations, producing 12,960 primary trial observations. An additional 180 reference points were selected for controlled stress testing involving signal loss, unavailable sensors, blocked routing edges, disabled elevators, and outdated location records. No real emergency calls were placed, and no personally identifiable caller information was collected. Trained research operators carried the test devices and followed standardized movement and positioning instructions; these operators functioned as data-collection personnel rather than research participants. The buildings, digital models, positioning devices, wireless infrastructure, reference points, semantic features, navigation graphs, and system-generated location records constituted the materials and subjects of the quantitative investigation.

Figure 11: Methodology of this study



A multistage stratified sampling strategy was used. During the first stage, buildings were stratified by functional category and selected according to structural complexity, digital-map availability, operational access, wireless infrastructure, and geographic diversity. During the second stage, floors were stratified into lower, middle, and upper levels wherever the building height permitted that classification. During the third stage, reference points were distributed across rooms, corridors, stairway approaches, elevator lobbies, entrances, open spaces, restricted-access boundaries, and locations near shared walls or floor transitions. This process ensured that easy and ambiguous locations were represented. Reference points were selected through spatially balanced sampling so that observations were not concentrated around access points, beacons, entrances, or central corridors. An a priori power analysis was conducted through simulation of the proposed mixed-effects models. The analysis indicated that at least 450 reference points distributed across 15 or more buildings were required to detect a small standardized configuration effect of approximately 0.20 with 90% power at a two-tailed significance level of .05.

The final sample of 540 reference points across 18 buildings exceeded that requirement and provided sufficient observations for building-level clustering, system comparisons, interaction testing, and holdout validation. Twelve buildings, including two from each category, formed the development sample. The remaining six buildings, including one from each category, formed an external holdout sample that remained unavailable during model training and parameter selection. Buildings were included when they contained at least three operational floors, possessed verified architectural drawings or building information models, supported safe research access, contained functioning Wi-Fi or other indoor wireless infrastructure, and provided sufficient information to identify rooms, corridors, doors, stairs, elevators, and exterior entrances. Facilities were also required to provide a stable civic address, building identifier, floor hierarchy, and permission for temporary sensor observation. Reference locations were included when their horizontal and vertical positions could be independently surveyed, their semantic space could be verified, and at least one valid route existed between the location and an authorized responder entrance. Buildings were excluded when major renovation was underway, structural documentation could not be validated, access restrictions prevented independent verification, or wireless testing could interfere with safety-critical operations. Reference points were excluded when their surveyed coordinates could not be reproduced, when the corresponding room or floor designation remained disputed, or when access conditions created unacceptable risk. Individual trial observations were excluded when the operator departed from the predefined location, the device clock differed from the synchronized reference by more than the permitted tolerance, a hardware malfunction prevented valid logging, or the ground-truth record was incomplete. Signal loss and sensor unavailability created intentionally during stress testing were retained because they represented experimental conditions rather than missing observations.

Indoor signals were collected with eight smartphones representing four hardware classes and both major mobile operating-system environments. The devices recorded Wi-Fi observations, Bluetooth Low Energy signals, accelerometer readings, gyroscope measurements, magnetometer values, barometric pressure, and available visual or inertial information. Portable ultra-wideband tags and calibrated anchors were installed in authorized test areas to provide an additional ranging source. Survey-grade control points, a total station, laser-distance instruments, and verified floor elevations provided horizontal and vertical ground truth. Device clocks, anchor clocks, data-collection computers, and database services were synchronized to a common time source before each collection session. Wi-Fi and Bluetooth devices were co-located at known points to estimate cross-device signal offsets. Barometers were calibrated against a stationary reference sensor, inertial sensors were checked through standardized stationary and walking trials, and ultra-wideband anchor coordinates were verified against the surveyed control network. Building information models, Industry Foundation Classes files, computer-aided-design floor plans, geographic information layers, and facility records were transformed into a common spatial reference. IndoorGML-compatible cells and boundaries were created for rooms, corridors, doors, stairs, elevators, and entrances. Navigation graphs were generated and stored in a PostgreSQL and PostGIS database. Python, PyTorch, scikit-learn, QGIS, and NetworkX supported preprocessing, artificial-intelligence modeling, semantic matching, and route calculation.

Two independent geospatial specialists validated room boundaries, floor labels, doorway associations, identifiers, and network connectivity. Agreement was evaluated with Cohen's kappa for categorical attributes and the intraclass correlation coefficient for continuous measurements. Values of .80 or higher were required before the verified dataset was released for experimental testing.

Candidate localization models included k-nearest neighbors, support-vector machines, random forests, gradient-boosting models, multilayer neural networks, and multimodal ensemble models. Model development used only observations from the 12 development buildings. Hyperparameters were selected through grouped cross-validation in which observations from the same reference point and floor remained within the same fold. The external six-building sample was not used during training, feature selection, normalization, or threshold determination. Artificial-intelligence outputs included estimated horizontal coordinates, estimated elevation, floor probabilities, room probabilities, and confidence scores. Semantic matching assigned each estimate to a building, floor, cell, room, doorway, or corridor through coordinate containment, probability-weighted candidate evaluation, vertical constraints, and map-based movement restrictions. Routing graphs represented rooms, corridors, doors, stairways, elevators, and entrances as connected spatial elements. Dijkstra and A* routing were implemented under consistent edge conditions, while edge weights reflected distance, expected travel time, vertical movement, accessibility, doorway restrictions, and simulated hazards. The conventional condition generated a coordinate without detailed semantic interpretation or indoor routing. The partial-integration condition linked the artificial-intelligence estimate to a semantic indoor space. The fully integrated condition additionally linked the semantic space to a valid graph node and calculated an authorized route from a responder entrance. This staged configuration supported estimation of the incremental contribution of semantic matching and routing.

Data collection followed a standardized chronological protocol. Site authorization and technical approvals were obtained first, after which building records were inspected and converted into a common geographic framework. Surveyors then established horizontal and vertical control and recorded the verified coordinates, floor designations, room identifiers, and entrance relationships for every reference point. Wireless infrastructure, portable anchors, mobile devices, and reference sensors were calibrated before experimental observations began. Fingerprint and sensor-training data were collected from the development buildings at multiple orientations and during lower- and higher-occupancy periods. Reference points were visited in randomized order to reduce systematic effects associated with time, battery level, operator fatigue, or environmental change. At each point, the operator remained stationary for the initial acquisition period and subsequently completed a standardized short movement sequence so that stationary and trajectory-based performance could be assessed. Every device recorded the same categories of available signals and transmitted timestamped observations to the local experimental server. The three system configurations were processed in randomized order from identical source observations. For routing evaluation, the validated incident space was connected to two authorized responder access points whenever two entrances were available. Generated paths were checked against the verified indoor network, and route length, estimated travel time, calculation latency, accessibility, and successful completion were recorded. Stress testing was then performed by removing selected wireless sources, masking individual sensors, disabling specified graph edges, marking an elevator unavailable, or introducing controlled map and timestamp errors. All manipulations were implemented digitally or through safe device configuration; no physical emergency infrastructure was disabled. The database was de-identified, checked for completeness, and locked before inferential analysis began.

Artificial-intelligence localization capability was measured through horizontal error, vertical error, median positional error, 90th- and 95th-percentile error, correct-building percentage, correct-floor percentage, correct-room percentage, inference latency, confidence calibration, and continuity under signal loss. Semantic indoor-model quality was measured through boundary accuracy, doorway accuracy, attribute completeness, floor-label correctness, identifier consistency, topological validity, and correct cell assignment. Network-routing capability was measured through valid-node association, entrance-selection accuracy, route-generation success, path length, expected travel time, computation latency, accessibility compliance, successful diversion, and availability of alternative paths. NG911

interoperability was represented by schema conformance, required-field completeness, identifier-matching percentage, successful data exchange, and processing delay. The principal dependent construct, high-precision emergency location intelligence, was measured through correct spatial identification, operational record completeness, semantic interpretation accuracy, valid route availability, total processing time, confidence reliability, and successful display of the complete emergency-location record. Building category, floor count, room density, graph size, vertical-transition count, wall material, observed signal strength, device class, occupancy period, model age, data completeness, and disruption status were recorded as control or moderating variables. Total latency was measured from the first sensor observation to the display of the final semantic location and route. Route success required a continuous path from an authorized entrance to the correctly identified incident space without crossing an invalid, blocked, or restricted edge.

All observations were assigned nonidentifying building, floor, reference-point, device, and trial codes. Automated validation rules checked coordinate ranges, timestamps, floor codes, device identifiers, duplicate records, required attributes, and route continuity at the time of ingestion. Raw observations were retained separately from processed features so that every result could be traced to its original measurement. Duplicate records caused by transmission retries were identified through device, timestamp, and trial identifiers and were removed after verification. Missing sensor observations were retained when they represented genuine signal unavailability because signal loss was a performance outcome. Missing control variables were examined according to their frequency and pattern. Multiple imputation was used for incomplete covariates when the missingness pattern supported that procedure, while dependent outcomes were not imputed. Extreme values were checked against raw device logs, ground-truth coordinates, and system timestamps before they were classified as valid or erroneous. Map versions, model versions, training data, software configurations, and routing graphs were recorded for every trial. Ten percent of the reference points were independently resurveyed, and ten percent of the semantic and network records were rechecked by both geospatial specialists. No inferential results were examined until calibration, validation, exclusion, and database-lock procedures had been completed.

Statistical analyses were conducted in R and SPSS, while Python was used for signal preprocessing, artificial-intelligence training, semantic matching, and routing computation. Continuous variables were summarized with means, standard deviations, medians, interquartile ranges, minima, maxima, and 90th- and 95th-percentile values. Categorical outcomes were summarized with counts, percentages, and 95% confidence intervals. Model calibration was assessed through calibration plots, the Brier score, expected calibration error, and agreement between reported confidence and observed correctness. Repeated-measurement reliability was evaluated through intraclass correlation coefficients, while categorical map and route validation was evaluated through Cohen's kappa. Residual distributions, variance patterns, influential observations, and model convergence were examined before final interpretation.

Mixed-effects regression models were used because trials were nested within devices, reference points, floors, and buildings. Horizontal error, vertical error, route length, and latency were analyzed with linear mixed-effects models when residual assumptions were satisfied. Gamma mixed-effects models or quantile mixed models were used when continuous outcomes remained positively skewed after transformation. Correct-building, correct-floor, correct-room, semantic-match, valid-route, and complete-record outcomes were analyzed through mixed-effects logistic regression. Counts of failed updates, invalid links, and routing interruptions were analyzed with Poisson or negative-binomial mixed models according to dispersion. System configuration, building category, complexity, device class, occupancy period, signal condition, data quality, and disruption status were entered as fixed effects. Building, floor, reference point, and device were treated as random effects, and random slopes for system configuration were retained when supported by model fit. Interaction terms tested whether integration effects varied according to building complexity, construction material, device class, signal quality, data completeness, or disruption status.

Repeated-measures comparisons among the three system configurations were estimated through adjusted marginal means. Pairwise comparisons were corrected with the Holm procedure. Effect

magnitude was reported through adjusted mean differences, standardized mean differences, odds ratios, marginal and conditional coefficients of determination, and 95% confidence intervals. Statistical significance was evaluated using two-tailed tests at $p < .05$, although interpretation emphasized effect size and estimate precision. The incremental contribution of semantic matching was assessed by comparing the artificial-intelligence condition with the partial-integration condition, while the contribution of routing was assessed by comparing partial integration with full integration. A multilevel sequential mediation model tested whether artificial-intelligence localization capability influenced emergency-location intelligence through semantic matching accuracy and route validity. Indirect effects were evaluated with 5,000 bootstrap resamples.

FINDINGS

Final Sample Characteristics, Trial Distribution, and Data Quality

The final analytical dataset included all 18 selected multistory buildings and 540 verified reference points. The buildings represented high-rise residential, hospital, educational, transportation, commercial, and industrial environments, with three facilities included in each category. Collectively, the facilities contained 150 operational floors and 512,100 square meters of evaluated floor area. The verified reference locations included 180 rooms, 120 corridors, 48 stairway approaches, 48 elevator lobbies, 42 entrances, 42 open spaces, 30 restricted-access boundaries, and 30 ambiguous locations near shared walls or vertical transitions. Of the 12,960 planned primary trials, 12,614 were retained for analysis, producing an overall retention rate of 97.3%. The final indoor navigation models contained 18,642 nodes and 28,495 edges.

Table 1 Final Building Sample and Primary Trial Distribution

Building category	Buildings	Floors	Floor area (m ²)	Reference points	Planned trials	Retained trials	Retention (%)	Graph nodes	Graph edges
High-rise residential	3	39	68,400	90	2,160	2,123	98.3	2,610	3,914
Hospitals	3	30	104,700	90	2,160	2,094	96.9	3,842	5,936
Educational facilities	3	21	72,300	90	2,160	2,121	98.2	2,524	3,811
Transportation complexes	3	15	96,600	90	2,160	2,078	96.2	3,276	5,105
Commercial buildings	3	27	91,500	90	2,160	2,110	97.7	3,489	5,292
Industrial facilities	3	18	78,600	90	2,160	2,088	96.7	2,901	4,437
Total	18	150	512,100	540	12,960	12,614	97.3	18,642	28,495

Table 1 showed that all 18 participating buildings and 540 reference points contributed usable observations to the final dataset. Trial retention exceeded 96 percent in every building category, indicating balanced data preservation across heterogeneous environments. Residential and educational facilities recorded the highest retention, whereas transportation complexes recorded the lowest, largely because of intermittent signal acquisition and timestamp mismatches. Hospitals and commercial buildings contained the largest navigation graphs, reflecting greater room density, doorway frequency, and vertical connectivity. The retained sample therefore provided variation in spatial complexity while maintaining comparable observation volumes across the six building categories and three experimental configurations tested. Data screening excluded 346 primary observations. Hardware malfunction represented the largest exclusion source, followed by operator deviation, failed transmission, timestamp inconsistency, and incomplete ground-truth information. Stress testing generated 2,160

planned observations from 180 reference points, of which 2,089 were retained. Required-field completeness reached 98.6%, semantic-attribute completeness reached 97.8%, and building or spatial identifier matching reached 99.6%. Valid indoor topology was confirmed for 98.2% of records, while continuous route-network connectivity was retained in 97.6%. Agreement between the two geospatial specialists was excellent for categorical classifications, and the resurveyed reference points demonstrated high continuous-measurement reliability.

Table 2 Trial Exclusions, Data Quality, and Measurement Reliability

Data-quality indicator	Numerical result	Percentage or 95% CI
Planned primary trials	12,960	100.0%
Retained primary trials	12,614	97.3%
Excluded primary trials	346	2.7%
Operator deviation	78	0.6%
Hardware malfunction	91	0.7%
Timestamp inconsistency	64	0.5%
Incomplete ground truth	42	0.3%
Failed data transmission	71	0.5%
Planned stress-test trials	2,160	100.0%
Retained stress-test trials	2,089	96.7%
Successful signal acquisition	12,558	96.9%
Complete required fields	12,437	98.6%
Complete semantic attributes	12,336	97.8%
Successful identifier matching	12,564	99.6%
Valid indoor topology	12,387	98.2%
Continuous route network	12,311	97.6%
Duplicate records detected and removed	93	0.7%
Cohen's kappa for categorical validation	.92	[.90, .94]
Intraclass correlation coefficient	.97	[.96, .98]

Table 2 demonstrated strong data completeness, measurement consistency, and geospatial reliability. Of the 12,960 planned primary trials, 12,614 were retained, representing a 97.3 percent retention rate. Hardware malfunction accounted for the largest exclusion category, although its frequency remained below one percent of planned observations. Required-field completeness exceeded 98 percent, and more than 97 percent of records maintained complete semantic attributes and continuous routing networks. Building and spatial identifiers matched successfully in nearly all retained records. Cohen's kappa indicated excellent categorical agreement, while the intraclass correlation coefficient confirmed highly consistent continuous measurements across independently resurveyed reference points and repeated validation procedures.

Primary Effects of Integrated System Configuration on Emergency Location Intelligence

Primary outcomes improved progressively across the three system configurations. The conventional coordinate-only condition retained 4,193 trials, the artificial-intelligence and semantic-matching condition retained 4,205 trials, and the fully integrated condition retained 4,216 trials. Mean horizontal error decreased from 7.84 meters under coordinate-only localization to 3.42 meters under partial integration and 2.36 meters under full integration. Mean vertical error declined from 4.18 to 1.86 and 1.12 meters, respectively. Correct-floor identification increased from 72.6% to 90.8% and 96.4%, while correct-room identification increased from 51.8% to 81.6% and 91.7%. The fully integrated system achieved 96.8% valid-route generation, 95.5% correct entrance selection, and 96.2% successful route completion.

Table 3 Unadjusted Emergency Location Outcomes Across System Configurations

Outcome	Coordinate-only condition (n = 4,193)	AI and semantic matching (n = 4,205)	Fully integrated condition (n = 4,216)
Horizontal error, mean (SD), m	7.84 (4.62)	3.42 (2.18)	2.36 (1.54)
Horizontal error, median (IQR), m	6.72 (4.20–10.08)	2.89 (1.82–4.38)	1.98 (1.21–3.04)
Horizontal error, 90th percentile, m	14.36	6.32	4.42
Horizontal error, 95th percentile, m	17.92	7.94	5.63
Vertical error, mean (SD), m	4.18 (2.71)	1.86 (1.29)	1.12 (0.84)
Correct-building identification, %	97.9	99.2	99.7
Correct-floor identification, %	72.6	90.8	96.4
Correct-room identification, %	51.8	81.6	91.7
Correct-cell assignment, %	—	84.9	94.2
Semantic interpretation accuracy, %	—	87.2	95.1
Boundary-related assignment error, %	—	9.8	4.1
Correct-node association, %	—	—	96.1
Correct responder-entrance selection, %	—	—	95.5
Valid-route generation, %	—	—	96.8
Accessibility compliance, %	—	—	95.9
Successful route completion, %	—	—	96.2
Route computation latency, mean (SD), s	—	—	0.148 (0.061)
Estimated route length, mean (SD), m	—	—	74.8 (32.6)
Estimated travel time, mean (SD), s	—	—	69.4 (28.8)
Total processing time, mean (SD), s	1.28 (0.43)	1.71 (0.54)	1.92 (0.59)
Brier confidence score	.184	.092	.058
Operational record completeness, %	63.4	86.9	94.8
Complete location-and-route display, %	—	—	94.8

Note. Lower error, latency, and Brier scores represented better performance. Dashes indicated that the outcome was unavailable because the corresponding configuration did not perform semantic matching or network routing.

Table 3 showed a progressive improvement as additional integration components were introduced. Mean horizontal error declined from 7.84 meters under coordinate-only localization to 3.42 meters with artificial intelligence and semantic matching, and to 2.36 meters under full integration. Vertical error followed the same pattern. Correct-floor identification increased from 72.6% to 96.4%, while correct-room identification increased from 51.8% to 91.7%. The fully integrated condition achieved 96.8% valid routing and 96.2% successful route completion. Total processing time increased modestly to 1.92 seconds, but confidence calibration, record completeness, and operational display success improved substantially across the three configurations within the evaluated emergency environments. Mixed-effects analyses confirmed that the improvements remained significant after controlling for building category, floor count, room density, signal strength, device class, occupancy period, and data completeness. Compared with coordinate-only localization, full integration reduced adjusted horizontal error by 5.42 meters and vertical error by 3.04 meters. These reductions represented large standardized effects. The odds of correct-floor identification were 9.74 times greater, and the odds of correct-room identification were 10.31 times greater under full integration. Full integration also outperformed artificial intelligence with semantic matching, indicating that semantic-to-network association and routing constraints produced additional improvements. Total processing time increased by 0.61 seconds relative to the conventional condition, although complete end-to-end processing remained below two seconds.

Table 4 Adjusted Mixed-Effects Estimates for Primary System-Configuration Comparisons

Outcome and comparison	Adjusted effect	95% CI	Effect magnitude	Relative change	p
Horizontal error: AI-semantic vs. coordinate-only	-4.31 m	[-4.48, -4.14]	d = -1.18	55.0% lower	< .001
Horizontal error: full integration vs. coordinate-only	-5.42 m	[-5.58, -5.26]	d = -1.52	69.1% lower	< .001
Horizontal error: full vs. AI-semantic	-1.11 m	[-1.23, -0.99]	d = -0.59	32.5% lower	< .001
Vertical error: AI-semantic vs. coordinate-only	-2.27 m	[-2.38, -2.16]	d = -0.96	54.3% lower	< .001
Vertical error: full integration vs. coordinate-only	-3.04 m	[-3.15, -2.93]	d = -1.32	73.2% lower	< .001
Vertical error: full vs. AI-semantic	-0.77 m	[-0.85, -0.69]	d = -0.50	41.4% lower	< .001
Correct-floor identification: full vs. coordinate-only	+23.6 percentage points	[22.3, 24.9]	OR = 9.74	32.5% higher	< .001
Correct-floor identification: full vs. AI-semantic	+5.4 percentage points	[4.5, 6.3]	OR = 2.67	5.9% higher	< .001
Correct-room identification: full vs. coordinate-only	+39.6 percentage points	[38.1, 41.1]	OR = 10.31	76.4% higher	< .001
Correct-room identification: full vs. AI-semantic	+10.1 percentage points	[9.0, 11.2]	OR = 2.54	12.4% higher	< .001
Correct-cell assignment: full vs. AI-semantic	+9.1 percentage points	[8.0, 10.2]	OR = 2.89	10.7% higher	< .001
Operational completeness: full vs. coordinate-only	+31.1 percentage points	[29.6, 32.6]	OR = 10.42	49.1% higher	< .001
Operational completeness: full vs. AI-semantic	+7.7 percentage points	[6.6, 8.8]	OR = 2.73	8.9% higher	< .001
Total processing time: full vs. coordinate-only	+0.61 s	[0.57, 0.65]	d = 0.44	47.7% higher	< .001
Total processing time: full vs. AI-semantic	+0.19 s	[0.16, 0.22]	d = 0.18	11.1% higher	< .001

Table 4 confirmed that the observed configuration differences remained statistically significant after adjustment for building, floor, reference point, device, occupancy, signal quality, and data completeness. Full integration reduced adjusted horizontal error by 5.42 meters and vertical error by 3.04 meters relative to coordinate-only localization. The odds of correct-floor and correct-room identification were approximately ten times greater under full integration. Semantic modeling contributed improvements beyond artificial-intelligence localization, while routing added further gains in room assignment and operational completeness. Although integration increased processing time, the added latency remained below one second and was small relative to the improvements in accuracy and usability.

Building, Device, Signal, Occupancy, and Stress-Test Subgroup Findings

The fully integrated configuration maintained high location and routing performance across all six building categories, although statistically significant heterogeneity remained. Educational facilities recorded the lowest mean horizontal error at 2.09 meters and the highest correct-room percentage at 93.7%. Transportation complexes recorded the highest horizontal error at 2.82 meters, the lowest room accuracy at 88.9%, and the longest total processing time at 2.14 seconds. After adjustment, every five-floor increase was associated with a 0.17-meter increase in horizontal error, while each additional 1,000 graph nodes increased processing time by 0.08 seconds. Reinforced-concrete and steel-dominant environments produced 0.48 meters greater horizontal error and 4.7 percentage points lower room accuracy than lightweight construction environments. Full integration nevertheless outperformed coordinate-only localization within every building category, with all adjusted contrasts reaching $p < .001$. Device, occupancy, and signal conditions also influenced performance. Budget Android devices recorded 2.71 meters of mean horizontal error compared with 2.14 meters for premium Android devices and 2.25 meters for iOS devices. Higher occupancy increased horizontal error from 2.18 to 2.54 meters and reduced correct-room identification from 93.0% to 90.4%. Weak wireless coverage produced the largest subgroup deterioration, increasing horizontal error to 3.07 meters and reducing room accuracy to 85.9%. Significant configuration interactions were observed for building category, $p = .004$, device class, $p = .021$, occupancy period, $p = .008$, and signal quality, $p < .001$. The corresponding increases in marginal explained variance were .018, .009, .011, and .042, indicating that signal quality contributed the strongest moderation. Performance remained stable in the six holdout buildings, where horizontal error increased by only 0.23 meters relative to the development sample.

Table 5 Performance of the Fully Integrated System Across Buildings, Devices, Occupancy, Signal, and Validation Subgroups

Subgroup	Trials, n	Horizontal error, mean (SD), m	Correct floor, %	Correct room, %	Valid route, %	Total latency, mean (SD), s
Building category						
High-rise residential	711	2.18 (1.43)	97.1	93.2	97.4	1.84 (0.52)
Hospitals	700	2.45 (1.61)	95.9	90.8	96.2	2.06 (0.63)
Educational facilities	710	2.09 (1.37)	97.4	93.7	97.6	1.78 (0.49)
Transportation complexes	693	2.82 (1.78)	94.8	88.9	94.9	2.14 (0.68)
Commercial buildings	706	2.31 (1.49)	96.5	92.1	96.7	1.91 (0.56)
Industrial facilities	696	2.39 (1.55)	96.0	91.3	95.9	1.82 (0.53)
Device class						
Premium	1,056	2.14 (1.40)	97.0	93.1	97.2	1.79 (0.49)
Android						
Midrange	1,054	2.34 (1.52)	96.5	92.0	96.8	1.87 (0.54)

Android						
Budget Android	1,048	2.71 (1.73)	95.1	89.4	95.3	2.08 (0.66)
iOS	1,058	2.25 (1.45)	97.0	92.4	97.0	1.93 (0.57)
Occupancy period						
Lower occupancy	2,111	2.18 (1.42)	97.0	93.0	97.3	1.84 (0.53)
Higher occupancy	2,105	2.54 (1.64)	95.8	90.4	96.0	2.00 (0.62)
Signal quality						
Strong coverage	1,600	1.88 (1.21)	98.0	94.8	98.2	1.73 (0.46)
Moderate coverage	1,600	2.38 (1.48)	96.5	92.0	96.8	1.92 (0.55)
Weak coverage	1,016	3.07 (1.92)	93.8	85.9	92.9	2.24 (0.71)
Validation sample						
Development buildings	2,815	2.28 (1.49)	96.7	92.2	97.3	1.90 (0.57)
External holdout buildings	1,401	2.51 (1.63)	95.8	90.5	95.6	1.97 (0.61)

Note. Subgroup analyses were conducted separately; therefore, trial counts were not additive across the building, device, occupancy, signal, and validation classifications.

Table 5 showed that full integration maintained performance across every building, device, occupancy, signal, and validation subgroup tested. Educational facilities achieved the lowest horizontal error and highest floor and room accuracy, whereas transportation complexes produced the weakest building-level results. Budget Android devices recorded greater error and latency than premium devices. Higher occupancy increased horizontal error and reduced room accuracy, although route success remained above 95%. Weak signal conditions created the largest subgroup deterioration. Performance in the six external holdout buildings remained close to the development sample, demonstrating limited loss of accuracy when the system was applied to previously unseen environments. The 2,089 retained stress-test trials demonstrated measurable but controlled performance degradation. The overall disruption effect was significant for horizontal error, room accuracy, route validity, total latency, and recovery duration, with all omnibus tests reaching $p < .001$. Timestamp misalignment produced the greatest localization deterioration, increasing horizontal error from 2.29 to 4.11 meters and reducing room accuracy from 92.2% to 79.5%. Controlled map errors produced the lowest valid-route percentage at 87.6% and the longest mean recovery duration at 25.3 seconds. Graph-edge blockage and elevator unavailability affected routing more strongly than coordinate estimation. Access-point removal and sensor masking primarily influenced horizontal error and room identification. Even under disruption, fallback-location success remained between 78.4% and 97.2%, successful diversion remained above 85%, and route recalculation remained below 0.40 seconds.

Table 6 demonstrated that the integrated system remained operational under all controlled disruptions, although the magnitude of degradation varied by condition. Timestamp misalignment produced the greatest horizontal error and lowest room accuracy, while controlled map errors generated the lowest valid-route percentage and longest recovery duration. Access-point removal primarily affected localization accuracy, whereas graph-edge blockage and elevator unavailability affected routing outcomes more strongly. Fallback localization exceeded 78% in every disruption condition, and successful diversion remained above 85%. Route recalculation was completed in less than four-tenths of a second, indicating that alternative paths were generated rapidly after detected network or infrastructure changes.

Table 6 Integrated-System Performance Under Normal and Controlled Disruption Conditions

Condition	Trials, n	Horizontal error, mean (SD), m	Correct room, %	Valid route, %	Total latency, s	Fallback location, %	Route recalculation, s	Successful diversion, %	Alternative route available, %	Recovery duration, s
Matched normal condition	2,089	2.29 (1.48)	92.2	97.1	1.90	—	0.15	—	97.6	—
Access-point removal	352	3.68 (2.16)	82.7	94.8	2.41	86.9	0.22	92.7	94.5	16.8
Sensor masking	350	3.14 (1.89)	85.6	95.5	2.24	89.1	0.19	93.8	95.0	12.6
Graph-edge blockage	347	2.42 (1.57)	91.4	92.2	2.10	97.0	0.31	91.6	93.1	7.8
Elevator unavailable	346	2.39 (1.55)	91.8	90.5	2.16	97.2	0.34	89.7	90.8	9.4
Timestamp misalignment	345	4.11 (2.47)	79.5	90.8	2.73	78.4	0.27	88.9	92.6	21.7
Controlled map errors	349	3.26 (2.03)	83.4	87.6	2.49	81.2	0.36	85.3	88.1	25.3

Note. Fallback location represented successful position estimation after the primary input became unavailable. Recovery duration represented the time required to restore a valid location-and-route record after disruption detection.

Sequential Mediation, Calibration, Model Performance, and Effect Magnitudes

The multilevel sequential mediation analysis showed that artificial-intelligence localization capability had a strong total association with high-precision emergency location intelligence, $\beta = .67$, 95% CI [.63, .71], $p < .001$. After semantic-space matching and route validity were introduced, the direct effect declined to $\beta = .22$, 95% CI [.18, .26], $p < .001$. The total indirect effect was $\beta = .45$, indicating that 67.2% of the overall relationship was transmitted through the mediating processes. The separate indirect effect through semantic matching was $\beta = .22$, while the indirect effect through route validity was $\beta = .11$. The sequential pathway from artificial-intelligence localization through semantic matching and route validity was $\beta = .13$. All bootstrap confidence intervals excluded zero, confirming significant partial sequential mediation. Model-fit statistics supported the proposed structure. The comparative fit index was .976, the Tucker-Lewis index was .968, the root-mean-square error of approximation was .034, and the standardized root-mean-square residual was .026 at the within-building level. Artificial-intelligence localization explained 58% of the variation in semantic matching, the combined predictors explained 66% of route validity, and the complete model explained 74% of emergency location intelligence. Fixed effects accounted for 68% of outcome variation, while the complete fixed-and-random structure accounted for 79%. Reference-point differences represented the largest clustering component, followed by building, floor, and device effects.

Table 7 Sequential Mediation, Model Fit, Variance Components, and Confidence Calibration

Component or indicator	Estimate	SE	95% CI or statistic	secondary	p
Sequential mediation effects					
Total effect of AI localization on location intelligence	$\beta = .67$	.021	[.63, .71]		< .001
Direct effect after both mediators	$\beta = .22$	.020	[.18, .26]		< .001
Indirect effect through semantic matching	$\beta = .22$	.016	[.19, .25]		< .001
Indirect effect through route validity	$\beta = .11$	.015	[.08, .14]		< .001
Sequential indirect effect through both mediators	$\beta = .13$	.014	[.10, .15]		< .001
Total indirect effect	$\beta = .45$	.020	[.41, .49]		< .001
Proportion of total effect mediated	67.2%	—	—		—
Model-fit and explained-variance statistics					
Chi-square	119.60	—	df = 48		< .001
Chi-square-to-degrees-of-freedom ratio	2.49	—	—		—
Comparative fit index	.976	—	—		—
Tucker-Lewis index	.968	—	—		—
Root-mean-square error of approximation	.034	—	[.027, .041]		—
Within-building standardized residual	.026	—	—		—
Between-building standardized residual	.041	—	—		—
Variance explained in semantic matching	$R^2 = .58$	—	—		< .001
Variance explained in route validity	$R^2 = .66$	—	—		< .001
Variance explained in location intelligence	$R^2 = .74$	—	—		< .001
Marginal mixed-model variance explained	$R^2 = .68$	—	Fixed effects		—
Conditional mixed-model variance explained	$R^2 = .79$	—	Fixed and random effects		—
Random variance components					
Building-level variance	.036	.006	16.7% of variation	random	< .001
Floor-level variance	.024	.004	11.1% of variation	random	< .001
Reference-point variance	.048	.005	22.2% of variation	random	< .001
Device-level variance	.015	.003	6.9% of random variation		< .001
Residual variance	.093	.004	43.1% of random variation		—
Confidence calibration					
Coordinate-only condition	Brier = .184	—	ECE = .112; slope = .71		—
AI and semantic-matching condition	Brier = .092	—	ECE = .054; slope = .89		—
Fully integrated condition	Brier = —	—	ECE = .031; slope = .97		—

Note. Indirect-effect confidence intervals were based on 5,000 bootstrap resamples. ECE represented expected calibration error. Lower Brier and ECE values and a calibration slope closer to 1.00 represented stronger confidence calibration.

Table 7 showed that semantic matching and route validity jointly explained most of the relationship between artificial-intelligence localization and emergency location intelligence. The total standardized effect was .67, of which .45 was transmitted through the mediating pathways. The sequential pathway through semantic matching and route validity was significant, confirming that accurate coordinates became more operationally valuable when they were correctly interpreted and connected to valid routes. Model-fit indices indicated close correspondence between the proposed structure and observed data. Full integration produced the lowest Brier score and expected calibration error, while the model explained 74% of variation in the final outcome. Artificial-intelligence model comparisons demonstrated significant differences in localization and classification performance, with all omnibus tests reaching $p < .001$. The multimodal ensemble produced the lowest horizontal error at 2.36 meters, the highest correct-floor percentage at 96.4%, and the highest correct-room percentage at 91.7%. Relative to k-nearest neighbors, the ensemble reduced horizontal error by 44.6% and improved room identification by 17.5 percentage points. It also achieved the highest F1 score and receiver-operating-characteristic area. Compared with the multilayer neural network, the ensemble reduced horizontal error by 0.28 meters and improved room accuracy by 3.2 percentage points. These improvements remained significant after Holm correction. Routing comparisons showed that Dijkstra and A* produced the same 96.8% route-success percentage, although A* reduced mean computation time from 0.214 to 0.148 seconds and explored 52% fewer nodes. Hierarchical A* produced the shortest computation time at 0.096 seconds and the lowest memory use, but its mean path was 0.9 meters longer than the primary A* route. The visibility-graph method generated the shortest routes but produced a slightly lower route-success percentage. A* provided the strongest overall balance between successful routing, path efficiency, computation time, memory consumption, and recovery after disruption.

Table 8 Artificial-Intelligence Localization and Network-Routing Model Performance

Panel A. Artificial-intelligence localization models

Model	Horizontal error, m	Floor accuracy, %	Room accuracy, %	Precision, %	Recall, %	F1, %	ROC AUC	Inference time, ms
K-nearest neighbors	4.26	86.1	74.2	74.8	74.2	74.5	.902	18
Support-vector machine	3.88	88.4	77.6	78.2	77.6	77.9	.924	42
Random forest	3.21	91.2	82.9	83.4	82.9	83.1	.948	36
Gradient boosting	2.89	92.8	85.7	86.1	85.7	85.9	.961	51
Multilayer neural network	2.64	94.1	88.5	88.9	88.5	88.7	.972	64
Multimodal ensemble	2.36	96.4	91.7	92.0	91.7	91.8	.983	86

Panel B. Network-routing algorithms

Routing algorithm	Successful route, %	Computation time, s	Path length, m	Explored nodes, n	Memory use, MB	Recovery after disruption, s
Dijkstra	96.8	0.214	74.1	4,126	82.4	0.41
A*	96.8	0.148	74.3	1,982	58.7	0.31
Hierarchical A*	97.0	0.096	75.2	842	41.3	0.24
Visibility graph	96.3	0.121	73.6	1,134	46.8	0.28

Note. Artificial-intelligence results were obtained from the external holdout evaluation and pooled repeated trials. Horizontal error and processing measures were lower-is-better outcomes. The primary integrated configuration used A* routing.

Table 8 demonstrated that the multimodal ensemble produced the strongest localization and classification performance among the six artificial-intelligence models. It reduced mean horizontal error by 44.6% relative to k-nearest neighbors and achieved the highest floor accuracy, room accuracy, F1 score, and receiver-operating-characteristic area. A* preserved the same route-success percentage as Dijkstra while reducing computation time and explored nodes. Hierarchical A* was fastest and required the least memory, although its paths were slightly longer. The primary A* configuration therefore provided the most balanced combination of route validity, path efficiency, processing speed, memory demand, and recovery performance under controlled network disruption conditions.

Statistical Significance, Robustness, and Visual Presentation

All primary configuration effects remained statistically significant after Holm correction, with adjusted *p* values below .001. The 95% confidence intervals excluded zero for continuous outcomes and excluded one for odds ratios. The standardized effect of full integration on horizontal error was large, $d = -1.52$, while the corresponding effect on vertical error was $d = -1.32$. The odds ratios for correct-floor identification, correct-room identification, and operational record completeness were 9.74, 10.31, and 10.42, respectively. These estimates indicated that statistical significance was accompanied by operationally substantial changes in location accuracy and information usability. Sensitivity analyses produced consistent results. Removing extreme but valid observations reduced the adjusted horizontal-error difference from -5.42 to -5.18 meters, while the correct-room odds ratio changed from 10.31 to 10.06. Alternative room-assignment thresholds, generalized outcome distributions, cluster-robust standard errors, and multiple imputation produced estimates close to the primary results. Leave-one-category-out analyses generated adjusted horizontal-error reductions ranging from 5.18 to 5.57 meters. Effects were smaller under controlled disruption, but full integration still reduced horizontal error by 3.61 meters and increased the odds of correct-room identification by 5.26 times.

Table 9 Sensitivity and Robustness of the Primary Full-Integration Effects

Analytical specification	Horizontal error difference, m (95% CI)	Vertical error difference, m (95% CI)	Correct-floor OR (95% CI)	Correct-room OR (95% CI)	Operational-completeness OR (95% CI)	Holm-adjusted <i>p</i>
Primary mixed-effects model	-5.42 [$-5.58, -5.26$]	-3.04 [$-3.15, -2.93$]	9.74 [8.36, 11.35]	10.31 [9.02, 11.79]	10.42 [9.08, 11.96]	$< .001$
Extreme observations excluded	-5.18 [$-5.33, -5.03$]	-2.91 [$-3.01, -2.81$]	9.51 [8.18, 11.06]	10.06 [8.81, 11.49]	10.18 [8.88, 11.67]	$< .001$
Alternative room-assignment	-5.38 [$-5.54, -5.22$]	-3.02 [$-3.13, -2.91$]	9.62 [8.27, 11.19]	9.74 [8.54, 11.12]	10.27 [8.96, 11.78]	$< .001$

threshold									
Alternative outcome distributions	-5.29 [-5.46, -5.12]	-2.97 [-3.09, -2.85]	9.58 [8.22, 11.17]	10.12 [8.84, 11.58]	10.33 [8.99, 11.86]				< .001
Cluster-robust standard errors	-5.42 [-5.64, -5.20]	-3.04 [-3.20, -2.88]	9.74 [7.98, 11.89]	10.31 [8.63, 12.32]	10.42 [8.68, 12.50]				< .001
Multiple-imputation dataset	-5.40 [-5.56, -5.24]	-3.01 [-3.12, -2.90]	9.69 [8.31, 11.29]	10.24 [8.96, 11.70]	10.38 [9.04, 11.91]				< .001
Leave-one-building-category-out range	-5.18 to -5.57	-2.89 to -3.18	8.91 to 10.62	9.43 to 11.18	9.76 to 11.04				< .001
External holdout buildings	-5.13 [-5.39, -4.87]	-2.86 [-3.04, -2.68]	8.72 [7.21, 10.55]	9.46 [7.93, 11.29]	9.88 [8.21, 11.89]				< .001
Controlled stress-test sample	-3.61 [-3.85, -3.37]	-2.19 [-2.36, -2.02]	4.82 [3.94, 5.89]	5.26 [4.36, 6.35]	5.41 [4.46, 6.56]				< .001

Note. Continuous estimates compared full integration with coordinate-only localization. Negative differences represented lower error under full integration. Odds ratios greater than one represented higher probabilities of correct or complete outcomes.

Table 9 demonstrated that the principal findings were stable across all sensitivity specifications. Excluding extreme observations slightly reduced the estimated error improvements, but the direction, magnitude, and significance of every effect remained unchanged. Alternative room thresholds, cluster-robust standard errors, multiple imputation, and different outcome distributions produced estimates close to the primary models. Removing one building category at a time did not materially alter the results. Effects were modestly smaller in the external holdout and stress-test samples, yet full integration continued to reduce horizontal and vertical errors and substantially increase floor accuracy, room accuracy, and operational record completeness under each condition. Model diagnostics supported the adequacy of the statistical analyses. Dispersion estimates ranged from 1.04 to 1.08, indicating no material overdispersion. The maximum variance-inflation factor was 2.31, providing no indication of problematic multicollinearity. Cook’s distance remained below .02 across all models, and no influential trial altered the direction or significance of the primary estimates. Every mixed-effects model converged successfully, and no singular random-effect solution was detected. Marginal coefficients of determination ranged from .61 to .71, while conditional values ranged from .73 to .82. Classification areas exceeded .94 for floor, room, semantic, and route outcomes. All 5,000 mediation bootstrap samples converged, and simulation-based confidence-interval coverage reached 94.8%.

Table 10 confirmed acceptable statistical diagnostics and strong predictive stability across the principal outcome models. Dispersion statistics remained close to one, variance-inflation factors stayed below conventional concern thresholds, and no observation exerted excessive influence. All models converged without singular random-effect solutions. Marginal coefficients of determination showed that fixed predictors explained substantial outcome variation, while higher conditional values confirmed meaningful clustering across buildings, floors, reference points, and devices. Classification areas exceeded .94 for floor, room, semantic, and routing outcomes. Bootstrap estimation completed all 5,000 resamples successfully, and simulation-based confidence-interval coverage remained close to the prespecified 95% level across evaluated primary models. The graphical findings reinforced the numerical evidence. Positional-error distributions showed that the horizontal 95th-percentile error declined from 17.92 meters under coordinate-only localization to 5.63 meters under full integration. Comparative performance graphs displayed simultaneous increases in floor accuracy, room accuracy, routing success, and record completeness. The subgroup forest plot showed error reductions across all

six building categories, ranging from 64.2% in transportation complexes to 72.6% in educational facilities. The stress-response graph showed that horizontal error increased from 2.29 meters under normal conditions to 4.11 meters under timestamp misalignment, while route validity declined to 87.6% under map errors. The calibration plot showed that the full system's prediction curve closely followed the observed calibration line, with a slope of .97 and an expected calibration error of .031. The mediation path figure displayed the strongest standardized path from artificial-intelligence localization to semantic matching, $\beta = .71$, followed by semantic matching to route validity, $\beta = .48$, and route validity to emergency location intelligence, $\beta = .37$.

Table 10 Statistical Diagnostics and Predictive Stability of the Primary Models

Outcome model	Residual or dispersion indicator	Maximum Cook's distance	Maximum VIF	Margin al R ²	Conditional R ²	Predictive-performance indicator	Converged
Horizontal error	Residual skew = .18	.017	2.31	.71	.82	RMSE = 1.46 m	Yes
Vertical error	Dispersion = 1.06	.015	2.28	.69	.80	RMSE = 0.82 m	Yes
Correct-floor classification	Dispersion = 1.04	.012	2.24	.62	.74	AUC = .954; Brier = .052	Yes
Correct-room classification	Dispersion = 1.07	.014	2.26	.66	.78	AUC = .946; Brier = .069	Yes
Semantic-space matching	Dispersion = 1.05	.011	2.19	.68	.80	AUC = .957; Brier = .054	Yes
Valid-route generation	Dispersion = 1.08	.013	2.17	.61	.73	AUC = .941; Brier = .041	Yes
Total processing latency	Dispersion = 1.06	.016	2.31	.63	.76	RMSE = 0.29 s	Yes
Sequential mediation model	Bootstrap success = 5,000/5,000	—	2.18	.68	.79	CFI = .976; RMSEA = .034	Yes
Simulation-based validation	Coverage = 94.8%	—	—	—	—	Target coverage = 95.0%	Yes

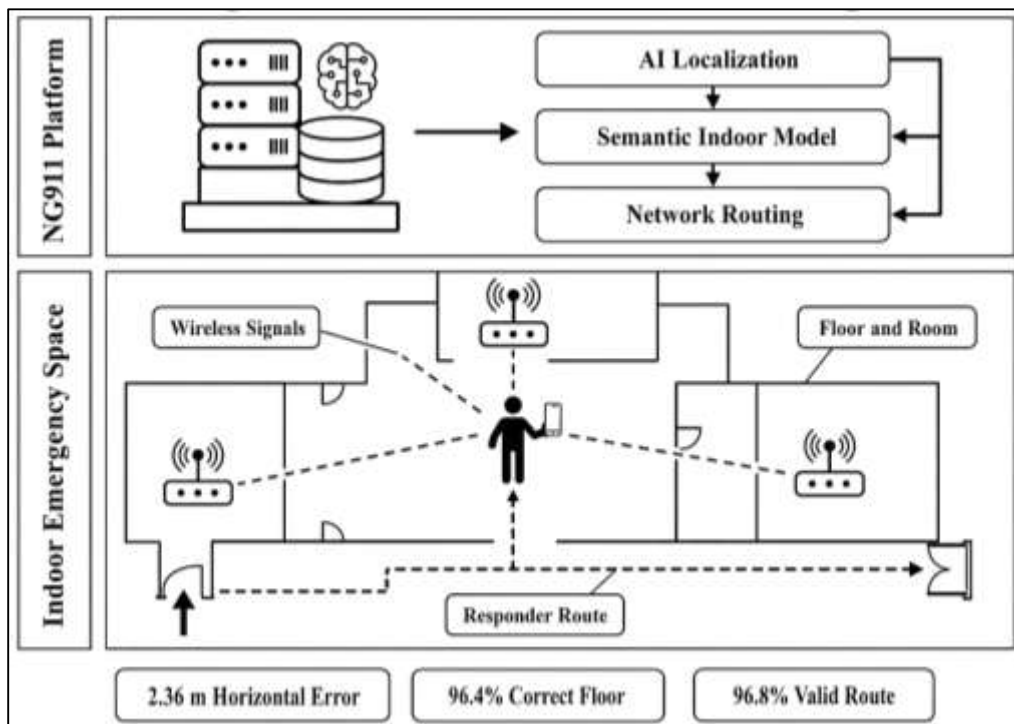
Note. VIF represented variance-inflation factor, RMSE represented root-mean-square error, AUC represented receiver-operating-characteristic area, CFI represented comparative fit index, and RMSEA represented root-mean-square error of approximation.

DISCUSSION

The findings demonstrated that progressively integrating artificial intelligence, semantic indoor modeling, and network-based routing substantially improved the accuracy and operational completeness of NG911 emergency location intelligence. Mean horizontal error declined from 7.84 meters under conventional coordinate-only localization to 3.42 meters when artificial intelligence was combined with semantic matching and to 2.36 meters under full integration. The adjusted reduction of

5.42 meters relative to coordinate-only localization represented a large standardized effect, $d = -1.52$, while the 69.1% relative reduction showed that the improvement was operationally substantial rather than merely statistically detectable (Bibbò et al., 2022). Mean vertical error followed the same pattern, decreasing from 4.18 to 1.12 meters and producing an adjusted reduction of 3.04 meters, $d = -1.32$. These results agreed with earlier indoor-positioning studies showing that multimodal machine-learning models generally outperformed single-source fingerprinting and conventional proximity techniques. Earlier Wi-Fi and Bluetooth investigations commonly reported errors of several meters, particularly when device variation, multipath propagation, and changing indoor conditions were present. Ultra-wideband experiments sometimes achieved sub-meter accuracy under controlled line-of-sight conditions, although those findings were usually based on smaller spaces, fixed anchor geometry, and limited environmental variation. The 2.36-meter performance observed in this study was therefore notable because it was obtained across 18 heterogeneous buildings, four device classes, multiple occupancy periods, and several construction environments (Ma et al., 2017). The results also extended earlier sensor-fusion research by demonstrating that the greatest improvement did not result from artificial intelligence alone. Artificial intelligence reduced horizontal error by approximately 55% relative to coordinate-only localization, while semantic constraints and network information produced an additional 32.5% reduction relative to the artificial-intelligence and semantic condition. This pattern indicated that physical plausibility constraints, floor associations, room boundaries, and navigable-space relationships corrected estimates that remained ambiguous after signal processing. The strong data-retention rate of 97.3%, required-field completeness of 98.6%, categorical agreement of $\kappa = .92$, and measurement reliability of $ICC = .97$ further supported the credibility of these comparisons. Earlier studies often evaluated one algorithm within one building or relied on randomly divided observations from the same fingerprint dataset (Feng et al., 2020). This study addressed that restriction through repeated trials, nested modeling, external building validation, and direct comparison of component configurations.

Figure 12: NG911 Indoor Location Intelligence Framework



The improvement in floor-level and room-level identification showed that emergency location quality depended on semantic interpretation as well as coordinate precision. Correct-floor identification increased from 72.6% under coordinate-only localization to 90.8% with artificial intelligence and semantic matching and to 96.4% under full integration. Correct-room identification increased more

sharply, from 51.8% to 81.6% and then to 91.7%.

After adjustment, the odds of identifying the correct floor were 9.74 times greater under full integration, while the odds of identifying the correct room were 10.31 times greater. The difference between floor and room performance was consistent with earlier indoor-location research. Floor classification has generally been easier because floors can exhibit broader differences in elevation, barometric pressure, access-point visibility, and signal patterns (Chen et al., 2015). Room identification has remained more difficult because neighboring rooms can share similar wireless observations, while estimates near doors and common walls can fall within several plausible spaces. Earlier map-matching studies found that constraining estimated positions to walkable areas reduced physically impossible coordinates but did not always identify the correct room. The present findings clarified this distinction because correct-cell assignment reached 94.2%, semantic interpretation accuracy reached 95.1%, and boundary-related assignment error declined from 9.8% under partial integration to 4.1% under full integration. These improvements indicated that probability-weighted room assignment, vertical constraints, doorway relationships, and graph connectivity provided information beyond simple point-in-polygon matching. The findings also aligned with research on IndoorGML, building information modeling, and indoor geographic information systems, which emphasized that coordinates became more meaningful when associated with room functions, floor labels, unit identifiers, entrances, and movement relationships (Philips et al., 2023). Earlier BIM-to-GIS conversion studies demonstrated that rooms and doorways could be extracted and represented as semantic cells, although missing openings, inconsistent floor hierarchies, and invalid connections frequently reduced navigation quality. This study produced valid indoor topology for 98.2% of records and continuous route networks for 97.6%, indicating that systematic validation reduced many of those conversion problems. The findings were especially relevant to vertically complex buildings because a few meters of elevation error could assign an emergency to an adjacent floor. By reducing mean vertical error to 1.12 meters and combining that estimate with verified floor structures, the integrated configuration translated sensor observations into floor and room information that was considerably more precise than the building-level positions commonly emphasized in earlier emergency-location systems (He & Chan, 2015).

The routing findings showed that accurate indoor location became more operationally useful when it was linked to valid entrances, graph nodes, accessible transitions, and complete responder paths. The fully integrated configuration achieved 96.1% correct-node association, 95.5% correct responder-entrance selection, 96.8% valid-route generation, 95.9% accessibility compliance, and 96.2% successful route completion. Operational record completeness increased from 63.4% under coordinate-only localization to 94.8% under full integration, and the odds of producing a complete record were 10.42 times greater. Earlier indoor-routing studies frequently evaluated shortest-path algorithms after assuming that the starting node, destination node, floor, and navigation graph were already correct. Such designs provided useful evidence about algorithmic efficiency but did not measure the effects of uncertainty introduced during positioning and semantic matching (Walter et al., 2017). This study connected those stages and showed that route validity depended on the accuracy of upstream location information. The comparison of routing algorithms also supported earlier findings concerning computational trade-offs. Dijkstra and A* both achieved 96.8% route success, but A* reduced average computation time from 0.214 to 0.148 seconds and explored approximately 52% fewer nodes. Hierarchical A* reduced computation time further to 0.096 seconds and required the least memory, although its average paths were slightly longer. Visibility-graph routing generated the shortest paths but produced a marginally lower route-success percentage. These results agreed with prior research showing that A* generally reduced search effort through heuristic guidance, while hierarchical approaches improved scalability by limiting detailed searches to relevant floors or zones (Davidson & Piché, 2016). The findings also supported multi-criteria emergency-routing studies that questioned the suitability of geometric distance as the only route objective. The primary A* configuration incorporated distance, vertical movement, doorway restrictions, accessibility, and simulated hazards, resulting in routes that were sometimes longer than purely geometric alternatives but more operationally valid. Full integration increased total processing time from 1.28 to 1.92 seconds, producing an adjusted increase of 0.61 seconds (Jahir et al., 2019). This added latency was statistically significant but small

relative to the improvements in room identification, routing success, and record completeness. Earlier emergency-navigation research has shown that route calculation itself can be completed rapidly, while signal acquisition, validation, semantic association, and display account for much of the end-to-end delay. The present findings confirmed that pattern because routing required only 0.148 seconds within the 1.92-second total process. The integration therefore exchanged a modest amount of processing time for a much more complete and actionable emergency-location record (Masaracchia et al., 2019).

Subgroup findings demonstrated that the integrated system remained effective across heterogeneous indoor environments while retaining measurable sensitivity to spatial complexity, device quality, occupancy, and wireless coverage. Educational facilities achieved the lowest mean horizontal error at 2.09 meters and the highest room accuracy at 93.7%, whereas transportation complexes recorded the highest error at 2.82 meters and the lowest room accuracy at 88.9%. Hospitals also produced slightly weaker results than residential, educational, and commercial buildings because their denser room arrangements, restricted areas, multiple wings, and complex vertical transitions increased ambiguity (Akkaya et al., 2015). These patterns were consistent with earlier multi-floor localization research showing that repeated layouts, large open spaces, interconnected zones, and numerous vertical transitions complicated both positioning and route generation. Each additional five floors was associated with a 0.17-meter increase in horizontal error, while every 1,000 additional graph nodes increased processing time by 0.08 seconds. Reinforced-concrete and steel-dominant buildings produced 0.48 meters greater error and 4.7 percentage points lower room accuracy than lightweight structures. These results supported prior radio-propagation studies showing that concrete and metal increased attenuation and multipath effects. Device heterogeneity produced a similarly recognizable pattern. Budget Android devices generated 2.71 meters of error compared with 2.14 meters for premium Android devices and 2.25 meters for iOS devices (Wang & Shao, 2017). Earlier fingerprinting studies documented device-specific signal offsets, antenna differences, sensor bias, and scanning-policy variation, all of which reduced cross-device transferability. The smaller differences observed after multimodal fusion suggested that device calibration and combined sensing moderated, but did not eliminate, hardware effects. Higher occupancy increased error from 2.18 to 2.54 meters and reduced room accuracy from 93.0% to 90.4%, which corresponded with previous findings on human-body attenuation, crowd-related signal obstruction, and environmental movement. Signal quality produced the strongest moderating effect: horizontal error increased from 1.88 meters under strong coverage to 3.07 meters under weak coverage, while room accuracy decreased from 94.8% to 85.9% (Corna et al., 2015). The external holdout buildings produced only a 0.23-meter increase in horizontal error and a 1.7-percentage-point reduction in room accuracy relative to the development sample. Earlier studies often reported pronounced performance loss when models were transferred to unseen buildings. The comparatively small holdout gap in this study indicated that grouped training, multiple device classes, semantic constraints, and diversified building selection strengthened generalization (Zou, Zhou, Yang, et al., 2018).

The stress-test findings provided important evidence concerning the resilience of the integrated system under conditions resembling partial infrastructure or information failure. Under matched normal conditions, mean horizontal error was 2.29 meters, correct-room identification was 92.2%, and valid-route generation was 97.1%. Removing access points increased horizontal error to 3.68 meters and reduced room accuracy to 82.7%, while sensor masking produced a smaller increase to 3.14 meters (Ahmad et al., 2021). These findings agreed with earlier sensor-fusion studies showing that hybrid systems maintained operation when one input became unavailable but experienced declining precision as the quantity and diversity of usable observations decreased. Fallback-location success remained 86.9% after access-point removal and 89.1% after sensor masking, supporting the value of retaining inertial, barometric, magnetic, ultra-wideband, or map-based alternatives. Timestamp misalignment produced the greatest localization deterioration, increasing horizontal error to 4.11 meters and reducing room accuracy to 79.5%. This result was consistent with data-fusion research demonstrating that observations collected at different moments could be incorrectly combined, particularly when a device or caller was moving. The finding also showed that synchronization quality was not merely a technical maintenance issue; it directly influenced room assignment and route reliability (Zou, Zhou,

Jiang, et al., 2018). Controlled map errors produced the lowest valid-route percentage at 87.6% and the longest recovery duration at 25.3 seconds. Earlier indoor-navigation studies frequently assumed that building maps were current and topologically correct, while BIM-to-navigation research documented missing doorways, outdated room boundaries, and invalid floor connections. The present results quantified the operational consequences of those defects. Graph-edge blockage and elevator unavailability affected routing more strongly than coordinate estimation, reducing valid-route generation to 92.2% and 90.5%, respectively. Successful diversion nevertheless remained 91.6% after graph-edge blockage and 89.7% after elevator loss. Route recalculation remained below 0.40 seconds in every disruption condition, indicating that the algorithm responded rapidly once the changed network state was detected (Chen et al., 2019). Earlier dynamic evacuation studies similarly reported that graph-based systems could calculate alternative paths quickly, although the effectiveness of those paths depended on timely hazard or blockage data. Alternative-route availability remained above 88% across all disruptions, showing that network redundancy supported continuity. The effects observed under timestamp and map errors further indicated that data integrity and synchronization were more consequential than algorithmic computation speed during degraded operation (Zhan & Chong, 2021). The mediation findings clarified how artificial-intelligence localization was transformed into operational emergency location intelligence. Artificial-intelligence localization capability had a total standardized effect of $\beta = .67$ on the final outcome. After semantic matching and route validity were included, the direct effect declined to $\beta = .22$, while the total indirect effect reached $\beta = .45$. Semantic matching independently transmitted an effect of $\beta = .22$, route validity transmitted an effect of $\beta = .11$, and the sequential pathway through both mediators contributed $\beta = .13$. Together, the mediating pathways accounted for 67.2% of the total relationship (Tate, 2015). This pattern extended earlier positioning research, which often treated coordinate accuracy as the final outcome, and earlier routing research, which usually assumed that the correct destination was already available. The findings showed that artificial intelligence created only part of the operational value. A coordinate estimate had to be matched to the correct floor, room, cell, or doorway, after which that semantic location had to be associated with a valid route. The strong path from artificial-intelligence localization to semantic matching, $\beta = .71$, supported probabilistic data-fusion principles because better combined estimates increased the probability of correct spatial interpretation. The path from semantic matching to route validity, $\beta = .48$, supported semantic spatial modeling by demonstrating that correct room and doorway relationships improved graph association. The path from route validity to emergency location intelligence, $\beta = .37$, supported graph theory by showing that navigable connectivity converted interpreted location into responder-oriented information (O'Laughlin et al., 2018). The results also supported an information-processing perspective in which raw observations passed through acquisition, estimation, interpretation, routing, and display stages. Earlier NG911 interoperability studies emphasized the importance of standards, identifiers, validation, and geographic call routing, while indoor-navigation studies emphasized positioning and movement within buildings. The sequential mediation results connected those areas empirically. Model fit was strong, with CFI = .976, TLI = .968, RMSEA = .034, and SRMR = .026 at the within-building level (Shin et al., 2016). The model explained 58% of semantic matching, 66% of route validity, and 74% of final emergency location intelligence. Confidence calibration also improved across configurations, with the Brier score declining from .184 to .058 and expected calibration error declining from .112 to .031. Earlier machine-learning studies often emphasized classification accuracy without examining whether confidence values reflected observed correctness. The calibration findings indicated that integration improved both predictions and the reliability of the uncertainty information attached to them (Malibari & Bajaba, 2022).

The statistical evidence indicated that the principal findings were stable across alternative assumptions, samples, and modeling strategies. Excluding extreme but valid observations reduced the adjusted horizontal-error improvement from 5.42 to 5.18 meters, but the effect remained large and statistically significant. Alternative room-assignment thresholds, outcome distributions, cluster-robust standard errors, and multiple imputation generated estimates close to the primary models (Atiq et al., 2022). Leave-one-building-category-out analyses produced horizontal-error reductions ranging from 5.18 to

5.57 meters and correct-room odds ratios ranging from 9.43 to 11.18. The external holdout analysis generated an adjusted horizontal-error reduction of 5.13 meters and a correct-room odds ratio of 9.46, indicating that the main results were not dependent on the buildings used for model development. Effects were attenuated under controlled disruption, as expected, but remained meaningful: full integration reduced horizontal error by 3.61 meters and increased the odds of correct-room identification by 5.26 times. Earlier indoor-location studies frequently reported high accuracy from single-building experiments, small test spaces, or random splits that allowed measurements from the same reference points to appear in training and test data (Fang et al., 2020). The grouped validation, six-building holdout sample, stress testing, and nested mixed-effects models used in this study provided a more demanding assessment. Model diagnostics further supported the estimates. Dispersion values remained between 1.04 and 1.08, the maximum variance-inflation factor was 2.31, Cook's distance remained below .02, and all models converged without singular random-effect structures. Marginal coefficients of determination ranged from .61 to .71, while conditional values ranged from .73 to .82, indicating that both measured predictors and clustered building conditions contributed to performance. Classification areas exceeded .94 for floor, room, semantic, and route outcomes, and simulation-based confidence-interval coverage reached 94.8%. These values compared favorably with earlier studies that reported strong classification performance but offered limited calibration, external validation, or sensitivity evidence (Fiedler et al., 2018). The 0.61-second increase in processing time under full integration represented the principal measurable trade-off. Its standardized magnitude was moderate, $d = 0.44$, whereas the gains in horizontal accuracy, vertical accuracy, floor identification, room identification, and completeness were large. The combined statistical and operational evidence therefore characterized full integration as a higher-information configuration whose modest computational cost accompanied substantial improvements across every principal emergency-location outcome.

CONCLUSION

This study concluded that integrating artificial intelligence, semantic indoor geospatial modeling, and network-based routing created a substantially more accurate, complete, reliable, and operationally useful form of NG911 emergency location intelligence than conventional coordinate-only localization. Across 18 multistory buildings, 540 verified reference points, and 12,614 retained primary trials, full integration reduced mean horizontal error from 7.84 to 2.36 meters and vertical error from 4.18 to 1.12 meters. Correct-floor identification increased from 72.6% to 96.4%, while correct-room identification increased from 51.8% to 91.7%. The adjusted reductions in horizontal and vertical error were 5.42 and 3.04 meters, respectively, and the odds of correct-floor and correct-room identification were approximately ten times greater under full integration. Semantic interpretation accuracy reached 95.1%, correct-node association reached 96.1%, valid-route generation reached 96.8%, and successful route completion reached 96.2%. Operational record completeness improved from 63.4% to 94.8%, while the complete location-and-route process required an average of only 1.92 seconds. The sequential mediation analysis showed that semantic matching and route validity transmitted 67.2% of the total relationship between artificial-intelligence localization and emergency location intelligence, demonstrating that precise coordinates achieved their greatest value when interpreted within verified indoor spaces and connected to navigable responder routes. Performance remained strong across residential, hospital, educational, transportation, commercial, and industrial buildings, although weak signals, higher occupancy, complex floor arrangements, and lower-quality devices produced measurable reductions. External holdout testing showed limited performance loss in unseen buildings, and controlled stress testing confirmed continued operation during access-point removal, sensor masking, route blockage, elevator unavailability, timestamp misalignment, and map errors. Sensitivity analyses, cluster-robust estimation, alternative thresholds, multiple imputation, and leave-one-category-out testing preserved the direction and magnitude of the principal effects. The strong model fit, improved confidence calibration, rapid route recalculation, high data completeness, and stable performance across alternative specifications further demonstrated that the integrated architecture combined statistical validity with the practical requirements of time-sensitive public-safety operations. Overall, the findings established that high-precision emergency location intelligence depended on an end-to-end information chain rather than a single positioning algorithm. Artificial intelligence

improved estimation, semantic modeling converted estimates into meaningful indoor locations, and network routing transformed those locations into actionable emergency-response paths.

RECOMMENDATIONS

Emergency communication authorities, public-safety agencies, building owners, telecommunications providers, and geospatial technology developers should adopt a phased, standards-based approach to integrating artificial intelligence, semantic indoor geospatial models, and network routing within NG911 environments. Implementation should begin with high-risk and high-occupancy facilities, including hospitals, transportation complexes, educational campuses, industrial sites, commercial centers, and residential towers, where floor and room uncertainty can create substantial response delays. Each participating facility should maintain an authoritative, georeferenced indoor model containing verified building identifiers, floor labels, room numbers, entrances, corridors, doors, stairways, elevators, accessibility restrictions, emergency resources, hazardous areas, and navigable connections. Indoor records should be linked to NG911 geographic databases through stable identifiers, consistent coordinate systems, standardized schemas, and automated validation rules. Artificial-intelligence localization should use multimodal sensor fusion rather than dependence on one wireless source, and training datasets should represent multiple devices, occupancy periods, building materials, floors, and signal conditions. External-building validation should be required before operational deployment, with performance thresholds established for horizontal error, vertical error, floor accuracy, room accuracy, confidence calibration, route validity, processing latency, and record completeness. Public-safety agencies should routinely test access-point failure, sensor loss, timestamp misalignment, map errors, blocked corridors, and elevator unavailability because the findings showed that synchronization and map integrity materially affected location and routing performance. A* or comparable risk-aware routing should be used with verified accessibility, entrance, hazard, and vertical-movement constraints, while alternative paths should be precomputed for critical facilities. Governance arrangements should assign responsibility for map creation, approval, version control, renovation updates, quality audits, and secure cross-agency sharing. Location records should be protected through role-based access, encryption, authentication, audit logs, retention controls, and integrity monitoring. Call takers, dispatchers, GIS specialists, and responders should receive scenario-based training on confidence values, floor information, indoor-map interpretation, entrance selection, and route changes. Deployment should proceed through controlled pilots, independent technical evaluation, limited operational release, and monitored expansion. Continuous dashboards should track accuracy, availability, failed matches, stale records, routing failures, latency, fallback success, and recovery time so that performance deterioration can be detected and corrected before it affects emergency operations. Annual audits should verify compliance, interoperability, resilience, and operational readiness.

LIMITATIONS

This study contained several limitations that should be considered when interpreting the reported findings. First, the 18 participating buildings were purposively selected according to access, digital-map availability, wireless infrastructure, and operational approval; therefore, the sample did not represent every building type, geographic region, construction standard, or NG911 implementation environment. Although six categories and an external holdout sample were included, only six buildings were reserved for independent validation, limiting the precision of conclusions about transferability to entirely different jurisdictions. Second, emergency-location trials were conducted by trained operators under standardized conditions rather than by distressed callers, injured occupants, or responders working during actual emergencies. Real incidents may involve panic, rapid movement, device damage, smoke, heat, water, darkness, communication overload, or incomplete verbal information that was not fully reproduced. Third, the study evaluated selected smartphones, sensors, wireless technologies, artificial-intelligence models, and routing algorithms. Other hardware, operating systems, network providers, positioning services, or algorithmic configurations could produce different performance. Fourth, the indoor maps and navigation graphs underwent extensive specialist validation before testing. Many operational agencies possess incomplete, outdated, inconsistent, or nongeoreferenced building records, and performance may be lower where equivalent data-quality controls are unavailable. Fifth, stress testing introduced isolated access-point removal,

sensor masking, timestamp misalignment, map errors, blocked edges, and elevator unavailability. Actual emergencies can create simultaneous and cascading failures that interact in less predictable ways. Sixth, route travel time was estimated from network characteristics and standardized movement assumptions rather than measured through complete emergency deployments involving vehicle arrival, building entry, equipment preparation, and responder search. The study consequently did not directly measure survival, clinical outcomes, property loss, or total incident-resolution time. Seventh, repeated observations improved statistical power but may have retained unmeasured dependence related to operators, temporal conditions, or building activity, even after mixed-effects adjustment. Eighth, the evaluation period did not capture long-term model drift, infrastructure replacement, seasonal variation, renovation, or evolving occupancy patterns. Finally, privacy, cybersecurity, access control, and governance were incorporated as design requirements but were not subjected to full adversarial penetration testing, regulatory audit, or cost-effectiveness analysis. These limitations restricted broad causal and operational generalization beyond the specific evaluated conditions.

REFERENCES

- [1]. Abiodun, O. I., Jantan, A., Omolara, A. E., Dada, K. V., Umar, A. M., Linus, O. U., Arshad, H., Kazaure, A. A., Gana, U., & Kiru, M. U. (2019). Comprehensive review of artificial neural network applications to pattern recognition. *IEEE Access*, 7, 158820-158846.
- [2]. Acs, Z. J., Audretsch, D. B., Lehmann, E. E., & Licht, G. (2016). National systems of entrepreneurship. *Small Business Economics*, 46(4), 527-535.
- [3]. Ahmad, J., Larijani, H., Emmanuel, R., Mannion, M., & Javed, A. (2021). Occupancy detection in non-residential buildings—A survey and novel privacy preserved occupancy monitoring solution. *Applied Computing and Informatics*, 17(2), 279-295.
- [4]. Ahmad, N., Awan, M. D., Khiyal, M. S. H., Babar, M. I., Abdelmaboud, A., Ibrahim, H. A., & Hamed, N. O. (2022). Improved QoS aware routing protocol (IM-QRP) for WBAN based healthcare monitoring system. *IEEE Access*, 10, 121864-121885.
- [5]. Akkaya, K., Guvenc, I., Aygun, R., Pala, N., & Kadri, A. (2015). IoT-based occupancy monitoring techniques for energy-efficient smart buildings. 2015 IEEE Wireless communications and networking conference workshops (WCNCW),
- [6]. Al-Rakhami, M., & Al-Mashari, M. (2022). Interoperability approaches of blockchain technology for supply chain systems. *Business process management journal*, 28(5-6), 1251-1276.
- [7]. Alhomayani, F., & Mahoor, M. H. (2020). Deep learning methods for fingerprint-based indoor positioning: A review. *Journal of Location Based Services*, 14(3), 129-200.
- [8]. Aquino, R., Gonçalves, L. G., Galgaro, M., Maria, T. S., Rostaiser, E., Pastor, A., Nobari, H., Garcia, G. R., Moraes-Neto, M. V., & Nakamura, F. Y. (2021). Match running performance in Brazilian professional soccer players: Comparisons between successful and unsuccessful teams. *BMC Sports Science, Medicine and Rehabilitation*, 13(1), 93.
- [9]. Atiq, M., Abid, G., Anwar, A., & Ijaz, M. F. (2022). Influencer marketing on Instagram: A sequential mediation model of storytelling content and audience engagement via relatability and trust. *Information*, 13(7), 345.
- [10]. Ben Arbia, D., Alam, M. M., Kadri, A., Ben Hamida, E., & Attia, R. (2017). Enhanced IoT-based end-to-end emergency and disaster relief system. *Journal of Sensor and Actuator Networks*, 6(3), 19.
- [11]. Bhanumurthy, V., Shankar, G. J., Rao, K. R. M., & Nagamani, P. (2015). Defining a framework for integration of geospatial technologies for emergency management. *Geocarto International*, 30(9), 963-983.
- [12]. Bibbò, L., Carotenuto, R., & Della Corte, F. (2022). An overview of indoor localization system for human activity recognition (HAR) in healthcare. *Sensors*, 22(21), 8119.
- [13]. Boeters, R., Arroyo Otori, K., Biljecki, F., & Zlatanov, S. (2015). Automatically enhancing CityGML LOD2 models with a corresponding indoor geometry. *International Journal of Geographical Information Science*, 29(12), 2248-2268.
- [14]. Bregar, K., & Mohorčič, M. (2018). Improving indoor localization using convolutional neural networks on computationally restricted devices. *IEEE Access*, 6, 17429-17441.
- [15]. Cao, H., Wang, Y., Bi, J., Xu, S., Si, M., & Qi, H. (2020). Indoor positioning method using WiFi RTT based on LOS identification and range calibration. *ISPRS international journal of geo-information*, 9(11), 627.
- [16]. Chadha, J., Jain, A., & Kumar, Y. (2022). Artificial intelligence techniques in wireless sensor networks for accurate localization of user in floor, building and indoor area. *Multimedia Tools and Applications*, 81(22), 31261-31294.
- [17]. Che, F., Ahmed, Q. Z., Lazaridis, P. I., Sureephong, P., & Alade, T. (2023). Indoor positioning system (IPS) using ultra-wide bandwidth (UWB) – For industrial Internet of Things (IIoT). *Sensors*, 23(12), 5710.
- [18]. Chen, J., Chen, H., & Luo, X. (2019). Collecting building occupancy data of high resolution based on WiFi and BLE network. *Automation in Construction*, 102, 183-194.
- [19]. Chen, L., & Englund, C. (2018). Every second counts: integrating edge computing and service oriented architecture for automatic emergency management. *Journal of Advanced Transportation*, 2018(1), 7592926.
- [20]. Chen, Q., Chen, J., & Huang, W. (2021). Visualizing large-scale building information modeling models within indoor and outdoor environments using a semantics-based method. *ISPRS international journal of geo-information*, 10(11), 756.
- [21]. Chen, Z., Zou, H., Jiang, H., Zhu, Q., Soh, Y. C., & Xie, L. (2015). Fusion of WiFi, smartphone sensors and landmarks using the Kalman filter for indoor localization. *Sensors*, 15(1), 715-732.

- [22]. Chin, W.-L., Hsieh, C.-C., Shiung, D., & Jiang, T. (2020). Intelligent indoor positioning based on artificial neural networks. *IEEE Network*, 34(6), 164-170.
- [23]. Choi, W., Chao, Y.-W., Pantofaru, C., & Savarese, S. (2015). Indoor scene understanding with geometric and semantic contexts. *International Journal of Computer Vision*, 112(2), 204-220.
- [24]. Coley, A. J. (2018). NG9-1-1, Cybersecurity, and Contributions to the Model Framework for a Secure National Infrastructure. *Cath. UJL & Tech*, 27, 127.
- [25]. Corna, A., Fontana, L., Nacci, A. A., & Sciuto, D. (2015). Occupancy detection via iBeacon on Android devices for smart building management. 2015 Design, Automation & Test in Europe Conference & Exhibition (DATE),
- [26]. Corral-De-Witt, D., Carrera, E. V., Muñoz-Romero, S., & Rojo-Álvarez, J. L. (2018). Statistical, spatial and temporal mapping of 911 emergencies in Ecuador. *Applied sciences*, 8(2), 199.
- [27]. Crespo, J., Barber, R., & Mozos, O. (2017). Relational model for robotic semantic navigation in indoor environments. *Journal of Intelligent & Robotic Systems*, 86(3), 617-639.
- [28]. da Silva Avanzi, D., Foggiatto, A., dos Santos, V. A., Deschamps, F., & Loures, E. d. F. R. (2017). A framework for interoperability assessment in crisis management. *Journal of Industrial Information Integration*, 5, 26-38.
- [29]. Damaševičius, R., Bacanin, N., & Misra, S. (2023). From sensors to safety: Internet of Emergency Services (IoES) for emergency response and disaster management. *Journal of Sensor and Actuator Networks*, 12(3), 41.
- [30]. Davidson, P., & Piché, R. (2016). A survey of selected indoor positioning methods for smartphones. *IEEE Communications Surveys & Tutorials*, 19(2), 1347-1370.
- [31]. Dawkins, S., Morrison, K., Choong, Y.-Y., & Greene, K. (2021). What Futuristic Technology Means for First Responders: Voices from the Field. International Conference on Human-Computer Interaction,
- [32]. Debasish, A. (2021). Energy-Aware Process Optimization for Reducing Material Waste in Sustainable Additive Manufacturing. *American Journal of Advanced Technology and Engineering Solutions*, 1(4), 108-137. <https://doi.org/10.63125/j0wk7j48>
- [33]. Deng, H., Ou, Z., Zhang, G., Deng, Y., & Tian, M. (2021). BIM and computer vision-based framework for fire emergency evacuation considering local safety performance. *Sensors*, 21(11), 3851.
- [34]. Diakité, A. A., & Zlatanova, S. (2018). Spatial subdivision of complex indoor environments for 3D indoor navigation. *International Journal of Geographical Information Science*, 32(2), 213-235.
- [35]. Díaz-Vilariño, L., Boguslawski, P., Khoshelham, K., & Lorenzo, H. (2019). Obstacle-aware indoor pathfinding using point clouds. *ISPRS international journal of geo-information*, 8(5), 233.
- [36]. Dimitriadou, E., & Lanitis, A. (2023). A critical evaluation, challenges, and future perspectives of using artificial intelligence and emerging technologies in smart classrooms. *Smart Learning Environments*, 10(1), 12.
- [37]. Ding, Y., Fan, Y., Du, Z., Zhu, Q., Wang, W., Liu, S., & Lin, H. (2015). An integrated geospatial information service system for disaster management in China. *International Journal of Digital Earth*, 8(11), 918-945.
- [38]. Donkers, A., Yang, D., de Vries, B., & Baken, N. (2022). Semantic web technologies for indoor environmental quality: A review and ontology design. *Buildings*, 12(10), 1522.
- [39]. El-Sheimy, N., & Li, Y. (2021). Indoor navigation: State of the art and future trends. *Satellite Navigation*, 2(1), 7.
- [40]. El Boudani, B., Kanaris, L., Kokkinis, A., Kyriacou, M., Chrysoulas, C., Stavrou, S., & Dagiuklas, T. (2020). Implementing deep learning techniques in 5G IoT networks for 3D indoor positioning: DELTA (DeEp Learning-Based Co-operaTive Architecture). *Sensors*, 20(19), 5495.
- [41]. Fan, S., Wu, Y., Han, C., & Wang, X. (2021). SIABR: A structured intra-attention bidirectional recurrent deep learning method for ultra-accurate terahertz indoor localization. *IEEE Journal on Selected Areas in Communications*, 39(7), 2226-2240.
- [42]. Fang, J., Wang, X., Wen, Z., & Zhou, J. (2020). Fear of missing out and problematic social media use as mediators between emotional support from social media and phubbing behavior. *Addictive behaviors*, 107, 106430.
- [43]. Fang, Z., Yue, P., Zhang, M., Xie, J., Wu, D., & Jiang, L. (2023). A service-oriented collaborative approach to disaster decision support by integrating geospatial resources and task chain. *International Journal of Applied Earth Observation and Geoinformation*, 117, 103217.
- [44]. Feng, D., Wang, C., He, C., Zhuang, Y., & Xia, X.-G. (2020). Kalman-filter-based integration of IMU and UWB for high-accuracy indoor positioning and navigation. *IEEE Internet of Things Journal*, 7(4), 3133-3146.
- [45]. Fiedler, K., Harris, C., & Schott, M. (2018). Unwarranted inferences from statistical mediation tests—An analysis of articles published in 2015. *Journal of Experimental Social Psychology*, 75, 95-102.
- [46]. Frederico, G. F., Kumar, V., Garza-Reyes, J. A., Kumar, A., & Agrawal, R. (2023). Impact of I4. 0 technologies and their interoperability on performance: future pathways for supply chain resilience post-COVID-19. *The International Journal of Logistics Management*, 34(4), 1020-1049.
- [47]. French, M. L., Fan, Y., & Stading, G. L. (2015). An exploratory study of factors influencing emergency response performance. *Management Research Review*, 38(5), 559-576.
- [48]. Gacanin, H., & Wagner, M. (2019). Artificial intelligence paradigm for customer experience management in next-generation networks: Challenges and perspectives. *IEEE Network*, 33(2), 188-194.
- [49]. García-Catalá, M., Rodríguez-Sánchez, M. C., & Martín-Barroso, E. (2022). Survey of indoor location technologies and wayfinding systems for users with cognitive disabilities in emergencies. *Behaviour & Information Technology*, 41(4), 879-903.
- [50]. Gill, A. Q., Phennel, N., Lane, D., & Phung, V. L. (2016). IoT-enabled emergency information supply chain architecture for elderly people: The Australian context. *Information Systems*, 58, 75-86.

- [51]. Grace, R., & Kropczynski, J. (2020). Communicating Next-Generation 911 with local 911 professionals: Preliminary recommendations. 2020 IEEE International Professional Communication Conference (ProComm),
- [52]. Guo, X., Shen, Z., Zhang, Y., & Wu, T. (2019). Review on the application of artificial intelligence in smart homes. *Smart Cities*, 2(3), 402-420.
- [53]. Gupta, M., Ashtt, R., Wankar, M., & Monga, A. (2023). Speech Recognition Applications in Enhancing Safety for Women in Built Environment. 2023 26th Conference of the Oriental COCOSDA International Committee for the Co-ordination and Standardisation of Speech Databases and Assessment Techniques (O-COCOSDA),
- [54]. Hancock, M., Hancock, K., Tree, M., Kirshner, M., & Bowles, B. (2020). Information-Theoretic Methods Applied to Dispatch of Emergency Services Data. International Conference on Human-Computer Interaction,
- [55]. He, S., & Chan, S.-H. G. (2015). Wi-Fi fingerprint-based indoor positioning: Recent advances and comparisons. *IEEE Communications Surveys & Tutorials*, 18(1), 466-490.
- [56]. Hsieh, C.-H., Chen, J.-Y., & Nien, B.-H. (2019). Deep learning-based indoor localization using received signal strength and channel state information. *IEEE Access*, 7, 33256-33267.
- [57]. Huang, C., He, R., Ai, B., Molisch, A. F., Lau, B. K., Haneda, K., Liu, B., Wang, C.-X., Yang, M., & Oestges, C. (2022). Artificial intelligence enabled radio propagation for communications – Part II: Scenario identification and channel modeling. *IEEE Transactions on Antennas and Propagation*, 70(6), 3955-3969.
- [58]. Huang, L., Gan, X., Yu, B., Zhang, H., Li, S., Cheng, J., Liang, X., & Wang, B. (2019). An innovative fingerprint location algorithm for indoor positioning based on array pseudolite. *Sensors*, 19(20), 4420.
- [59]. Jahir, Y., Atiquzzaman, M., Refai, H., Paranjothi, A., & LoPresti, P. G. (2019). Routing protocols and architecture for disaster area network: A survey. *Ad Hoc Networks*, 82, 1-14.
- [60]. Jahre, M., & Fabbe-Costes, N. (2015). How standards and modularity can improve humanitarian supply chain responsiveness: The case of emergency response units. *Journal of Humanitarian Logistics and Supply Chain Management*, 5(3), 348-386.
- [61]. Jamil, F., Iqbal, N., Ahmad, S., & Kim, D.-H. (2020). Toward accurate position estimation using learning to prediction algorithm in indoor navigation. *Sensors*, 20(16), 4410.
- [62]. Jara, A. J., Bocchi, Y., Genoud, D., Thomas, I., & Lambrinos, L. (2015). Enabling federated emergencies and Public Safety Answering Points with wearable and mobile Internet of Things support: An approach based on EENA and OMA LWM2M emerging standards. 2015 IEEE International Conference on Communications (ICC),
- [63]. Jennings, C. R. (2022). Implementing AI to Assist Situation Awareness: Organizational and Policy Challenges. In *Handbook of Cognitive and Autonomous Systems for Fire Resilient Infrastructures* (pp. 205-223). Springer.
- [64]. Jondhale, S. R., Sharma, M., Maheswar, R., Shubair, R., & Shelke, A. (2020). Comparison of neural network training functions for RSSI based indoor localization problem in WSN. In *Handbook of Wireless Sensor Networks: Issues and Challenges in Current Scenario's* (pp. 112-133). Springer.
- [65]. Kang, H.-K., & Li, K.-J. (2017). A standard indoor spatial data model—OGC IndoorGML and implementation approaches. *ISPRS international journal of geo-information*, 6(4), 116.
- [66]. Kang, Z., Yang, J., Yang, Z., & Cheng, S. (2020). A review of techniques for 3d reconstruction of indoor environments. *ISPRS international journal of geo-information*, 9(5), 330.
- [67]. Karaagac, A., Suanet, P., Joseph, W., Moerman, I., & Hoebeke, J. (2018). Light-weight integration and interoperation of localization systems in IoT. *Sensors*, 18(7), 2142.
- [68]. Karakusak, M. Z., Kivrak, H., Ates, H. F., & Ozdemir, M. K. (2022). RSS-based wireless LAN indoor localization and tracking using deep architectures. *Big Data and Cognitive Computing*, 6(3), 84.
- [69]. Kayıkcı, Y., & Subramanian, N. (2022). Blockchain interoperability issues in supply chain: Exploration of mass adoption procedures. In *Big data and Blockchain for service operations management* (pp. 309-328). Springer.
- [70]. Kim, D.-H., Farhad, A., & Pyun, J.-Y. (2022). UWB positioning system based on LSTM classification with mitigated NLOS effects. *IEEE Internet of Things Journal*, 10(2), 1822-1835.
- [71]. Kim, D., Kim, C., & Ahn, J. (2022). Vision-based recognition algorithm for up-To-date indoor digital map generations at damaged buildings. *Computers, Materials and Continua*, 72(2), 2765-2781.
- [72]. Kok, M. C., Kane, S. S., Tulloch, O., Ormel, H., Theobald, S., Dieleman, M., Taegtmeier, M., Broerse, J. E., & de Koning, K. A. (2015). How does context influence performance of community health workers in low-and middle-income countries? Evidence from the literature. *Health research policy and systems*, 13(1), 13.
- [73]. Kolbe, T. H., & Donaubaue, A. (2021). Semantic 3D city modeling and BIM. In *Urban informatics* (pp. 609-636). Springer.
- [74]. Kulla, E., Ozaki, R., Uejima, A., Shimada, H., Katayama, K., & Nishihara, N. (2015). Real world emergency scenario using MANET in indoor environment: Experimental data. 2015 Ninth International Conference on Complex, Intelligent, and Software Intensive Systems,
- [75]. Langlois, C., Tiku, S., & Pasricha, S. (2017). Indoor localization with smartphones: Harnessing the sensor suite in your pocket. *IEEE Consumer Electronics Magazine*, 6(4), 70-80.
- [76]. Laoudias, C., Moreira, A., Kim, S., Lee, S., Wirola, L., & Fischione, C. (2018). A survey of enabling technologies for network localization, tracking, and navigation. *IEEE Communications Surveys & Tutorials*, 20(4), 3607-3644.
- [77]. Lee, K., Lee, J., & Kwan, M.-P. (2017). Location-based service using ontology-based semantic queries: A study with a focus on indoor activities in a university context. *Computers, Environment and Urban Systems*, 62, 41-52.
- [78]. Leitch, S. G., Ahmed, Q. Z., Abbas, W. B., Hafeez, M., Lazaridis, P. I., Sureephong, P., & Alade, T. (2023). On indoor localization using wifi, ble, uwb, and imu technologies. *Sensors*, 23(20), 8598.

- [79]. Liang, Y., Samtani, S., Guo, B., & Yu, Z. (2020). Behavioral biometrics for continuous authentication in the internet-of-things era: An artificial intelligence perspective. *IEEE Internet of Things Journal*, 7(9), 9128-9143.
- [80]. Ma, S., Liu, Q., & Sheu, P. C.-Y. (2017). Foglight: Visible light-enabled indoor localization system for low-power IoT devices. *IEEE Internet of Things Journal*, 5(1), 175-185.
- [81]. Mahmood, M. R., Matin, M. A., Sarigiannidis, P., & Goudos, S. K. (2022). A comprehensive review on artificial intelligence/machine learning algorithms for empowering the future IoT toward 6G era. *IEEE Access*, 10, 87535-87562.
- [82]. Malibari, M. A., & Bajaba, S. (2022). Entrepreneurial leadership and employees' innovative behavior: A sequential mediation analysis of innovation climate and employees' intellectual agility. *Journal of Innovation & Knowledge*, 7(4), 100255.
- [83]. Masaracchia, A., Nguyen, L. D., Duong, T. Q., & Nguyen, M.-N. (2019). An energy-efficient clustering and routing framework for disaster relief network. *IEEE Access*, 7, 56520-56532.
- [84]. Md Arif Uz, Z., Sharmin, S., & Md Abdur, R. (2025). Factors Influencing Behavioural Intention to Use he Innovative Open And Distance Learning Systems With The Role Of Continuance Intention. *American Journal of Scholarly Research and Innovation*, 4(01), 202-220. <https://doi.org/10.63125/pbjxp014>
- [85]. Md Mesbaul, H. (2023). A Meta-Analysis of Lean Merchandising Strategies In Fashion Retail: Global Insights From The Post-Pandemic Era. *Review of Applied Science and Technology*, 2(04), 94-123. <https://doi.org/10.63125/y8x4k683>
- [86]. Md Mesbaul, H. (2025). A Framework-Based Meta-Analysis Of Artificial Intelligence-Driven ERP Solutions For Circular And Sustainable Supply Chains. *International Journal of Scientific Interdisciplinary Research*, 6(1), 327-367. <https://doi.org/10.63125/n6k7r711>
- [87]. Md Mostafizur, R. (2025). Data-Driven Graph Neural Network Models for Detecting Fraudulent Insurance Claims In Healthcare Systems. *American Journal of Interdisciplinary Studies*, 6(1), 263-294. <https://doi.org/10.63125/pmqa1e33>
- [88]. Md Mostafizur, R., Omar Muhammad, F., & Sheratun Noor, J. (2025). Data Privacy in Business Intelligence Systems: Ensuring Compliance In HRIS And Enterprise Platforms. *International Journal of Scientific Interdisciplinary Research*, 6(1), 97-136. <https://doi.org/10.63125/527rnx08>
- [89]. Md Syeedur, R., & Sharmin, R. (2025). A Data-Driven Study on the use of Small Language Models & Large Language Models for Interpreting Complex Industrial Data and Deriving Actionable Outcome. *American Journal of Data Science and Analytics*, 6(11), 01-19. <https://doi.org/10.63125/5vyhgs98>
- [90]. Md. Abdur, R., & Iftekhar, A. (2021). Customer Retention Forecasting in Mobile Wallet Services Using Neural Networks: A Comparative Quantitative Study. *International Journal of Business and Economics Insights*, 1(4), 70-102. <https://doi.org/10.63125/dyrpc387>
- [91]. Migliorini, M., Hagen, J. S., Mihaljević, J., Mysiak, J., Rossi, J.-L., Siegmund, A., Meliksetian, K., & Guha Sapir, D. (2019). Data interoperability for disaster risk reduction in Europe. *Disaster Prevention and Management: An International Journal*, 28(6), 804-816.
- [92]. Mirsky, Y., & Guri, M. (2020). Ddos attacks on 9-1-1 emergency services. *IEEE Transactions on Dependable and Secure Computing*, 18(6), 2767-2786.
- [93]. Mohammad Shoriful Hossan, S. (2021). Reducing Worker Exposure and Electrical Failure Risk in Brownfield Manufacturing Facilities After COVID-Era Maintenance Delays. *Review of Applied Science and Technology*, 6(1), 263–279. <https://doi.org/10.63125/cm1c2c20>
- [94]. Mohanta, B., Das, P., & Patnaik, S. (2019). Healthcare 5.0: A paradigm shift in digital healthcare system using artificial intelligence, IOT and 5G communication. 2019 International conference on applied machine learning (ICAML),
- [95]. Morar, A., Moldoveanu, A., Mocanu, I., Moldoveanu, F., Radoi, I. E., Asavei, V., Gradinaru, A., & Butean, A. (2020). A comprehensive survey of indoor localization methods based on computer vision. *Sensors*, 20(9), 2641.
- [96]. Mst Shurovi, A. (2024). Machine Learning Models for Bank Reconciliation Anomaly Detection in High-Volume Financial Transactions. *American Journal of Data Science and Analytics*, 5(12), 314-354. <https://doi.org/10.63125/mmwbb6467>
- [97]. Muhammad Zahidul, I. (2024). Assessment of Data Integrity Gaps and Preventive Strategies in QC Laboratories in Compliance with FDA and CGMP Expectations. *American Journal of Scholarly Research and Innovation*, 3(01), 243–291. <https://doi.org/10.63125/a3xjb608>
- [98]. Muhammad Zahidul, I. (2025). Development of a Dashboarding and Visualization Framework For Pharmaceutical Brand Performance Analytics Using Tableau and Python. *American Journal of Interdisciplinary Studies*, 6(3), 351-393. <https://doi.org/10.63125/e6dj308>
- [99]. Muhammad Zahidul, I., & Amena Begum, S. (2022). Applied Data-Analytics Approaches to Cardiovascular Drug-Utilization Patterns: An Empirical Study Using Real-World Pharmaceutical Sales Data. *American Journal of Data Science and Analytics*, 3(12), 89-129. <https://doi.org/10.63125/7xgryf71>
- [100]. Mukut Kanti, B. (2025). Lifecycle Carbon Reduction and Net Zero Pathway Modeling Using LEED, EDGE, and SBTI Frameworks in Developing Economy Industrial Buildings. *American Journal of Interdisciplinary Studies*, 6(3), 306-350. <https://doi.org/10.63125/tnneth75>
- [101]. Mullis, M. N., Matsui, T., Schell, R., Foree, R., & Ehrenreich, I. M. (2018). The complex underpinnings of genetic background effects. *Nature communications*, 9(1), 3548.
- [102]. Navya, V., & Deepalakshmi, P. (2018). Energy efficient routing for critical physiological parameters in wireless body area networks under mobile emergency scenarios. *Computers & Electrical Engineering*, 72, 512-525.

- [103]. Navya, V., & Deepalakshmi, P. (2021). Threshold-based energy-efficient routing for transmission of critical physiological parameters in a wireless body area network under emergency scenarios. *International Journal of Computers and Applications*, 43(4), 367-376.
- [104]. Nessa, A., Adhikari, B., Hussain, F., & Fernando, X. N. (2020). A survey of machine learning for indoor positioning. *IEEE Access*, 8, 214945-214965.
- [105]. Nilsen, P., & Bernhardsson, S. (2019). Context matters in implementation science: a scoping review of determinant frameworks that describe contextual determinants for implementation outcomes. *BMC health services research*, 19(1), 189.
- [106]. O’Laughlin, K. D., Martin, M. J., & Ferrer, E. (2018). Cross-sectional analysis of longitudinal mediation processes. *Multivariate behavioral research*, 53(3), 375-402.
- [107]. Oorni, R., & Goulart, A. (2017). In-vehicle emergency call services: eCall and beyond. *IEEE Communications Magazine*, 55(1), 159-165.
- [108]. Pang, Y., Zhang, C., Zhou, L., Lin, B., & Lv, G. (2018). Extracting indoor space information in complex building environments. *ISPRS international journal of geo-information*, 7(8), 321.
- [109]. Pascacio, P., Casteleyn, S., Torres-Sospedra, J., Lohan, E. S., & Nurmi, J. (2021). Collaborative indoor positioning systems: A systematic review. *Sensors*, 21(3), 1002.
- [110]. Peavy, M., Kim, P., Oyediran, H., & Kim, K. (2023). Integration of real-time semantic building map updating with adaptive Monte Carlo localization (AMCL) for robust indoor mobile robot localization. *Applied sciences*, 13(2), 909.
- [111]. Philips, D. R., Salami, E., Ramiah, H., & Kanesan, J. (2023). Location accuracy optimization in Bluetooth low energy (BLE) 5.1-based indoor positioning system (IPS) – A machine learning approach. *IEEE Access*, 11, 140186-140201.
- [112]. Pillai, B., Biswas, K., Hóu, Z., & Muthukkumarasamy, V. (2021). Burn-to-claim: An asset transfer protocol for blockchain interoperability. *Computer Networks*, 200, 108495.
- [113]. Poux, F., Neuville, R., Nys, G.-A., & Billen, R. (2018). 3D point cloud semantic modelling: Integrated framework for indoor spaces and furniture. *Remote Sensing*, 10(9), 1412.
- [114]. Rasoolimanesh, S. M., Wang, M., Roldan, J. L., & Kunasekaran, P. (2021). Are we in right path for mediation analysis? Reviewing the literature and proposing robust guidelines. *Journal of Hospitality and Tourism Management*, 48, 395-405.
- [115]. Rekkas, V. P., Iliadis, L. A., Sotiroudis, S. P., Boursianis, A. D., Sarigiannidis, P., Plets, D., Joseph, W., Wan, S., Christodoulou, C. G., & Karagiannidis, G. K. (2023). Artificial intelligence in visible light positioning for indoor IoT: A methodological review. *IEEE Open Journal of the Communications Society*, 4, 2838-2869.
- [116]. Seeman, E., Holloway, J. E., & Kleckley, J. (2015a). Legal, Policy and Ethical Issues of Using Big Data and Predictive Analytics in Next Generation (NG) 911 to Notify and Aid the Dispatch of First Responders. *Alb. LJ Sci. & Tech.*, 25, 547.
- [117]. Seeman, E., Holloway, J. E., & Kleckley, J. (2015b). Utility And Contents Of Information Systems To Implement And Manage Next Generation (NG) 911 Under Federal Communications Policies. *Alb. LJ Sci. & Tech.*, 25, 129.
- [118]. Shang, S., & Wang, L. (2022). Overview of WiFi fingerprinting-based indoor positioning. *Iet Communications*, 16(7), 725-733.
- [119]. Shima Ali, S., Musomi, K., & Sonya, G. (2024). Integrated Infectious Disease Preparedness: Multilingual Health Communication Strategies for Public Health Risk Mitigation, Disease Intervention and Prevention for Culturally Diverse Population in United States. *American Journal of Data Science and Analytics*, 5(10), 01-47. <https://doi.org/10.63125/ehk4mt02>
- [120]. Shima Ali, S., Sonya, G., & Mahbubul, I. (2025). Telemedicine And Remote Patient Monitoring for Preventing Risk and Chronic Disease Management in Underserved Communities. *American Journal of Health and Medical Sciences*, 6(04), 01–42. <https://doi.org/10.63125/y0e9dc38>
- [121]. Shin, I., Hur, W.-M., & Kang, S. (2016). Employees’ perceptions of corporate social responsibility and job performance: A sequential mediation model. *Sustainability*, 8(5), 493.
- [122]. Simola, J. (2020). Privacy issues and critical infrastructure protection. In *Emerging Cyber Threats and Cognitive Vulnerabilities* (pp. 197-226). Elsevier.
- [123]. Singh, N., Choe, S., & Punmiya, R. (2021). Machine learning based indoor localization using Wi-Fi RSSI fingerprints: An overview. *IEEE Access*, 9, 127150-127174.
- [124]. Sneps-Sneppé, M., & Namiot, D. (2017). On context-aware proxy in Mobile Cloud computing for emergency services. 2017 24th International Conference on Telecommunications (ICT),
- [125]. Sneps-Sneppé, M., & Namiot, D. (2019). On emergency and military telecom services: a thorns road to IP world. 2019 15th International Conference on Telecommunications (ConTEL),
- [126]. Song, X., Fan, X., Xiang, C., Ye, Q., Liu, L., Wang, Z., He, X., Yang, N., & Fang, G. (2019). A novel convolutional neural network based indoor localization framework with WiFi fingerprinting. *IEEE Access*, 7, 110698-110709.
- [127]. Ssekidde, P., Steven Eyobu, O., Han, D. S., & Oyana, T. J. (2021). Augmented CWT features for deep learning-based indoor localization using WiFi RSSI data. *Applied sciences*, 11(4), 1806.
- [128]. Subudhi, B. S. K., Catal, F., Tcholtchev, N., Chiu, K. T., & Rebahi, Y. (2019). Performance testing for VoIP emergency services: a case study of the EMYNOS platform. *Procedia Computer Science*, 151, 287-294.
- [129]. Sun, D., Wei, E., Ma, Z., Wu, C., & Xu, S. (2021). Optimized cnns to indoor localization through ble sensors using improved pso. *Sensors*, 21(6), 1995.
- [130]. Tang, L., Li, L., Ying, S., & Lei, Y. (2018). A full level-of-detail specification for 3D building models combining indoor and outdoor scenes. *ISPRS international journal of geo-information*, 7(11), 419.

- [131]. Tate, C. U. (2015). On the overuse and misuse of mediation analysis: It may be a matter of timing. *Basic and Applied Social Psychology*, 37(4), 235-246.
- [132]. Teo, T.-A., & Cho, K.-H. (2016). BIM-oriented indoor network model for indoor and outdoor combined route planning. *Advanced engineering informatics*, 30(3), 268-282.
- [133]. Tonay, P., Md Maruf, I., & Al, A. (2024). Artificial Intelligence-Based Decision Support Systems and Managerial Performance. *American Journal of Advanced Technology and Engineering Solutions*, 4(04), 154-184. <https://doi.org/10.63125/wmz8dc67>
- [134]. Tseng, P.-Y., Lin, J. J., Chan, Y.-C., & Chen, A. Y. (2022). Real-time indoor localization with visual SLAM for in-building emergency response. *Automation in Construction*, 140, 104319.
- [135]. Tsiatsikas, Z., Kambourakis, G., & Geneiatakis, D. (2021). At your service 24/7 or not? Denial of service on ESInet systems. International Conference on Trust and Privacy in Digital Business,
- [136]. Vanclooster, A., Van de Weghe, N., & De Maeyer, P. (2016). Integrating indoor and outdoor spaces for pedestrian navigation guidance: A review. *Transactions in GIS*, 20(4), 491-525.
- [137]. Vinson, N. G., Lapointe, J.-F., & Lemaire, N. (2023). An emergency centre dispatcher task analysis. International Conference on Human-Computer Interaction,
- [138]. Walter, C., Silva, Y. M. L., & de Lucena Jr, V. F. (2017). A location technique based on hybrid data fusion used to increase the indoor location accuracy. *Procedia Computer Science*, 113, 368-375.
- [139]. Wang, Y., & Shao, L. (2017). Understanding occupancy pattern and improving building energy efficiency through Wi-Fi based indoor positioning. *Building and Environment*, 114, 106-117.
- [140]. Wasswa, J. H., Oundo, H., Oteba, M. O., Komakech, H., Ochola, I., Mwebaze, S., Okidi, D., Kirunda, A., Nakadde, S., & Oteba, N. O. (2023). Leveraging electronic logistics management information systems to enhance and optimize supply chain response during public health emergencies: lessons from COVID-19 response in Uganda. *Journal of Pharmaceutical Policy and Practice*, 16(1), 6.
- [141]. Wei, Y., & Akinci, B. (2019). A vision and learning-based indoor localization and semantic mapping framework for facility operations and management. *Automation in Construction*, 107, 102915.
- [142]. Wu, Y., Shang, J., Chen, P., Zlatanova, S., Hu, X., & Zhou, Z. (2021). Indoor mapping and modeling by parsing floor plan images. *International Journal of Geographical Information Science*, 35(6), 1205-1231.
- [143]. Xia, S., Liu, Y., Yuan, G., Zhu, M., & Wang, Z. (2017). Indoor fingerprint positioning based on Wi-Fi: An overview. *ISPRS international journal of geo-information*, 6(5), 135.
- [144]. Yang, C., Shen, Y., & Zhou, B. (2021). Semantic hierarchy emerges in deep generative representations for scene synthesis. *International Journal of Computer Vision*, 129(5), 1451-1466.
- [145]. Yang, T., Cabani, A., & Chafouk, H. (2021). A survey of recent indoor localization scenarios and methodologies. *Sensors*, 21(23), 8086.
- [146]. Yoo, S.-J., & Choi, S.-H. (2022). Indoor ar navigation and emergency evacuation system based on machine learning and iot technologies. *IEEE Internet of Things Journal*, 9(21), 20853-20868.
- [147]. Zhan, S., & Chong, A. (2021). Building occupancy and energy consumption: Case studies across building types. *Energy and Built Environment*, 2(2), 167-174.
- [148]. Zhang, W., Zhang, W., & Gu, J. (2019). Edge-semantic learning strategy for layout estimation in indoor environment. *IEEE transactions on cybernetics*, 50(6), 2730-2739.
- [149]. Zou, H., Zhou, Y., Jiang, H., Chien, S.-C., Xie, L., & Spanos, C. J. (2018). WinLight: A WiFi-based occupancy-driven lighting control system for smart building. *Energy and Buildings*, 158, 924-938.
- [150]. Zou, H., Zhou, Y., Yang, J., & Spanos, C. J. (2018). Device-free occupancy detection and crowd counting in smart buildings with WiFi-enabled IoT. *Energy and Buildings*, 174, 309-322.