SAFESCAPE: AN INCLUSIVE AI-DRIVEN PLATFORM FOR DIGITAL FIRE SAFETY, RISK ASSESSMENT, EDUCATION, AND COMMUNITY PREPAREDNESS IN STA. CRUZ, LAGUNA

A Capstone Project
Presented to the
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In Partial Fulfillment of the requirements for the Degree
BACHELOR OF SCIENCE IN COMPUTER SCIENCE

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VISION

LSPU is a center of technology innovation that promotes interdisciplinary learning, sustainable utilization of resources, collaboration, and partnership with the community and stakeholders.

MISSION

LSPU, driven by progressive leadership, is a premier institution providing technology-mediated agriculture, fisheries, and other related emerging disciplines, significantly contributing to the growth and development of the region and nation.

QUALITY POLICY

LSPU delivers quality education through responsive instruction, distinctive research, sustainable extension, and production services. Thus, we are committed with continual improvement to meet applicable requirements to provide quality, efficient, and effective services to the university to the university stakeholders' highest level of satisfaction through an excellent management system imbued with utmost integrity, professionalism, and innovation.

I. COLLEGE OF COMPUTER STUDIES GOAL

The College of Computer Studies graduates are expected to become globally competitive and innovative computing professionals imbued with utmost integrity, contributing to the country's national development goals.

II. PROGRAM EDUCATIONAL OBJECTIVES

The Bachelor of Science in Information Technology graduates are professionals that can adapt with the fast-paced computing trends responsive to global IT demands. It is designed to enable students to achieve the following by the time they graduate:

1. Apply knowledge for solving computing problems employing design and development solutions for business-driven application, installation, processes, operation, maintenance, and administration of IT hardware and software.
2. Utilize modern computing tools and techniques in research and development projects.
3. Communicate effectively as a member or leader of the computing society with social, moral, and legal responsibilities to accomplish a common goal.
4. Engage in lifelong learning as a foundation for continuing professional advancement.

APPROVAL SHEET

ACKNOWLEDGEMENT

ABSTRACT

TABLE OF CONTENTS

Preliminary Pages **Page**

Title Page...

Vision, Mission, Quality Policy, Goals, and Objectives..................................

Approval Sheet..

Acknowledgement..

Abstract...

Table of Contents...

List of Tables..

List of Figures...

List of Equations...

List of Appendices...

Definition of Terms..

CHAPTER I: INTRODUCTION AND ITS BACKGROUND

Introduction and Its Background...

Research Problem...

Research Objectives...

Research Framework..

Theoretical Framework..

Conceptual Framework...

Scope and Limitations...

Significance of the Study..

CHAPTER II: REVIEW OF RELATED LITERATURE AND STUDIES

CHAPTER III: RESEARCH METHODOLOGY

LITERATURE CITED...

APPENDICES...

LIST OF TABLES

LIST OF FIGURES

LIST OF EQUATIONS

LIST OF APPENDICES

DEFINITION OF TERMS

CHAPTER I

INTRODUCTION AND ITS BACKGROUND

Fire safety is a major concern in the Philippines, yet its importance is often overlooked by the public. This persistent threat is clear from the very start of the year, with the Bureau of Fire Protection (BFP) reporting nine fire incidents in the National Capital Region on the first day of 2025 alone (Conejos, 2025). A big part of the problem comes from preventable hazards; BFP data shows that from January 1 to February 27, 2025, electrical issues were the leading cause of 625 fires nationwide (Rita, 2025). The BFP also points to other factors, linking the rise in fire incidents to extreme heat and fluctuations in electricity demand (Patron, 2025). This situation shows the limits of a reactive approach and points to the need for better, community-focused education that shifts the focus from reacting to emergencies to proactively reducing risk.

The scale of this challenge on a national level is significant. In 2024, the Bureau of Fire Protection recorded 18,217 fire incidents across the country, marking an 11.2 percent increase from the 16,387 incidents in 2023, with over 1,332 injuries reported (Villamente, 2024). These fires also caused an estimated P13.8 billion in property damage and 338 civilian fatalities (Chavez, 2024). These staggering national figures highlight the widespread nature of the issue and demonstrate the critical need for effective fire safety and preparedness programs at the community level.

The danger posed by these incidents is magnified in densely packed residential areas, where fires can spread with devastating speed. A catastrophic fire in the Isla Puting Bato community in Tondo, Manila, on November 23, 2024, serves as a stark example. The blaze originated in a single home (Hoey, 2024), spreading rapidly through the community's light, combustible materials to destroy approximately 1,000 houses

(Calucin, 2024) and displace 2,000 families within hours (Delizo, 2024). Such events demonstrate how structural vulnerabilities in densely built environments can turn a localized fire into a large-scale disaster, highlighting a critical risk factor present in many communities across the nation.

In Sta. Cruz, Laguna, fire safety is a major concern for the same reasons. Based on preliminary consultations with the local Bureau of Fire Protection (BFP), many high-risk areas in the municipality are characterized by high-density housing. While many structures are made of concrete, the primary hazard stems from how closely residential and commercial buildings are packed together, often with minimal to no spacing between them. This proximity means that a single fire can easily spread and endanger an entire neighborhood, a problem compounded by the municipality's mix of urban and rural zones that challenges the reach of conventional fire safety programs.

While the Bureau of Fire Protection (BFP) in Sta. Cruz is doing its best to educate the public, their current programs do not go far enough to address these specific risks. Based on consultations with Chief FINSP Cesar Morfe Jr. and FO3 Lorena Nanale, the main approach relies on social media for announcements and occasional community talks rather than structured education. These efforts are limited by several key problems: the lack of a single, centralized platform dedicated to fire safety; educational materials that are too general and not tailored to the interests of different age groups like children; and a lack of interactive tools that encourage engagement. This creates a significant gap where educational outreach is passive, leading to a situation where critical safety information is easily forgotten and fails to build the practical skills needed for proactive fire safety.

To address these issues, this study proposes the development of SafeScape, a web-based, AI-driven platform for fire safety education and risk assessment designed specifically for Sta. Cruz, Laguna. New technologies offer a chance to make fire safety programs better and more suited to local needs (Nagaraju et al., 2024). SafeScape will bring together several tools to bridge the identified gaps, including interactive educational lessons for different age groups, an AI-driven pipeline for creating dynamic 2D digital twins from floor plan images. This core feature enables agent-based modeling (ABM) to simulate evacuation scenarios, where autonomous agents with realistic human behaviors navigate complex, evolving fire spreads (Mirahadi et al., 2019). The system's evacuation strategies are optimized using deep reinforcement learning, moving beyond simple risk scores to generate proactive safety insights. This is complemented by an AI-powered chatbot for safety questions based on BFP protocols (Parekh, 2024). Furthermore, the SafeScape platform is designed with future extensibility in mind, proposing a conceptual framework for the integration of AR/VR technology. This framework outlines how immersive tools could be used for hands-on skills training, such as using a fire extinguisher (Kang et al., 2024), positioning it as a key enhancement for future versions of the platform. By integrating these modern tools, the goal is to equip residents with not just knowledge, but with practical digital tools to strengthen preparedness, encourage participation, and support a more coordinated emergency response within the community.

Research Problem

Current fire safety efforts in Sta. Cruz, Laguna, are often reactive, with significant limitations in community engagement and a lack of modern training tools for both residents and fire personnel. While the Bureau of Fire Protection (BFP) works diligently, their traditional methods such as social media posts and occasional talks are not sufficient to address the specific risks of a community with densely packed housing and a diverse population. This results in a critical gap where residents are aware of fire dangers but lack the specific, accessible education needed for proactive prevention and effective emergency response.

The absence of a centralized digital platform means that educational materials are difficult to access and are often too general to be effective for different age groups, particularly children. This lack of interactive and targeted tools hinders the development of practical skills and perpetuates a reactive mindset toward fire safety. Therefore, there is a clear need for a proactive, interactive, and inclusive digital system. Instead of predicting the likelihood of a fire, such a system should focus on assessing architectural vulnerabilities and simulating evacuation strategies. By enabling residents and BFP personnel to visualize how a fire might spread within a specific floor plan and analyze the effectiveness of different escape routes, this approach delivers personalized risk education by allowing users to visually analyze the effectiveness of different escape routes under simulated duress, thereby improving emergency preparedness and response coordination within Sta. Cruz, Laguna.

This study aims to address the following research questions:

1. How can an inclusive website be designed to effectively deliver age-appropriate educational content and interactive tools on fire safety to the community?
2. How can AI-driven digital twin simulations be implemented for modeling fire spread and assessing evacuation effectiveness, shifting fire safety measures from reactive to proactive?
3. How can immersive VR/AR training modules be created to provide safe, hands-on experience in fire scenarios for both BFP personnel and community members?

4. How can the system's usability, functionality, and effectiveness be evaluated in enhancing fire safety awareness and preparedness within the community?

Research Objectives

The main goal of this study is to design, develop, and evaluate SafeScape, an inclusive AI-driven platform that enhances fire safety, risk assessment, education, and community preparedness in Sta. Cruz, Laguna.

Specifically, it aims to:

1. To design and develop an inclusive website offering age-appropriate educational content, interactive tools, and multimedia resources on fire prevention and emergency response.
2. To implement an AI-driven digital twin simulation to model fire dynamics and optimize evacuation strategies using agent-based modeling and deep reinforcement learning within residential layouts, shifting fire safety measures from reactive to proactive.
3. To present a conceptual framework for an immersive VR/AR training module that includes information on its technological specifications, instructional design, and a clear plan for how it will eventually be integrated into the SafeScape platform.
4. To evaluate the system's usability, functionality, and effectiveness in enhancing fire safety awareness and preparedness within the community.

Research Framework

This section outlines the research framework that guides this study. It is composed of two main parts: the Theoretical Framework, which discusses the established scientific principles and existing research that form the foundation of the project, and the Conceptual Framework, which presents a specific model of the proposed SafeScape system.

Theoretical Framework

The development of the SafeScape platform is grounded in established principles from computer science, disaster management, and educational technology. This study is anchored on the recent developments in artificial intelligence, simulation, and immersive learning to support a web-based system that enhances proactive fire safety. The core philosophy of this approach is to leverage AI to shift the focus of fire safety from a reactive model centered on emergency response and recovery to a proactive model that prioritizes preparation and prevention, as conceptualized in Figure 1. To make this proactive stance tangible, the SafeScape platform operationalizes these principles through the creation of a Digital Twin, a virtual replica of a physical environment where dynamic events can be safely simulated (Z. Liu et al., 2023).

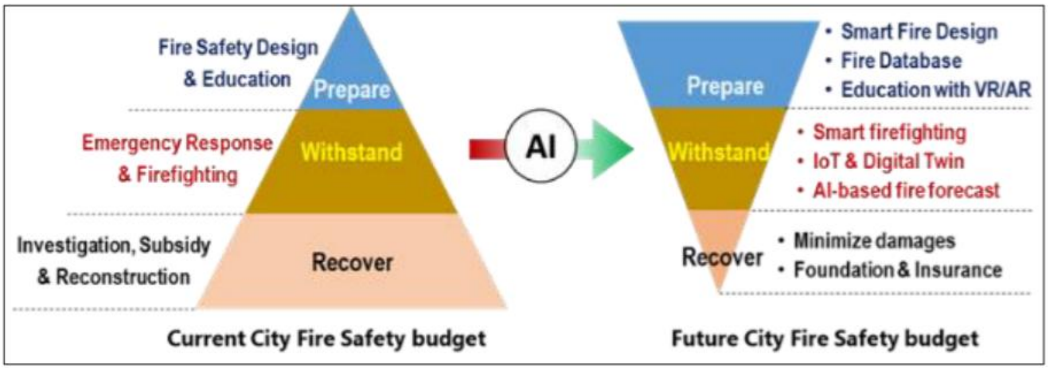

Figure 1. The vision of AI's role in shifting fire safety focus (Parekh, 2024).

The central innovation of SafeScape and its ability to assess and predict fire risk is anchored in the theory of Artificial Intelligence (AI) for predictive analytics. The use of Machine Learning (ML) models allows for this critical shift toward a proactive stance. A comprehensive review by Singh et al. (2024)on wildfire spread models reveals that ML models demonstrate superior efficiency and accuracy over traditional methods by leveraging diverse datasets for dynamic forecasting. This approach is validated on a global scale by McNorton et al. (2024), who developed a data-driven "Probability of Fire" (PoF) forecast using machine learning that outperforms existing fire danger indices. The implementation of such a model follows a structured methodology, as demonstrated by Hu et al. (2022), whose two-step machine learning process for casualty prediction provides a proven framework for developing reliable predictive systems for emergency scenarios, as illustrated in Figure 2.

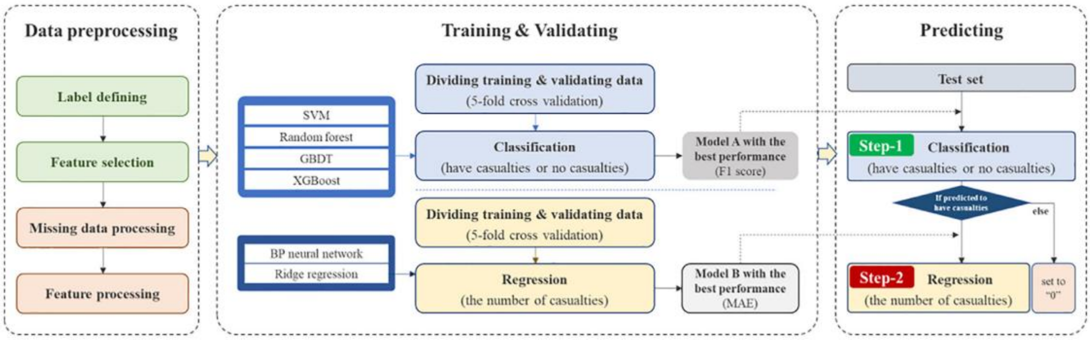

Figure 2. The two-step machine learning methodology flowchart (Hu et al., 2022).

This predictive capability is made tangible through Digital Twin technology, a virtual model of a real-world system that serves as a dynamic counterpart for simulation. As shown in the conceptual model by Liu et al. (2023), the core concept involves a continuous interaction between a physical entity and its virtual model, creating a closed loop of "perception-analysis-control" for safety management. To simulate dynamic events within this digital twin, SafeScape employs Agent-Based Modeling (ABM), a sophisticated technique for modeling the behavior of autonomous agents. Foundational work by Mirahadi et al. (2019) demonstrates a framework for integrating building models with fire dynamics and agent-based crowd simulations. SafeScape directly applies and extends this theory by using deep Reinforcement Learning (RL) to train autonomous agents that represent residents. As demonstrated by

Zhang et al. (2021a), RL is a powerful approach for discovering optimal strategies in emergency evacuation scenarios. Instead of simply predicting a static risk score, SafeScape uses RL to allow the AI to "learn" an optimal evacuation policy through thousands of interactive simulation trials, enabling the system to analyze and determine effective evacuation patterns based on the dynamic state of the environment.

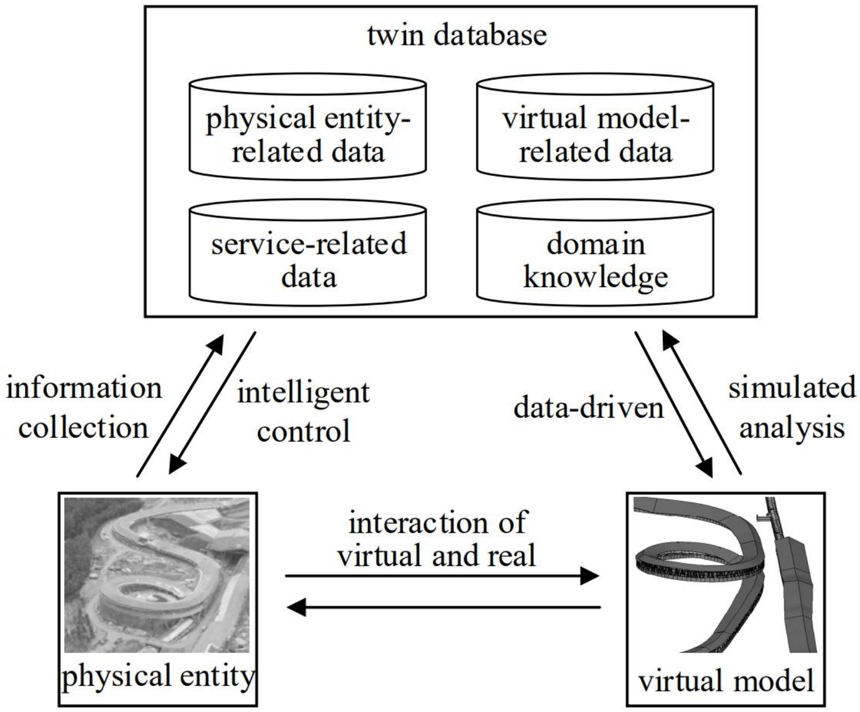

Figure 3. The conceptual model of a digital twin (Z. Liu et al., 2023).

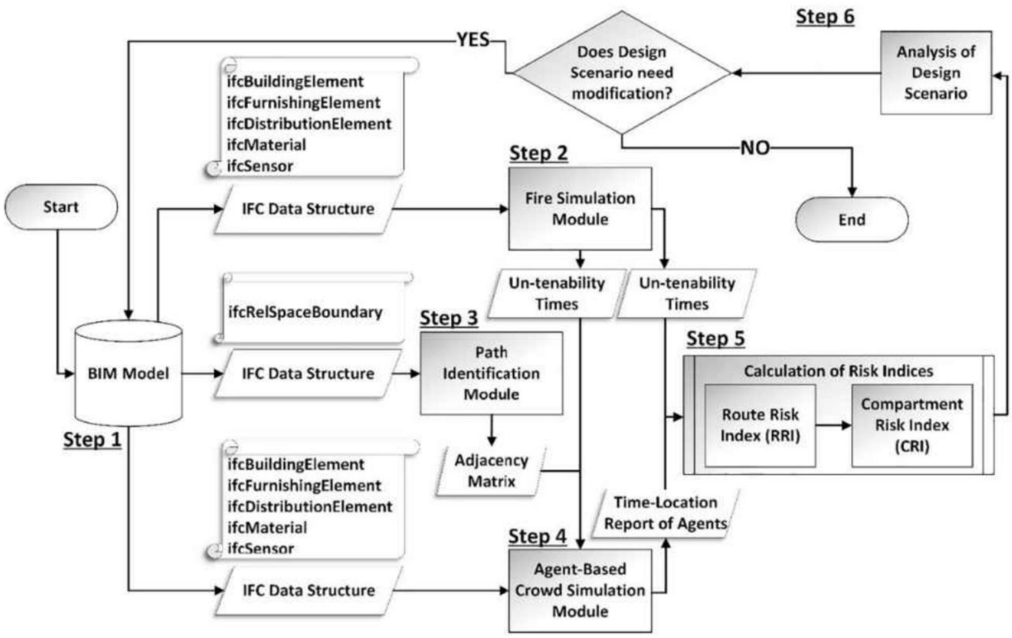

Figure 4. Framework for performance-based evaluation of building evacuations (Mirahadi et al., 2019).

However, simply visualizing risk is not enough to ensure preparedness; residents must also be trained on how to respond. Therefore, SafeScape's educational mission is supported by theories of immersive and interactive learning. To address the ineffectiveness of passive information delivery, the platform incorporates principles of Behavioral Skills Training (BST), a structured, four-step process involving instruction, modeling, rehearsal, and feedback, as illustrated in Figure 5. Research by Fu & Li (2024) on a Virtual Reality-based Serious Game (VR-SG) for fire safety demonstrated that this type of immersive and engaging training significantly improves the learning and retention of evacuation skills.

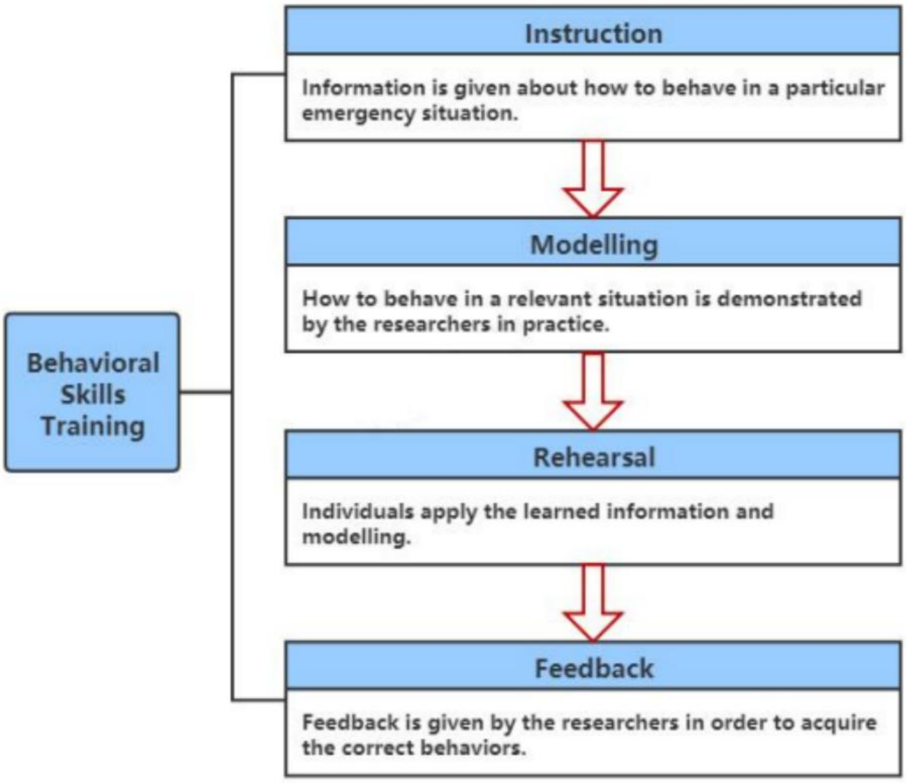

Figure 5. The four components of Behavioral Skills Training (Fu & Li, 2024).

To further enhance engagement and provide on-demand information, the platform includes an AI Chatbot grounded in the principles of Conversational AI. The successful avdoption of such a tool is supported by the Technology Acceptance Model (TAM), a foundational theory that posits that a user's intention to use a new technology is determined by its Perceived Usefulness and its Perceived Ease of Use, as shown in Figure 6. Research by De La Roca et al. (2024) applies this model to educational chatbots, emphasizing their role in enhancing user engagement through personalized, 24/7 assistance. SafeScape's chatbot is designed on this principle, providing a user-friendly interface for residents to ask fire safety questions and receive immediate, reliable answers based on BFP protocols.

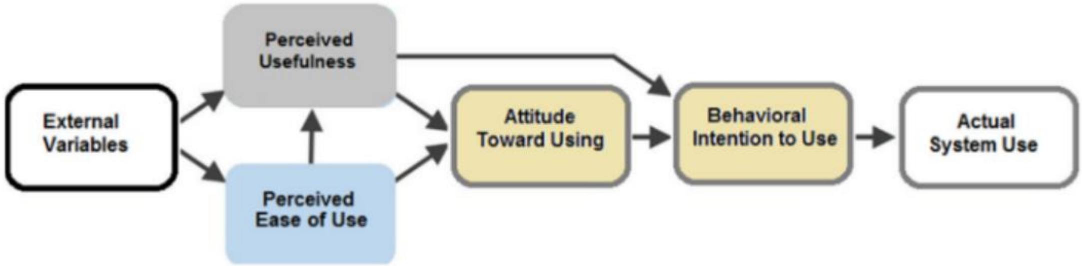

Figure 6. The Technology Acceptance Model (De La Roca et al., 2024).

Ultimately, the effectiveness of these advanced technological tools is dependent on their ability to foster genuine community preparedness. The theoretical basis for SafeScape's community-centric approach is the need to bridge the gap between perceived and actual readiness for disasters. Research by Cisternas et al. (2024) on household preparedness found that even in high-risk areas, residents rarely participate in preparedness activities, highlighting the importance of accessible tools that encourage community involvement. SafeScape is directly founded on this principle, aiming to overcome low participation by providing an engaging, user-friendly platform that promotes a proactive approach to fire safety, a critical need in vulnerable communities like Sta. Cruz, Laguna.

Conceptual Framework

The conceptual framework of this study presents the specific model for the proposed SafeScape system. As illustrated in Figure 7, this framework provides a visual representation of the system's architecture, demonstrating the logical flow of processes designed to address the identified limitations of traditional fire safety methods. It outlines how the system transforms foundational data and user-specific parameters into a predictive, interactive, and inclusive digital platform. The framework serves as the blueprint for the study, showing how each component from data ingestion to the AI simulation engine and final user outputs works in concert to shift fire safety in Sta. Cruz, Laguna, from a reactive to a proactive approach.

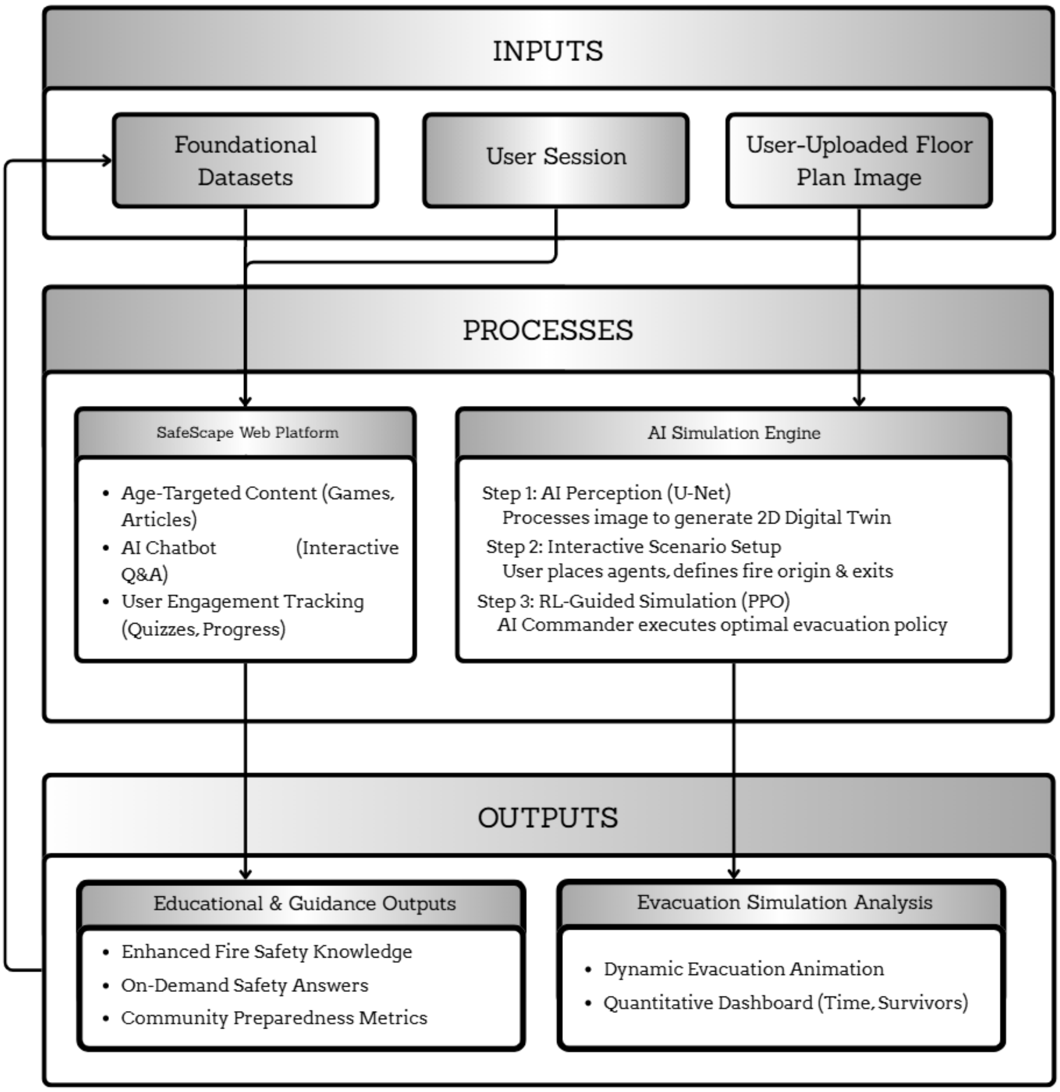

Figure 7. The Conceptual Framework for the SafeScape System

The framework's process begins with the Inputs, which are the essential data sources that power the entire system. These are grouped into three distinct components. The first, the User-Uploaded Floor Plan Image, serves as the primary trigger for the simulation engine. The second, Foundational Datasets, contains the BFP Knowledge Base the official manuals and protocols needed for accurate, tailored educational content. The third category, User Session parameters, allows for personalization during a user's interaction by incorporating details like user age to deliver age-appropriate content, ensuring the platform is both inclusive and effective.

From the inputs, data moves into the central Processes stage, which functions as the engine of the SafeScape system. This stage begins with the SafeScape Web Platform, the user-facing component that hosts the Educational Hub, AI Chatbot, and the interactive simulation interface. A user-provided floor plan image (a 2D Building Blueprint) is first fed into the system's computational core: the AI Simulation Engine.

The engine's process is realized in three key stages. First, the AI Perception Model, a trained U-Net, processes the blueprint to automatically generate a 2D Digital Twin of the environment, identifying the initial wall layout. Second, this digital twin is presented to the user in an interactive "Simulation Setup" interface. Here, the user can refine the AI's output by correcting wall segments and provide crucial context by annotating the locations of exits and firewalls. The user completes the setup by defining the simulation's initial conditions: the number and starting positions of the agents, and the origin point of the fire.

Once this complete scenario is defined, the final stage begins: the Agent-Based Simulation. This module deploys autonomous agents with realistic, human-like behaviors (such as panic and tripping) onto the digital twin. The evacuation is then managed by a pre-trained deep Reinforcement Learning (RL) agent, which executes an optimal evacuation policy to guide the agents. The engine computes the agents' evacuation patterns and routes, generating a complete history of the simulation. This complex data is then translated into intuitive, user-friendly visualizations, such as rendering the animated evacuation paths overlaid on the original floor plan.

The final stage of the framework produces the Outputs, which are the tangible, practical tools delivered to the community and are grouped into two categories. The first is the Evacuation Simulation Analysis, delivered as both a dynamic animation of the user-defined scenario and a quantitative dashboard summarizing the outcome (e.g., agents escaped, evacuation time). The second category, Educational and Guidance Outputs, includes age-targeted educational modules and provides interactive safety answers through the AI chatbot.

Scope and Limitations of the Study

This study focuses on the design, development, and implementation of SafeScape, an inclusive AI-driven platform for digital fire safety, risk assessment, education, and community preparedness in Sta. Cruz, Laguna. It aims to provide proactive, accessible, and data-informed tools for promoting residential fire safety awareness and risk mitigation.

Scope:

Geographical Focus: The project is specifically tailored for the municipality of Sta. Cruz, Laguna, and its community.

Primary Application: The system is centered on residential fire safety, providing educational resources and risk assessment tools for households.

Technological Components: The core of the project involves the development of a web-based educational platform and a sophisticated AI simulation engine. This engine is composed of three key technologies: (1) an AI Perception Model (U-Net) that generates a 2D digital twin from floor plan images; (2) an Agent-Based Model (ABM) that simulates complex, human-like evacuation behaviors; and (3) a deep

Reinforcement Learning (RL) agent that learns and executes optimal evacuation strategies within the simulation.

Training Module: The study includes the creation of a proof-of-concept VR/AR module to demonstrate potential applications for basic fire response training.

Limitations:

Generalizability: As the platform is designed specifically for the context of Sta. Cruz, Laguna, its findings and direct applicability may not be generalizable to other municipalities without further adaptation.

Data Dependency: The effectiveness of the system's AI components is dependent on two distinct factors. First, the accuracy of the AI Perception Model is highly dependent on the quality and diversity of the floor plan image dataset used for its training. Second, the effectiveness of the Reinforcement Learning agent's evacuation strategies is contingent upon the extent of its training and the fidelity of the agent-based simulation environment.

Conceptual Nature of the AR/VR Module: The AR/VR training described in this study is conceptual in nature and was not developed into a functional prototype. The primary focus of this research phase was the design, development, and validation of the core 2D AI-driven simulation engine, combining perception, agent-based modeling, and reinforcement learning, which serves as the foundational element of the SafeScape platform.

Significance of the Study

This research will contribute significantly to improving fire safety management by combining the technological expertise of the College of Computer Studies with the operational knowledge of the Bureau of Fire Protection (BFP). The development of the SafeScape platform is expected to provide substantial benefits to various stakeholders within the community of Sta. Cruz, Laguna.

The study will be beneficial to the following:

Community Residents. The platform will empower residents, including children, teens, and adults, with the knowledge and digital tools needed to proactively prevent and effectively respond to fires. Age-appropriate educational modules and interactive evacuation simulation tools will help foster a culture of preparedness at the household level.

BFP Sta. Cruz Personnel. SafeScape will serve as a modern digital platform and a strategic analysis tool to support and augment the BFP's public education and preparedness campaigns. The immersive VR/AR training modules will offer a safe and repeatable method for enhancing firefighter skills and readiness.

Schools and Educational Institutions. The platform will provide interactive, BFP-standard resources that can be used for more effective fire safety lessons and drills, helping to integrate modern safety education into the curriculum.

Barangay Leaders and Local Government Units (LGUs). Local leaders can utilize the platform to enhance community-wide preparedness campaigns, identify high-risk areas through the system's analytics, and promote a more coordinated emergency response strategy.

Future Researchers. This study will serve as a practical model for how an integrated system of AI perception, agent-based modeling, and deep reinforcement learning can be applied to improve disaster resilience in other municipalities, contributing to the broader fields of community resilience and smart emergency management systems.

CHAPTER II

REVIEW OF RELATED LITERATURE

This chapter presents a comprehensive review of related literature and studies which provide the theoretical and technical foundation for the development of SafeScape platform. The information presented was collected from various sources, including academic journals, articles, and previous research. This review will help the reader better understand the key concepts of the study and will provide the necessary foundation to justify the purpose and goals of the SafeScape project.

Proactive Fire Safety and Community Preparedness

Fire safety has long been recognized as a cornerstone of community resilience, yet in many regions, strategies remain predominantly reactive, focusing on suppression and emergency response after a fire incident has already occurred (Oboh et al., 2023). While such reactive approaches such as alarm systems, firefighting operations, and evacuation drills are essential for minimizing immediate damage, they often fail to address the root causes and conditions that enable fires to ignite and spread (Singla & Kaur, 2020). This overreliance on post-incident action leaves communities vulnerable, as hazards remain unmitigated until they escalate into emergencies.

In recent years, researchers and practitioners have called for a paradigm shift toward proactive fire safety management, which prioritizes prevention, early detection, and preparedness (Steen-Hansen et al., 2021). Proactive strategies leverage technological innovations such as artificial intelligence, predictive analytics, immersive learning environments, and data-informed decision-making to identify hazards before they materialize (Singla & Kaur, 2020). They also emphasize building community awareness and engagement, as demonstrated in wildfire management initiatives in

British Columbia, Canada, where education and participatory approaches were found to be the most widely supported proactive interventions (Copes-Gerbitz et al., 2022).

In the context of Sta. Cruz, Laguna where mixed residential layouts, limited safety infrastructure, and high population density present unique vulnerabilities there is an urgent need for integrated, technology-driven solutions. SafeScape is designed to address this gap by combining AI-driven predictive modeling, interactive fire safety education, VR/AR-based training, and risk assessments simulations into a single, accessible platform.

Fire safety research reveals a clear evolution from reactive to proactive models. At a human-factors level, elevated stress reactivity during emergencies can impair judgement and slow adaptive behavior, reinforcing the need to build capacity before crises (Kiecolt-Glaser et al., 2020). Oboh et al. (2023) highlighted how traditional firefighting relied heavily on suppression after incidents occurred, often leading to significant losses. Similarly, Steen-Hansen et al. (2021) emphasized the limits of reactive strategies, noting that prevention and preparedness consistently produce more sustainable outcomes. Singla and Kaur (2020) further demonstrated that integrating preventive frameworks significantly reduces fire-related casualties compared to reliance on post-event response. Complementing this, Mohammadi et al. (2020) provided empirical evidence showing that proactive safety measures directly correlate with reduced accident rates, underscoring the measurable benefits of prevention over reaction. Even with this shift, evacuation planning remains a vital reactive layer; a recent synthesis found that strategies such as vehicle reduction, phased evacuation, and temporary parking restrictions can improve clearance times in specific contexts but are not universally transferable (P. Li et al., 2024).

This shift in perspective has been accelerated by technology. Valarmathi and Ramkumar (2024) examined how Deep Learning and IoT provide predictive capabilities that move fire management into a proactive paradigm. Park (2024) reinforced this through South Korea's Forest Disaster Management System (FDMS), which combines GIS, drones, and big data to predict and monitor wildfire risks in real time. Complementing these hazard-focused systems, Barua et al. (2024) outline a proactive building fire risk management framework for the construction sector, clarifying lifecycle governance and process gaps that impede prevention at the project and organizational levels. Lacey et al. (2025) expanded the conversation by showing that proactive wildfire management can and should integrate social vulnerability and ecological value, highlighting the importance of inclusive, forward-looking fire safety planning. Together, these studies illustrate the paradigm shift from reaction to prevention, supported by both empirical evidence and technological innovation.

While technology advances, community engagement remains central to preparedness. Ryan et al. (2020) conducted a systematic review of disaster preparedness initiatives and found that face-to-face, participatory methods consistently outperformed mass media in building readiness and collective responsibility. Johnston et al. (2022) advanced this by presenting a conceptual model that traces the progression from agency-led efforts to genuine community-led preparedness, stressing risk personalization and local context. Ridzuan et al. (2020) echoed these findings in Southeast Asia, demonstrating that community trust and collaboration amplify the effectiveness of safety programs.

Building on these theoretical foundations, practical implementations provide concrete examples. Bali (2022) explored participatory fire management models, showing that involving residents in hazard mapping and drills enhanced local capacity. Flora (2025) highlighted the Community Fire Auxiliary Groups (CFAGs) in La Trinidad, Benguet, where trained volunteers acted as first responders, conducted awareness campaigns, and served as bridges between residents and the Bureau of Fire Protection. Similarly, Ruspanah et al. (2025) documented fire safety training in Ambon City, Indonesia, where hands-on education and practice significantly raised local knowledge of fire risks. Pike et al. (2024) described Canada's LEAD Fire Safety Toolkit, an evidence-based workbook guiding communities through structured preparedness steps, while Restaino and Eusden (2024) emphasized the role of private-sector professionals in creating defensible spaces through specialized certification. Together, these studies demonstrate that community preparedness whether through volunteers, structured toolkits, or professional training forms the backbone of proactive fire safety.

Despite these advances, vulnerabilities persist, particularly in densely populated and underserved areas. Marindayanti et al. (2024) examined preparedness levels in Samarinda City, Indonesia, where urban density and limited resources constrain fire readiness. The findings show that structural vulnerability magnifies fire risks, underscoring the need for tailored preparedness systems.

Although proactive frameworks and community initiatives demonstrate effectiveness, implementation challenges remain. Copes-Gerbitz et al. (2022b) revealed that fragmented strategies and inconsistent alignment with community needs often weaken fire safety programs, particularly in Indigenous contexts. Similarly, gaps in training participation (Renato Jr M Flora, 2025) and barriers to information dissemination (Ruspanah et al., 2025) highlight the persistent difficulties in sustaining engagement.

Current research demonstrates strong progress in both technological innovation and community-based strategies. However, gaps remain in integrating behavioral change theories, governance frameworks, and interdisciplinary approaches into fire safety planning. Studies such as Lacey et al. (2025) suggest expanding beyond hazard prediction to include social equity and ecological value, while Johnston et al. (2022) emphasize tailoring engagement frameworks to diverse populations.

Artificial Intelligence and Predictive Analytics in Disaster Management

The growing frequency and intensity of natural disasters caused by climate change have significantly increased the demand for advanced technologies to enhance disaster management and risk reduction. According to Tan et al. (2021), there has been a notable rise in natural disasters due to global climate variations. In response, artificial intelligence (AI) has been increasingly applied to handle nonlinear and high-dimensional data, achieving high levels of accuracy and efficiency. These characteristics make AI particularly suitable for various disaster management activities.

Tan et. al. (2021) conducted a systematic review of 278 studies applying AI across different stages of disaster management. Their analysis explored how methods such as machine learning (ML), data mining, and hybrid models have been utilized for hazard forecasting, damage assessment, response optimization, and recovery planning. They also identified methodological gaps such as poor model interpretability, data heterogeneity, and limited context-specific applicability.

Similarly, Sun et. al. (2020) reviewed the application of AI throughout the four main phases of disaster management mitigation, preparedness, response, and recovery. Their findings highlighted the broad use of AI methods for hazard forecasting, decision support, and resource allocation. However, they noted an overemphasis on the response phase, along with recurring issues related to model transparency and the integration of heterogeneous data. Collectively, these studies underscore the transformative potential of AI in disaster risk management while also emphasizing the need for interpretable and data-driven frameworks.

Adami et. al. (2021) conducted an experimental study comparing VR-based training and traditional in-person instruction for construction workers operating a demolition robot. Their findings showed that VR training resulted in significantly greater gains in knowledge, operational skill, and safety behavior compared to the in-person method).

AI techniques play a critical role in enhancing situational awareness and decision-making across all stages of disaster management. Abid et al. (2021) presented an integrative review examining how AI, Geographic Information Systems (GIS), remote sensing, and data analytics are collectively used in mitigation, preparedness, response, and recovery. Their findings demonstrate that AI significantly enhances mapping accuracy, hazard monitoring, and rapid response capabilities. Furthermore, the integration of these technologies allows for improved situational awareness in complex environments. Despite these advantages, Abid et al. (2021) emphasized enduring challenges related to data integration, model interpretability, and the unequal accessibility of advanced technology between regions.

Accurate disaster prediction depends heavily on the effective integration of diverse data sources. Li et. al. (2024) introduced StreetViewLLM, a framework that merges large language models (LLMs), chain-of-thought reasoning, and multimodal data inputs such as street-view images, geographic coordinates, and textual information. Applied across seven global cities, this framework demonstrated superior performance in predicting urban indicators like population density, building height, and land use when compared to baseline models. Although not specifically designed for disaster management, StreetViewLLM exemplifies how multimodal data fusion and large-scale AI reasoning can improve spatial understanding capabilities highly relevant for predictive disaster analytics.

In the field of real-time disaster prediction and response, Davila et. al. (2022) introduced ADAPT, an open-source payload designed for small unmanned aircraft systems (sUAS). This system integrates AI and computer vision for disaster monitoring and response missions. The payload includes a camera, processor, navigation system, and wireless communication interface, enabling onboard analytics such as image segmentation. In their validation case study focused on river ice segmentation for flood prediction, the authors demonstrated how ADAPT can deliver near real-time, georeferenced insights. Additionally, the integration of active learning in the model refined predictive performance during deployment, highlighting the potential of AI-enabled autonomous systems in disaster forecasting.

AI-driven disaster management systems offer several clear benefits across different domains of application. Cao (2023) outlined how AI and data science can facilitate a paradigm shift from reactive disaster management approaches toward proactive and intelligent resilience frameworks. The author introduced the concept of

AI for Smart Disaster Resilience (AISDR), emphasizing the potential of AI in addressing emergencies ranging from natural disasters and pandemics to misinformation crises. Cao (2023) also identified core research areas such as cross-domain AI modeling, data complexity management, and translational disaster AI, where insights from theoretical models are applied to real-world emergency contexts.

Despite their success, AI models in disaster management continue to face major limitations. Velev and Zlateva (2023) analyzed the challenges in applying AI to disaster risk management and found critical issues related to data quality, data diversity, integration with legacy systems, and ethical concerns, including privacy and social implications. They concluded that although AI holds significant potential for forecasting and decision support, its effectiveness depends on addressing these foundational challenges.

In a related study, Ghaffarian et. al. (2023) performed a systematic literature review of 68 studies focusing on explainable AI (XAI) within disaster risk management. Their review highlighted persistent challenges such as the “black box” nature of many AI models, the lack of interpretability, data heterogeneity, and the gap between model complexity and user trust. They also proposed future research directions involving the combination of XAI with digital twins, causal inference, and more integrated early warning systems. Together, these works point to the growing recognition of the importance of transparency and trust in AI-assisted disaster prediction and response.

Building on the identified gaps, recent literature points toward more explainable, multimodal, and hybrid AI frameworks. The integration of XAI within predictive disaster systems is increasingly emphasized as a way to improve stakeholder trust and interpretability (Ghaffarian et al., 2023). Similarly, Li et al. (2024)

demonstrated the potential of multimodal data integration and reasoning in improving spatial predictions, suggesting a broader future role for LLM-based and multimodal AI architectures in disaster analytics.

The emergence of AI-driven digital twins virtual replicas of physical systems capable of simulating disaster impacts is another promising trend noted in recent reviews (Cao, 2023; Ghaffarian et al., 2023). These trends collectively indicate a movement toward AI systems that are not only more powerful but also more transparent, contextualized, and responsive to human oversight.

Simulation Technologies for Risk Visualization

According to the study of Hosamo et al., (2022) Digital Twins is a broad concept that has many implications but the goal is always to create an emulation of the thing it is mirroring. Several industries are now using this concept more specifically engineering, space and air force, marine offshore, and aerospace thanks to that there are now multiple definitions however CIRP's definition of digital twin covers most fields and applications "A digital twin is a digital representation of a unique active product (real device, object, machine, service, or intangible asset) or unique product-service system (a system consisting of a product and a related service) that comprises its selected characteristics, properties, conditions, and behaviors through models, information, and data within a single or even across multiple life cycle phases."

In the study of Chen et al., (2023) states that smart homes are now more appealing due to wearable and wireless technology while digital twins are emerging game changers due to improved visualization, interactability, real time monitoring, anomaly prediction, intelligent interaction, and life cycle management. Digital Twin is capable of creating a real time visual representation and has the objective of healthcare monitoring in smart homes.

In the study of Yang et al., (2024) stated that construction is suffering from low productivity, lack of expertise, weak innovations and digital twin could solve those problems by pushing towards efficiency by using digital twin to strive for a precise simulation of phases necessary in a building project.

Meanwhile in the study of Qian et al., (2022) focusing on IoT (Internet of Things) and Digital Twin uses digital twin in order to avoid the risk of manipulating and updating the real system via the creation of a digital twin to find a way to solve said problems.

However in the study of Wang et al., (2023) focusing on IoT devices as well but for sustainable blockchain states that as IoT devices increase sustainability becomes a bottleneck and inefficient management and scarce resources can delay development and that digital twin can facilitate the interaction between IoT and digital services.

Agent-based modelling (ABM) has become a widely used approach for simulating complex systems, particularly those involving individual behaviors and interactions that collectively shape outcomes. Kaniyamattam (2022) traces the history of ABM from its origins in cellular automata to its current applications across ecology and social systems. This background underscores ABM's suitability for modeling dynamic human behavior in crises, reinforcing its relevance to fire preparedness. Building on this, Evans et al. (2023) demonstrate how spatial ABMs can capture human–environment interactions during hazards, while their work on graph-based ABMs shows how social ties influence collective responses.

ABM has been widely applied to model evacuation and disaster preparedness scenarios. Kwak et al. (2020) simulated evacuation dynamics in crowded facilities, showing how individual decision-making affects collective escape efficiency. Zhang et al. (2021b) developed an agent-based simulation of fire evacuations in built environments, systematically varying exit locations, exit widths, and initial crowd densities to measure evacuation times, flow patterns, and bottlenecks. Their results showed that strategic exit placement and lower crowd density markedly reduce evacuation time and risk. Beyond fire, Alhaider et al. (2025) applied ABM to healthcare crisis management, emphasizing how agent interactions shape resource allocation and insight transferable to evacuation planning. Fani et al. (2025) modeled waste management systems with ABM, highlighting its usefulness for infrastructure resilience, while Barua et al. (2024) applied ABM to assess fire safety in buildings, showing how occupant movement patterns, building design, and evacuation strategies interact to influence evacuation efficiency and risk outcomes, providing insights that SafeScape can adapt for proactive fire preparedness planning.

Several studies have advanced ABM by expanding its technical capabilities. Anjum et. al. (2023) developed TBAM, an ABM that replicates how users behave on Twitter during real events, generating realistic communication patterns from incomplete data. Boosse (2022) created the JavaScript Agent Machine (JAM), a lightweight ABM platform that runs in web browsers, enabling distributed simulations accessible to non-experts.

Similarly, Chiew, Amerudin, and Mohamed Chiew et. al. (2022) explored ABM in flood management, emphasizing the integration of sensor and geospatial data for more accurate disaster response models. Together with Cozzi et al. (2025) who proposed a framework named Learning Individual Behavior in Agent-Based Models with Graph Diffusion Networks. Their method learns individual agent behaviors from ABM simulation traces by combining graph neural networks (to model agent interactions) with diffusion models (to capture stochastic behavior). They validated the approach using classic ABMs like the Schelling segregation model and predator-prey ecosystems, showing it can replicate both micro-level agent patterns and macro-level emergent dynamics and Li et al. (2025), who examined how meta-modeling techniques (like linear regression, generalized additive models, and neural networks) can reduce stochastic noise in cost-effectiveness analyses (CEA), while preserving the uncertainty in model parameters. They apply these techniques to both a simpler “Sick-Sicker” Markov model and an agent-based HIV transmission model, showing that meta-modeling makes the simulation outcomes more stable and interpretable. introduced advanced methods for learning agent rules and stabilizing outcomes.

Case-based research shows how ABM can inform disaster strategies. Anantsuksomsri and Tontisirin (2022) reviewed disaster management in Thailand and highlighted the importance of integrating local knowledge into ABM frameworks. Anjum et al. (2023) applied ABM to study information diffusion on social networks, demonstrating its potential for crisis communication planning. Fani et al. (2025) showed ABM’s role in optimizing waste management systems, while Alhaider et al. (2025) modeled healthcare system responses during emergencies.

Despite its promise, ABM faces notable limitations. Li et al. (2025) highlighted the problem of stochastic variability, which can obscure clear results if not properly managed. Evans et al. (2023) discussed calibration challenges when empirical data are limited, a common issue in disaster contexts. Chiew et al. (2022) pointed out difficulties in integrating heterogeneous datasets, especially when models rely on multiple data sources.

Emerging research indicates that ABM is increasingly merging with data-driven and AI-based approaches. Cozzi et al. (2025) demonstrated how agent rules can be learned from data using graph diffusion methods, while Li et al. (2025) showed how meta-modeling can balance uncertainty with interpretability. Anjum et al. (2023) highlighted the use of ABM to generate synthetic communication data when real datasets are incomplete.

Immersive and Interactive Learning for Safety Education

Currently kids aged between 4-10 are now more active and play games due to the accessibility of phones, wifi, and even mobile data. Gamification has been applied in education for a better educational system with the goal of increasing a students focus, motivation to learn, and provide positive and fun interactive experiences to solve the problem of kids evasion, lack of motivation to learn certain topics such as fire safety and fire prevention. Games are interactive and can hook kids attention with fun and interactive game elements.

According to Saptiany et al., (2024) Students from Gen Z are increasingly using gamification which is improved by AI in language acquisition. Applications for gamified language acquisition are praised for their capability to improve vocabulary. They utilized SEM Structural Equation Modelling for data gathering through questionnaire and the results showed gamified vocabulary with AI assistance is very effective

Meanwhile in the study of Boja et al., (2024) Institution must adapt, embrace, and effectively utilize the possibilities that NTIC (New information and Communication Technologies) offers in today’s changing time especially during challenging times such as the pandemic as computers are becoming essential tools for learning in an active way.

In sustainable development gamification has been used in the studies of Di Paolo & Pizziol, (2024) to investigate how gamified system applied to a game based educational program can promote better practices regarding water usage and found that playing board games can enhance children's view on the environment and promotes sustainable behavior.

According to Becerra-Fernández, (2022) This type of active style must be used in the classroom because in the field of education, demotivation and a lack of enthusiasm in learning have become common issues. Gamification is therefore regarded as an important educational approach that provides advantageous experiences and encourages kids to learn more significantly, which means an increase of their motivation level and fundamental psychological demands.

Meanwhile in Navarro-Espinosa et al., (2022) research paper he stated that gamification appears to be an essential technique for developing suitable and long-lasting HEIs, mostly through performance enhancement and incentive. Gamification's relevance and application can improve learning in any topic, making scientific fields more relevant.

Now in the study of Fathi Najafi et al., (2025) stated that one aspect of human nature that encourages participation in collective projects is play. New teaching techniques have surfaced and are being employed today.

Gamification is one of these creative teaching strategies. The employment of game aspects in non-gaming settings is known as gamification. Gamification has the potential to boost people's motivation to learn. Gamification of instruction aims to improve learners' communication and internal and external motivations while maintaining their independence and earning the educated title in a serious setting. Gamification of education, particularly through digital games, can enhance creativity and problem-solving abilities while also expanding player knowledge because of the game's integration.

While in the study of Gkintoni et al., (2024) stated that the rapid growth of digital technology usage among children can be used to promote their physical and mental health through the application of gamification and states that promoting health is crucial to the wellbeing of kids and teenagers. The growing popularity of digital technology has made gamification a viable approach to encouraging and involving youth in health-related activities. And that using games can positively impact children’s behavior and improve health outcomes.

Now according to El-Tanahi et al., (2023) study they found out that many skills can be enhanced through the application of gamification and the skills are the following learning, cognitive, social, personal, and health behavior skills In terms of improved learning abilities and experiences, the authors found that gamification was effective in raising user engagement in the course, learning outcomes and experiences across a range of subject areas, and their constructive contribution to their educational journey.

Meanwhile in the study of Faculty of Engineering, Universitas Negeri Padang, Padang, West Sumatera, Indonesia & Nabawi, (2024) examines the outcomes of creating mobile gamification as an innovative teaching tool instrument for workplace safety and health that seeks to promote secure working conditions, as well as raise students' awareness of possible risks in the machining workshop.

In their study Khaldi et al., (2023) stated that university teaching practices have changed in recent years, and practically all institutions of higher learning now offer courses and learning activities via e-learning platforms. And that there is an alarming rate of dropout and low completion rates and the reason is the low level of student engagement and motivation. Applying game design aspects to non-gaming activities is known as gamification, and it has been used to combat learner distraction and increase student engagement in the classroom.

The study of Rincon-Flores & Santos-Guevara, (2021) focuses on Gamification during covid 19 due to the changes that occurred to accommodate learning in all levels. Keeping in line with the issues at hand during the pandemic they aimed to use the gamification techniques in an online environment using Zoom platform and show how a reward based system can be used to attract student attention, engagement, and keep their motivation to learn up.

Meanwhile in the study of Murillo-Zamorano et al., (2023) in their study stated that gamification has started to attract attention in higher education and that the problem is the relationship between gamification and students knowledge, engagement, and satisfaction is not explored enough whether it be theoretically or empirically. Due to this they proposed the 8 Pointed Higher Education Gamification Star, a conceptual framework that can have an improvement towards teaching and learning process that can be replicated in other higher education settings.

In another study by Huseinović, (2023) they highlighted the need of integration of game elements in courses all thanks to the presence of smartphones and application in students lives and that game based language applications has high potential to engage with students and can pique their interest and motivation to learn a new language and their proof of this are apps such as Duolingo, Bussuu, Babbel, and memrise. Students are more drawn towards these apps due to accessibility, entertaining and engaging, and convenience to use anytime anywhere.

Now in the study of Pineda-Martínez et al., (2023) focuses on the SDG. They stated that Gamification more specifically game based learning, and video games have evolved into various tools and ways to improve the learning process. The purpose of their study is to examine how games and technology can be used to support sustainability in education more specifically towards higher education.

In the study of Catedrilla et al., (2021) they stated a problem that the Philippines is facing and it is the amount of disasters more specifically natural disasters such as storms, earthquakes, typhoons, heat, etc. And that most Filipinos have a lack of knowledge when it comes to disaster preparation especially the teenagers and the solution they came up with is gamification. They planned to develop a mobile-based game that aims to spread awareness on what to do during disasters.

Meanwhile in the study of Ali Pitchay et al., (2024) focuses on the poor self rating of disaster preparedness knowledge. Even though their government has taken action to control disasters, community-level readiness is still lacking. The purpose of this study is to assess the target users' present knowledge and practices about disaster preparedness. In order to improve catastrophe preparedness and resilience, we create a user-centered mobile application that blends educational and entertaining components. DisasterPrep uses a metaverse concept to create a three-dimensional (3D) virtual world that simulates disasters in Malaysia by gamifying the experience and encouraging user participation.

As for Crosby et al., (2025) states that games are offering a promising way to get people interested in climate-related concerns, especially young people. And in order to assist locals with numerous aspects of hazard preparedness, efforts are being made to create gamified experiences and serious games, such as those that are especially centered around wildfires and that currently, drills, tabletop exercises, and presentations are used to educate locals in hazard preparedness. There is a great chance to modernize and gamify preparedness training through virtual exercises because virtual reality (VR) is becoming more and more accessible and affordable. To answer this call to action, we created the Fire Evacuation in Virtual Reality (FEVR) training game to get locals ready for what it would be like to evacuate before a wildfire.

Meanwhile in the study of Bai et al., (2024) focusing on disaster education due to climate change states the importance of disaster education especially due to the unpredictability of nature. Now people's reaction towards the unpredictability can be improved through education and training and they aimed to use gamification to demonstrate its potential in helping with disaster response.

Now in the study Wulandari et al., (2023) says that gamification is the right approach when it comes to providing awareness for students that would face natural disasters at any point in time.

Following up is the study Bai et al., (2025) Currently there is an issue with traditional teaching methods and that issue is disengagement and lack of enthusiasm to learn when it comes to studying. And now gamification teaching methods have proved that it has potential to enhance knowledge on emergency response, decision making, and teamwork in disaster nursing education and be effective in engagement.

Now in the study of Kankanamge et al., (2022) study provides a view that gamification of learning can be applied to disaster learning for community awareness especially now that there is a demand for change in disaster education for public safety and to be prepared in case the worst case scenario happens and a natural disaster occurs.

Gamification can not only be applied in fires whether it be natural fire or man made, it can also be applied in earthquakes as stated in the study of Saptaputra et al., (2024) in this study is the approach “Disaster Resilience” for high school teachers and students. The project applied gamification to act as a knowledge enhancer in a disaster prone region.

Garzón et. al (2020) conducted a meta-analysis of 46 empirical studies to examine how different pedagogical approaches (for example, collaborative learning, inquiry-based learning) influence the effectiveness of augmented reality (AR) interventions in education. Their findings indicate that AR interventions designed with collaborative pedagogical strategies produce larger effects on student learning outcomes than those using less interactive methods. This is relevant to SafeScape because it suggests that VR/AR components will be most effective when they are not just visually immersive, but also structured with active, collaborative learning.

Bodon (2024) argues that Virtual Reality (VR) and Augmented Reality (AR) are not just about creating alternate worlds, but about how we “assemble symbols” signs, images, sounds to interact with reality, using Peirce’s semiotics. The study treats VR/AR as “symbolic assemblies” that don’t replace reality but extend our sensory and cognitive engagement with it. Bodon’s work is mostly theoretical, examining how VR/AR reshape understanding and perception rather than testing particular training outcomes.

Juma et. al. (2022) examine how augmented reality (AR) and virtual reality (VR) can be used to enhance real-time learning experiences. Their chapter highlights the role of AR/VR in creating interactive, engaging environments where learners receive immediate feedback and can actively participate in realistic scenarios rather than passively consuming content.

Mathew & Pillai, (2022) review how immersive technologies (including virtual reality, augmented reality, and mixed reality) are used in healthcare training to improve competencies. They examine uses, benefits, and adoption challenges, and note how skills learned in simulations can transfer to real clinical settings. This is relevant to SafeScape because the VR/AR portion of your project aims to simulate fire scenarios (evacuation, use of equipment, safe behavior).

Juanes-Méndez et al., (2022) examine how immersive virtual reality (VR) and augmented reality (AR) simulations are used in medical training, exploring how these technologies enhance procedural learning, decision-making, and skill retention. They discuss how learners perform better when simulations are realistic, interactive, and include elements that mimic real-world emergencies.

Andrews, And Nelson (2022) explores a transmedia solution combining immersive simulation and augmented reality (AR) to train healthcare personnel in responding to the opioid crisis. The study examines how AR and simulation can be integrated across platforms to enhance training in identifying, intervening, and managing opioid misuse.

Koutitas et. al. (2021) evaluate how augmented reality (AR) and virtual reality (VR) training technologies perform for Emergency Medical Services (EMS) first responders. They compare metrics like accuracy, time-on-task, and learning rate across AR/VR training and traditional methods, using a design-thinking framework for real case simulations ("Ambulance Bus" scenario). Their results show that AR/VR training can improve accuracy substantially and reduce task execution time.

Daling and Schlittmeier (2024) conducted a scoping review of 24 studies that examine how AR, VR, and mixed reality (MR) trainings affect both objective performance (e.g., speed, accuracy) and subjective impressions (e.g., usability, satisfaction) in manual assembly tasks. They found that AR-based training often improves performance measures and is generally viewed favorably by participants, while VR-based training tends to perform as well as traditional methods but with more variability depending on hardware and task type.

Almaguer et al., (2023) explore how augmented, virtual, and immersive reality are used as learning supports within the TEC21 educational model. They examine how these technologies are integrated into classroom teaching to improve student engagement, motivation, and interaction. Their study finds that immersive realities enhance learning experiences by making content more engaging and interactive than traditional methods.

Kaplan et al., (2021) conducted a meta-analysis that reviewed empirical studies on VR, AR, and MR training to see if these technologies transfer well to real-world performance. They found that XR (extended reality)-based training is as effective as traditional methods in improving performance, which means users trained in VR/AR/MR do not perform worse than those trained by conventional means.

Chen et al. (2020)conducted a meta-analysis of 12 studies with 821 participants to evaluate how virtual reality (VR) affects nursing education, looking at outcomes such as knowledge, skills, satisfaction, confidence, and performance time. Their results show that VR significantly improves knowledge, but does *not* outperform other educational methods (e.g. traditional or simulation-based) in improving skills, satisfaction, confidence, or performance time.

Wu et al. (2020) conducted a meta-analysis of 35 randomized controlled trials or quasi-experimental studies (from 2013-2019) that compared immersive virtual reality (IVR) using head-mounted displays (HMDs) with less immersive methods (desktop VR or traditional instruction). They found that IVR with HMDs led to better learning performance overall, though the effect size was small (ES = 0.24). They also identified moderators: IVR was more effective for K-12 learners, in science or skill-based domains, when simulation or virtual worlds were used, and in comparison to lecture-based methods.

Basu, et al. (2023) explore how differences in spatial navigability in virtual reality (VR) environments affect users' privacy concerns. They point out that VR systems often track detailed user movement and behavior data like how a user moves, where they look which can make users uneasy. The study proposes machine learning based algorithms that can learn cooperatively with human users to reduce those privacy concerns, and suggests these methods could extend to augmented reality (AR) as well.

Liu et al., (2024) conducted a user study (N = 20) comparing real AR scenes with VR simulations of those AR environments ("virtual windows") to examine their effects on task performance and cognitive workload (measured via EEG and subjective questionnaires). They found that VR can effectively simulate AR content with similar performance, though frequent visual shifts (e.g. looking down to check a keyboard) increased cognitive workload.

Hanke et al., (2025) developed a virtual reality (VR) application using 360° video to train medical students in patient handover using the ISBAR communication method. They evaluated usability, immersion, eye strain, motion sickness, and confidence among students, comparing those who used VR training plus peer tutor support to those who followed the standard curriculum. Their results showed that students felt more confident in giving handovers after the VR training, with few issues of motion sickness or eye strain, though objective exam scores did not significantly differ between groups.

Wan et al., (2025) conducted a randomized, pilot trial to test whether a dual-task brain-computer interface (BCI) training protocol combining motor imagery (MI) and virtual reality (VR) could improve balance and attention among stroke patients compared to conventional pedaling training. Over 4 weeks, participants in the MI-VR dual-task group showed significantly greater improvements in balance (measured by the Berg Balance Scale), mobility (Timed Up and Go), and attention indices (Symbol Digit Modalities Test) than those in the control group.

He et al., (2025) conducted a randomized controlled trial with 48 ischemic stroke patients to test a brain-computer interface (BCI) rehabilitation system that integrates motor imagery (MI) and motor attempt (MA). The intervention group used real-time feedback via EEG, a virtual reality training module, and a robotic assist device, while the control group used similar hardware without real-time feedback. They found that the intervention group showed significantly greater improvement in upper limb motor function (measured via the Fugl-Meyer Assessment), increased muscle activity (EMG), and enhanced neural connectivity (fNIRS) after two weeks of training.

The emergence of Virtual Reality (VR) and Augmented Reality (AR) has transformed traditional learning environments by enabling immersive, experiential, and interactive educational experiences. Garzón et al. (2020) conducted a meta-analysis of 46 empirical studies to determine how pedagogical strategies influence AR's effectiveness in education. Their findings indicated that collaborative and inquiry-based approaches yielded significantly stronger learning outcomes than passive instructional methods, suggesting that AR interventions grounded in active engagement and social interaction enhance knowledge retention and conceptual understanding. This aligns with Kolb's Experiential Learning Theory, which emphasizes the cyclical process of concrete experience, reflection, conceptualization, and experimentation processes that VR/AR technologies can actively support through realistic simulation and iterative feedback.

Expanding the theoretical discourse, Bodon (2024) interprets VR and AR as symbolic assemblies through the lens of Peirce's semiotics. Rather than being alternate realities, VR/AR are viewed as extensions of human perception and cognition, restructuring how learners interpret and interact with their environments. This theoretical lens positions immersive learning as both a technological and semiotic process, enhancing the cognitive and emotional depth of experiential education.

In parallel, Juma et al. (2022) emphasize the pedagogical importance of real-time interactivity and feedback within AR/VR platforms, arguing that these features transform learners from passive receivers to active participants. Their study demonstrates that immersive technologies significantly strengthen engagement and motivation when aligned with behavioral learning models such as Behavioral Skills Training (BST), which involves instruction, modeling, rehearsal, and feedback.

The integration of VR/AR technologies into safety training has demonstrated notable success in improving preparedness and response accuracy in high-risk situations. Koutitas et al. (2021) evaluated AR/VR systems designed for Emergency Medical Services (EMS) first responders and found that immersive simulations significantly enhanced procedural accuracy and reduced task completion time compared to conventional training.

In a related domain, Tan et al. (2022) conducted a systematic review encompassing 82 studies that applied AR/VR technologies within the Architecture, Engineering, and Construction (AEC) industry. Their results indicated a moderate positive effect (SMD ≈ 0.44) on safety training outcomes, showing how immersive visualization tools strengthen spatial understanding and hazard recognition. Similarly, Osti et al. (2021) developed a VR training environment for novice construction workers and reported superior retention, faster learning, and greater engagement among participants compared to 2D instructional videos.

Adami et al. (2021) further demonstrated that VR-based training for robotic teleoperation led to significant improvements in knowledge, safety behavior, and operational performance, reinforcing that immersive environments facilitate skill transfer to real-world contexts. Collectively, these studies establish that VR/AR-based safety training not only enhances technical performance but also promotes proactive preparedness, an essential foundation for SafeScape's community-level evacuation and hazard response training.

The use of VR/AR in professional and community training settings has been particularly impactful in fields requiring precision, coordination, and rapid decision-making. Mathew and Pillai (2022) reviewed immersive technologies in healthcare training, finding that VR/AR simulations improved both technical proficiency and confidence, while facilitating safe, repeatable practice environments. Similarly, Juanes-Méndez et al. (2022) reported that medical students demonstrated stronger procedural learning and retention when trained with immersive simulations that mimicked real emergencies.

Andrews and Nelson (2022) examined how transmedia AR/VR solutions can be integrated across digital platforms to improve healthcare workers' responses to the opioid crisis, concluding that multi-modal immersive systems enhance interprofessional collaboration and scenario-based decision-making.

Fugate et al. (2025) and Barteit et al. (2021) provide further evidence from systematic reviews that extended reality (XR) applications consistently enhance learner engagement and competency while remaining non-inferior to traditional training. Likewise, Önder and Orhan (2024) reported that AR/VR applications in dental education significantly reduced error rates and improved manual skill development.

The effectiveness of VR/AR learning experiences depends significantly on technological accessibility, usability, and cognitive design. Wu et al. (2020) found that fully immersive head-mounted VR significantly improved learning performance compared to less immersive methods, particularly for skill-based domains. Chen et al. (2020) corroborated this through a meta-analysis showing that VR enhances knowledge acquisition though not always surpassing traditional methods in skill accuracy or satisfaction.

Liu et al. (2024) investigated how VR simulations of AR environments impact cognitive workload, discovering that while performance remained stable, frequent viewpoint transitions increased mental fatigue. Similarly, Basu et al. (2023) highlighted privacy and data concerns inherent in spatially navigable VR, advocating for adaptive AI-driven privacy protection.

Empirical evidence supports VR/AR's capacity to improve both objective performance and subjective learning experiences across disciplines. Kaplan et al. (2021) and Daling and Schlittmeier (2024) found that immersive training enhances engagement and cognitive retention without compromising skill accuracy compared to conventional instruction .

In medical and technical education, Lohre et al. (2020) and Portelli et al. (2020) demonstrated that immersive VR significantly improves procedural efficiency, reduces error rates, and enhances confidence during surgical training. However, Frederiksen et al. (2020) observed that excessive cognitive load can occasionally hinder performance, highlighting the need for adaptive difficulty and guided feedback in VR training.

Beyond medicine, Wan et al. (2025) and He et al. (2025) demonstrated that combining VR with brain–computer interface (BCI) systems improved balance, mobility, and motor recovery in stroke patients. Although clinical, these findings illustrate that repetitive immersive feedback loops can significantly accelerate skill mastery, an approach applicable to emergency preparedness education.

Research demonstrates that VR/AR technologies are effective across diverse educational contexts when properly localized, accessible, and theory-driven. Iyer et al. (2024) and Chiang et al. (2022) both affirm that immersive environments enhance vocational and procedural skill acquisition, especially when combined with AR overlays for real-time feedback. Ravichandran and Mahapatra (2023) further note that VR can increase student engagement and retention in vocational education, though challenges remain regarding equipment costs and technical support.

Zhou et al. (2025) integrate artificial intelligence with VR for adaptive and personalized training, finding that AI-VR systems enhance learner autonomy and performance compared to static simulations. Adhershini et al. (2024) and Long et al. (2025) similarly demonstrate that immersive learning systems improve technical proficiency and learner satisfaction, while advocating scalable, context-sensitive deployment in education and industry.

Finally, Uçar (2024) and Sophia et al. (2024) emphasize that while immersive technologies expand opportunities for interactive education, ensuring accessibility and inclusivity remains a crucial design consideration.

In synthesis, the reviewed literature collectively supports SafeScape's integration of VR/AR as a cornerstone of its digital preparedness ecosystem. By embedding experiential learning, adaptive feedback, and accessibility principles, SafeScape's VR/AR module can enhance both community resilience and individual safety competence, bridging the gap between theoretical understanding and real-world emergency behavior.

CHAPTER III

RESEARCH METHODOLOGY

This chapter details the methodology that will be employed to achieve the objectives of the study. It provides a comprehensive blueprint for the design, development, and evaluation of the SafeScape platform. The following sections will describe the research design, the locale of the study, the applied concepts and techniques, the data and model generation process, the system development methodology, the software tools, the system architecture, and the software testing procedures used to validate the system.

Research Design

The study utilizes a mixed-method research design, combining a developmental and an evaluative approach. This combination is necessary to address the study's dual objectives: first, to create a technological solution that addresses the identified gaps in current fire safety efforts, and second, to measure its effectiveness through quantitative, performance-based metrics.

The developmental component is grounded in the principles of developmental research, which Richey (1994) defines as "the systematic study of designing, developing, and evaluating instructional programs, processes, and products that must meet criteria of internal consistency and effectiveness." This design directly applies to the primary goal of this study: the systematic creation and implementation of the SafeScape AI simulation engine. It provides the framework for the engineering process required to build the functional system, including its AI perception model and agent-based simulation, to serve as the core interactive tool for the BFP E-Learning Platform.

The evaluative component of the study is guided by the principles of technical performance analysis. This approach is utilized to fulfill the study's fourth objective: to evaluate the system's effectiveness. The evaluative process assesses the SafeScape AI engine's performance against its intended goals, providing empirical evidence of its ability to learn and execute effective strategies. This is achieved through the analysis of key performance metrics generated during the AI training phases, specifically the validation loss for the perception model and the mean episode reward for the reinforcement learning agent, which serve as quantitative indicators of the system's success.

Locale of the Study

The locale of this study is the municipality of Santa Cruz, Laguna. The project is the result of a direct collaboration, formalized by a memorandum of agreement, between the Bureau of Fire Protection (BFP) Santa Cruz and the College of Computer Studies (CCS) of Laguna State Polytechnic University - Santa Cruz Campus (LSPU-SCC). The study was initiated after the BFP Santa Cruz reached out to the CCS to explore how modern digital technologies could address specific fire safety challenges and enhance preparedness within their community. The target beneficiaries of the study are the community residents of Santa Cruz, local schools and educational institutions, and the personnel of the BFP Santa Cruz station.

The data used for the development and training of the study's AI models were collected from two sources. To ensure the AI model could accurately interpret architectural layouts, the researchers utilized the zimhe/pseudo-floor-plan-12k dataset, a large, publicly available online source for floor plan images. For the AI Commander, the data was generated through the simulation process itself, where the Reinforcement

Learning agent gathered experience from thousands of self-contained evacuation scenarios. The real-world applicability and relevance of the system's final output were then validated in consultation with personnel from the BFP Santa Cruz, ensuring the simulation's features align with the operational needs and knowledge of fire safety professionals.

Applied Concepts and Techniques

This section discusses the core concepts and techniques that were applied to address the research problems and achieve the project's objectives. The study utilizes a combination of machine learning, simulation modeling, and artificial intelligence paradigms to create the SafeScape engine.

Machine Learning

Machine learning is a field of artificial intelligence concerned with the study of computer algorithms that can improve automatically through experience and the use of data. As defined in the foundational text by Bishop (2006), it is about creating systems that can learn from data to identify patterns and make decisions with minimal human intervention. This process, as illustrated in Figure 8, typically involves two primary phases. The first is a training phase, where an algorithm is fed a large set of "Training Data" to learn its underlying patterns. The second is an inference or prediction phase, where the trained model is deployed to make predictions on new, previously unseen input data.

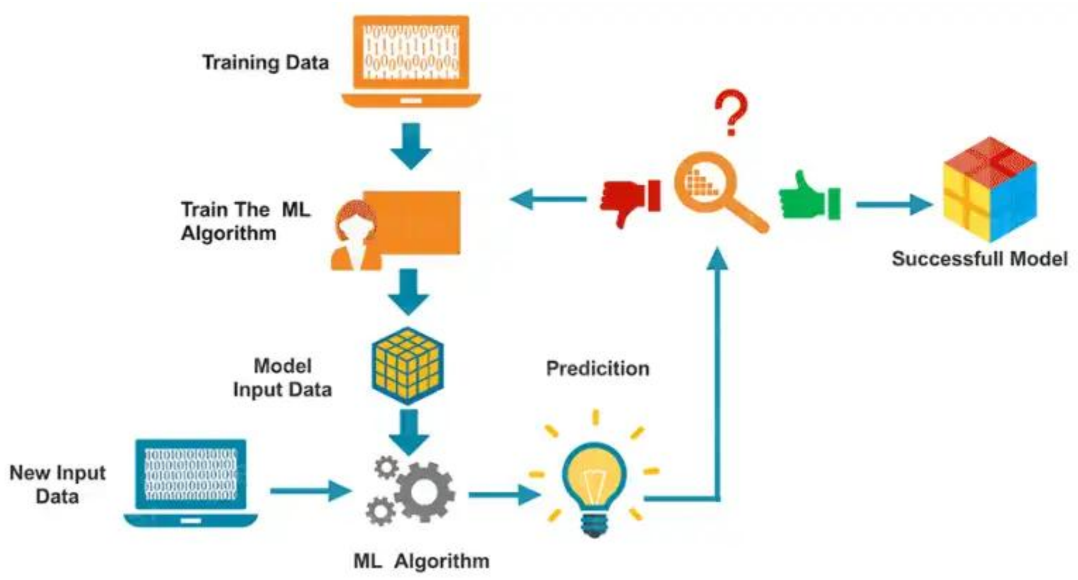

Figure 8. The general process of machine learning, from training to prediction (Corpnce, 2020).

In the SafeScape project, machine learning principles are applied to two critical components: environmental perception and strategic decision-making. For the perception task, a supervised machine learning model (a U-Net) is trained using a labeled "Training Data" set of floor plan images. Its purpose is to learn how to classify pixels and accurately segment wall structures, which aligns with the "prediction" step shown in the figure. For the strategic decision-making task, a different paradigm, reinforcement learning, is utilized. In this approach, the "ML Algorithm" (the PPO agent) learns not from a static dataset but through the dynamic experience of trial-and-error, where the feedback loop shown in Figure 8 is represented by a reward signal. This dual application of machine learning allows the system to move beyond pre-programmed rules, creating an adaptive and intelligent platform for both understanding a physical space and optimizing actions within it.

Deep Learning

Deep learning is a specific method of machine learning that involves neural networks with many layers. As defined by Bergmann (2021), these deep neural networks are designed to mimic the human brain, enabling them to learn from large amounts of complex, unstructured data like text and images. The defining characteristic of deep learning is the presence of multiple hidden layers between the input and output layers, as illustrated in Figure 9. Each layer learns to detect progressively more complex features from the data. This hierarchical feature learning allows deep learning models to achieve state-of-the-art performance on many tasks without the need for manual, human-engineered feature extraction.

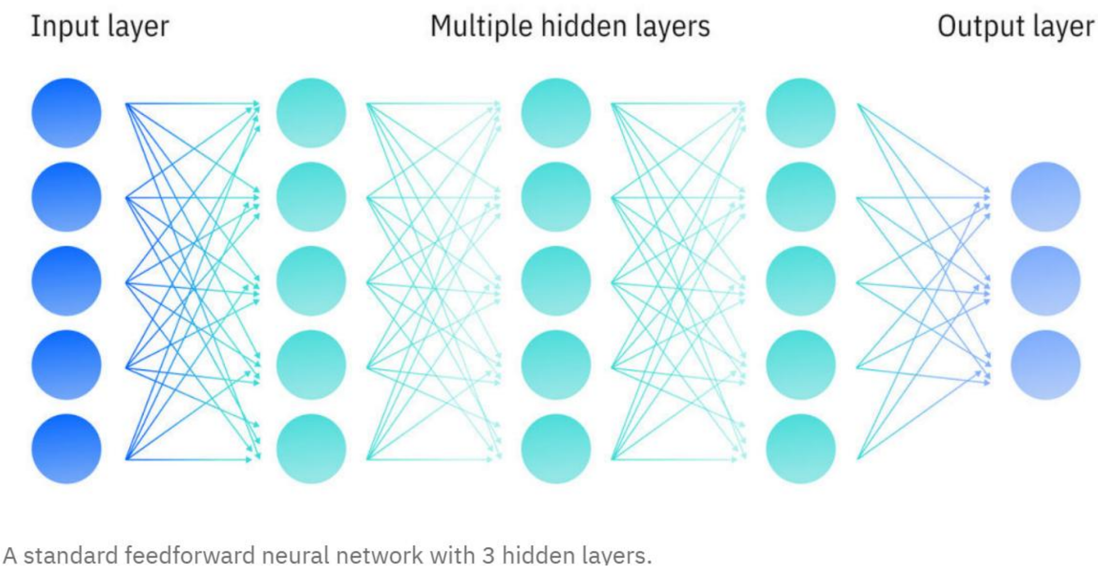

Figure 9. A standard deep neural network architecture with multiple hidden layers (Bergmann, 2021).

In this study, deep learning is employed for the most computationally complex task: the AI Perception Model for creating the digital twin. A deep neural network is specifically utilized because of its ability to learn intricate patterns directly from the raw pixel data of a floor plan image. Unlike traditional methods that might require an engineer to define what a "wall" looks like, the deep learning model autonomously learns to identify the relevant visual features, such as lines, corners, and textures, that distinguish walls from open spaces. This approach makes the system highly scalable and robust, as it can adapt to various styles of floor plans present in the training data, a task for which deep learning is exceptionally well-suited.

Convolutional Neural Network

A Convolutional Neural Network (CNN) is a specialized class of deep learning model designed for processing grid-like data, such as images. According to a comprehensive review by Gu et al. (2018), the architecture of a CNN is uniquely designed to automatically and adaptively learn spatial hierarchies of features. As illustrated in Figure 10, this is achieved through a sequence of specialized layers. The convolution layer applies a set of learnable filters to an input image to create feature maps that highlight specific patterns like edges or textures. The pooling layer then progressively down-samples these feature maps to reduce the data's dimensionality and create a more robust feature representation. After several cycles of convolution and pooling, the final feature maps are passed to a fully connected layer for classification or another processing task.

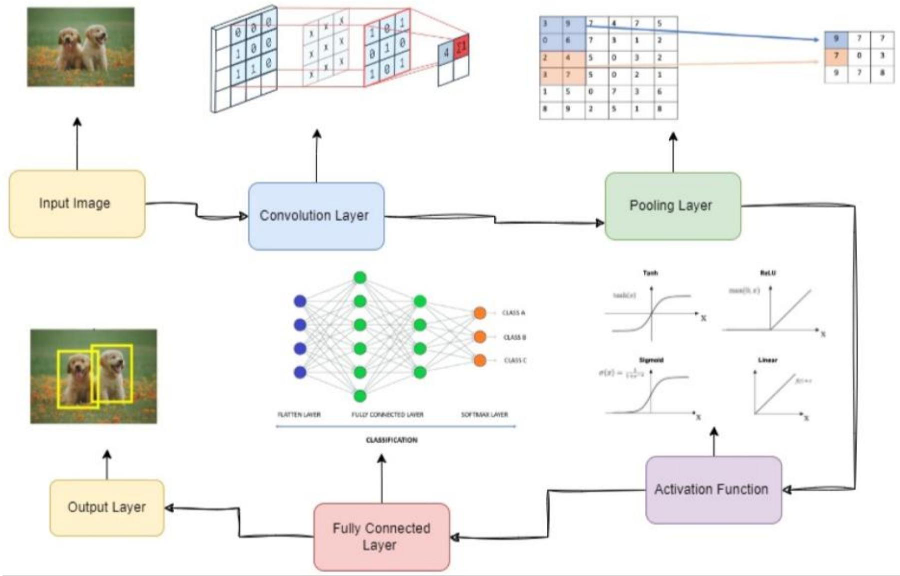

Figure 10. The fundamental components and workflow of a Convolutional Neural Network (Taye, 2023).

In the SafeScape project, a specific and advanced CNN architecture known as a U-Net was implemented for the AI Perception Model. While a standard CNN, as shown in the figure, is often used for image classification (e.g., identifying an object in an image), the U-Net is purpose-built for semantic segmentation, a more complex task that involves classifying every single pixel in an image. The U-Net's "encoder-decoder" structure allows it to capture the context of the entire image and then produce a high-resolution output mask of the same size. This capability was leveraged to process a user-uploaded floor plan and generate a precise, pixel-level 2D grid of the wall layout, which serves as the foundational digital twin for the simulation environment.

Digital Twin

A Digital Twin is a virtual model of a physical entity, where both are interconnected via a real-time exchange of data. According to a comprehensive review by Singh et al. (2021), the core concept involves a virtual copy that mimics the state of its physical counterpart. As conceptualized in Figure 11, this "Information Mirroring

Model" is based on a bidirectional flow of information: data from a "Real Space" is used to construct and update a "Virtual Space," and the information processed in this virtual environment can be used to inform decisions or actions related to the physical object. This creates a powerful framework for monitoring, simulation, and analysis in a virtual setting.

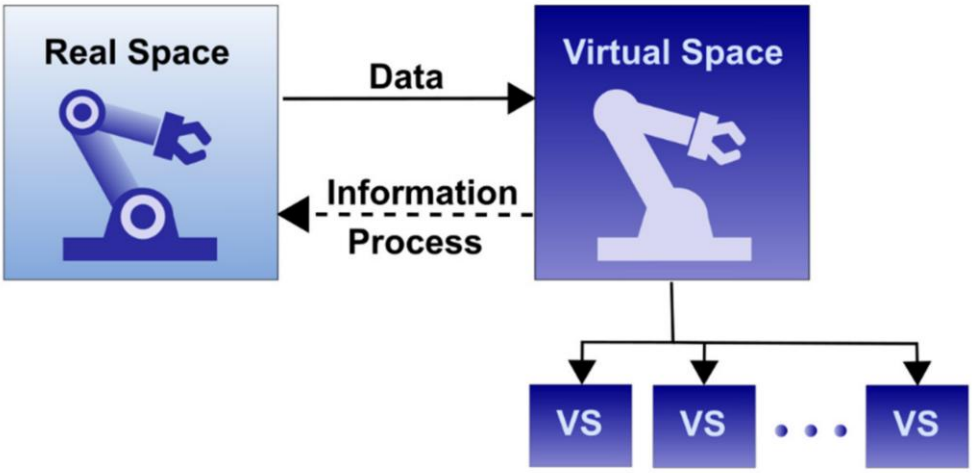

Figure 11. Conceptual model of a Digital Twin (M. Singh et al., 2021).

The SafeScape system fundamentally adopts the Digital Twin concept to create its simulation environment. In this study, the "Real Space" is a physical building represented by a user-uploaded floor plan image. The AI Perception Model (U-Net) acts as the primary "Data" transfer mechanism, processing the image to generate a 2D grid that serves as the "Virtual Space" a simplified, machine-readable replica of the building's layout. The entire fire spread and agent-based evacuation simulation then takes place within this digital twin. This approach allows the system to run thousands of complex "what-if" scenarios and analyze evacuation strategies in a safe, virtual environment, with the final "Information Process" being the delivery of the animated results and risk assessment back to the user.

Agent-Based Modeling

Agent-Based Modeling (ABM) is a methodology used to build formal models of real-world systems that are composed of individual, interacting units. According to Izquierdo et al. (2023) , the defining feature of the ABM approach is that it establishes a direct and explicit correspondence between the individual units in the target system and the agents that represent them in the model. As illustrated in Figure 12, this involves not only representing the people or objects from the "Real world" as simplified "agents," but also explicitly modeling the interactions between them. The goal is to observe the emergent, system-wide phenomena that arise from these individual-level interactions.

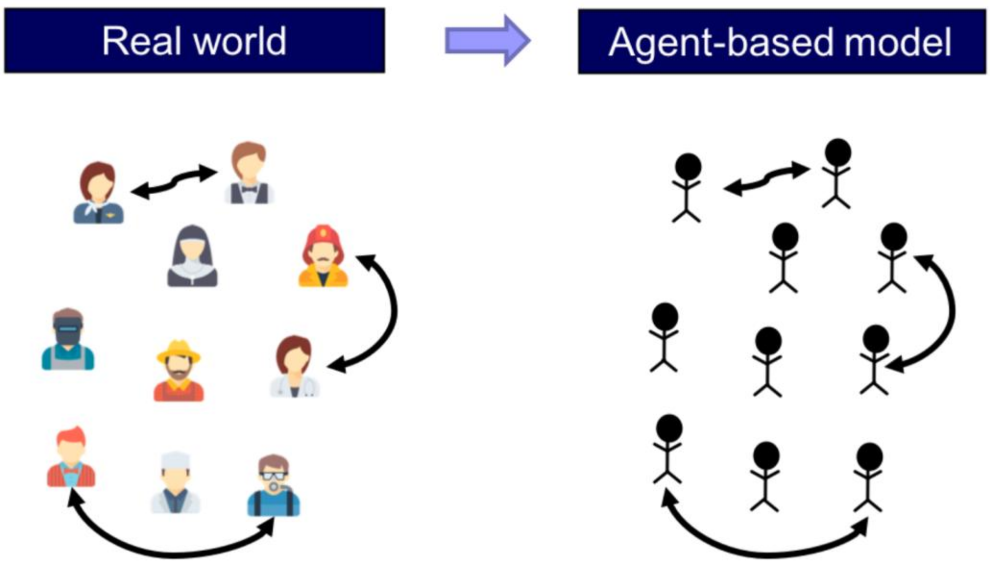

Figure 12. A conceptual illustration of Agent-Based Modeling (Izquierdo et al., 2023)

The SafeScape simulation engine directly employs Agent-Based Modeling to represent the residents evacuating a building, which aligns with established frameworks for crowd simulation (Mirahadi et al., 2019). In this study, each instance of the Person class is an autonomous agent. These agents are not merely passive dots; they are programmed with a set of rules and an internal state machine that dictates their behavior. Each agent individually perceives its environment (specifically its proximity to the fire), updates its internal state (CALM, ALERT, or PANICKED), and acts accordingly. These state-dependent actions include varying its movement speed and even having a probabilistic chance to "trip" and become temporarily immobile. The complex, unpredictable, and realistic evacuation patterns seen in the final animation are the emergent result of these individual agent behaviors.

Reinforcement Learning

Reinforcement Learning (RL) is a feedback-based machine learning paradigm where an autonomous agent learns to make optimal decisions through a process of trial and error in a dynamic environment. Seminal work by Sutton and Barto (1998) defines the core components as an Agent that interacts with an Environment by performing actions. In response to an action, the Environment transitions to a new State and provides a numerical Reward signal. The Agent's objective is not to maximize the immediate reward, but to learn a "policy" which is a strategy for choosing actions that maximizes the cumulative reward over an entire episode. This makes RL exceptionally well-suited for complex decision-making problems where the optimal strategy is not immediately obvious, such as in emergency scenarios (Zhang et al., 2021a).

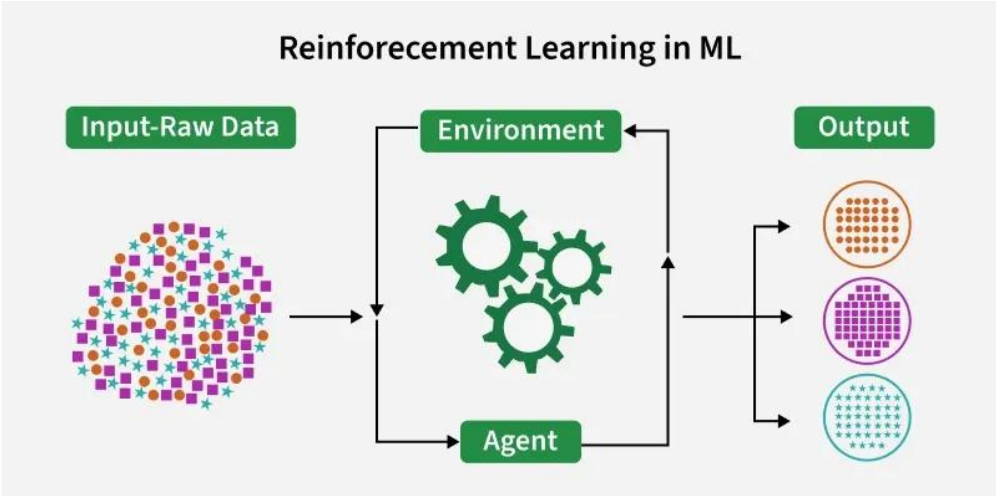

Figure 13. The fundamental feedback loop of Reinforcement Learning (*Reinforcement Learning*, 2025).

The SafeScape system utilizes deep reinforcement learning as the core intelligence for optimizing evacuation strategies, a powerful approach for complex decision-making in emergency scenarios (Zhang et al., 2021a). In this application, the Agent is the PPO model, which acts as a centralized "AI Commander." The Environment is the EvacuationEnv class, which contains the digital twin of the floor plan, the spreading fire, and the agent-based models of the residents. At each step, the AI Commander receives an observation of the environment's state, including the fire's location and the panic level of each resident. It then chooses a high-level action that all agents should target. The environment is updated, and a reward signal is calculated based on the study's custom reward function (+10 for an escape, -10 for a casualty, and -0.01 for time). By training for thousands of episodes, the AI Commander learns a policy that maximizes this reward, thereby discovering effective and robust evacuation strategies.

Algorithm analysis

In this section, the different algorithms and architectures that form the core of the SafeScape AI engine are analyzed. In choosing the most applicable models to be implemented in the system, a review of established, state-of-the-art architectures was conducted to select models that are well-suited to the study's specific objectives.

U-Net Architecture for Perception

A U-Net is a specialized type of convolutional neural network originally designed for fast and precise biomedical image segmentation. As described by its creators, Ronneberger et al. (2015), the U-Net's architecture consists of two main paths: a contracting path (the "encoder") and a symmetric expanding path (the "decoder"). As illustrated in Figure 14, the encoder follows a typical CNN structure, progressively down-sampling the image through a series of convolutions and max-pooling operations to capture high-level contextual features. The decoder then progressively up-samples these features, using up-convolutions to increase the resolution. The central innovation of the U-Net, as shown by the gray arrows in the figure, is the use of "skip connections" that concatenate feature maps from the encoder path with the corresponding up-sampled feature maps in the decoder. This unique, U-shaped architecture allows the network to combine high-level context with fine-grained spatial information, enabling it to generate a precise, pixel-by-pixel segmentation mask that is the same size as the input image.

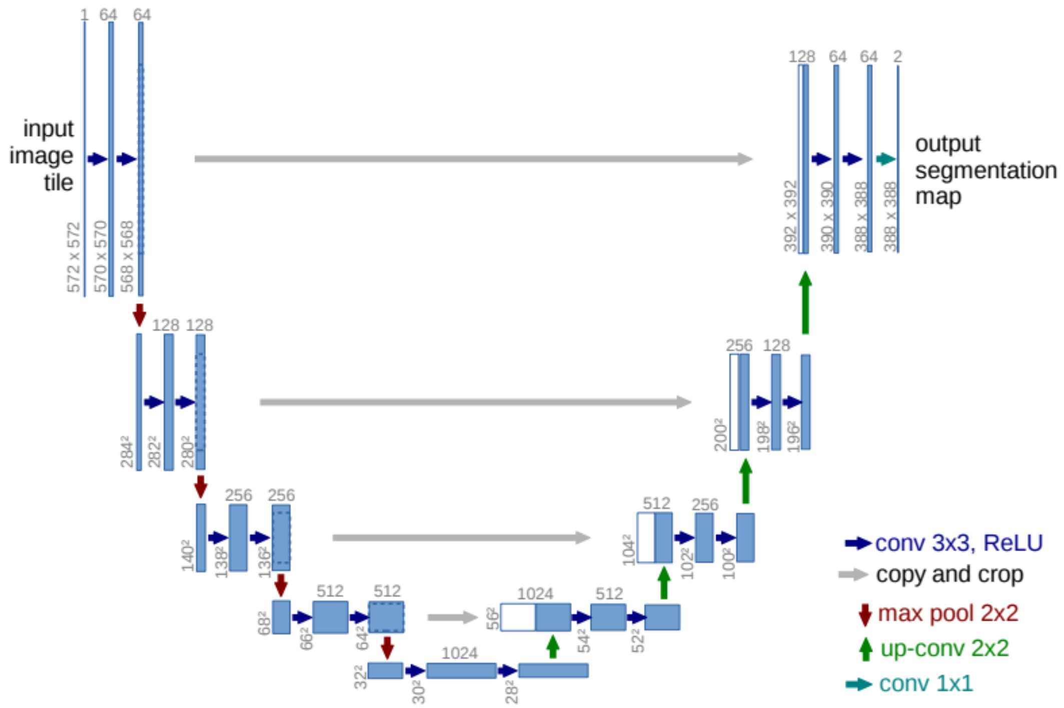

Figure 14. The U-Net architecture shows the contracting and expanding paths, along with the skip connections (Ronneberger et al., 2015).

In this study, the U-Net architecture was selected for the AI Perception Model due to its proven effectiveness in semantic segmentation tasks. The primary objective was to convert a floor plan image into a precise, pixel-level 2D grid to serve as the foundational digital twin. Unlike simpler classification models that identify only what is in an image, the U-Net is purpose-built for classifying every single pixel, making it the ideal choice for accurately delineating complex wall structures from navigable space. Furthermore, Ronneberger et al. (2015) note that the architecture performs effectively even with a limited number of training images due to its use of data augmentation, making it a robust and appropriate choice for this project's foundational task.

Proximal Policy Optimization (PPO)

Proximal Policy Optimization (PPO) is a state-of-the-art reinforcement learning algorithm that belongs to the family of policy gradient methods. The training process, as illustrated in Figure 15, is divided into two distinct phases. First, in the sampling phase, the current agent policy (πt) interacts with the environment over many steps, collecting a large batch of experiences known as "rollouts." This data consists of the states it observed, the actions it took, and the rewards it received. Second, in the training phase, these rollouts are used to compute a loss function, and the error is backpropagated through the neural network to produce an improved policy (πt+1).

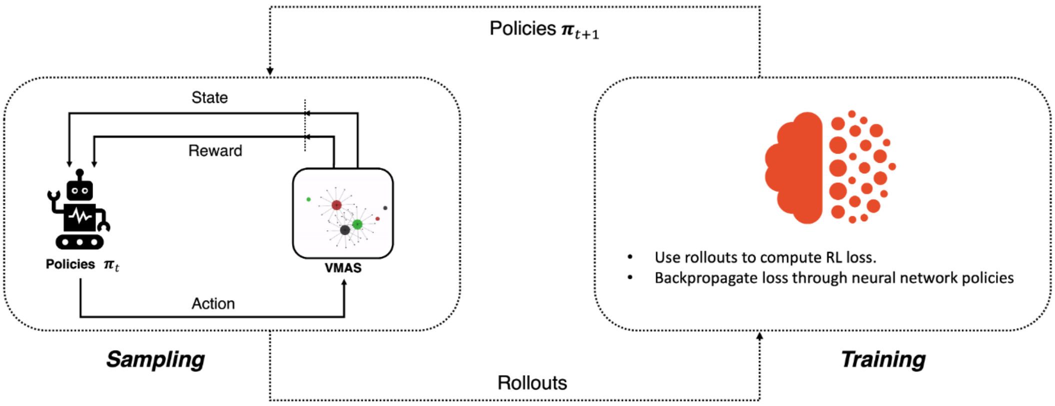

Figure 15. The feedback loop of a modern reinforcement learning algorithm (Bettini, 2022).

The primary challenge in this process is to ensure that the policy update is not so large that it destabilizes the learning process. As introduced by Schulman et al. (2017), PPO solves this by using a "clipped surrogate objective function." This specialized mechanism effectively constrains the size of the policy update at each training step, ensuring that the new policy does not stray too far from the old one. This provides an excellent balance between sample efficiency and training stability, which has made PPO one of the most widely used reinforcement learning algorithms in practice.

In the context of the SafeScape project, this model is directly applied. The "Agent" in the diagram is the PPO-based AI Commander, and the "Environment" is the custom EvacuationEnv class. The AI was implemented using Stable Baselines3, a well-vetted and professionally maintained library that provides a reliable and reproducible implementation of the PPO algorithm (Raffin et al., 2021). PPO was selected for its proven stability in complex and stochastic environments, such as our simulation where agent behaviors like "tripping" introduce significant randomness, making it the ideal choice for training the AI Commander.

Data Collection Method

To design, develop, and validate the SafeScape platform, the researchers used a multi-faceted approach to collect both qualitative and quantitative data. This process included direct stakeholder consultation to define the problem and system requirements, benchmarking against existing systems to guide design choices, and sourcing technical datasets to train the AI models. These methods ensured the resulting system was based on real-world operational needs and state-of-the-art technical foundations.

Consultation and Problem Identification

The SafeScape project originated from a direct partnership with the Bureau of Fire Protection (BFP) in Santa Cruz, Laguna. The BFP approached the College of Computer Studies (CCS) at Laguna State Polytechnic University - Santa Cruz Campus (LSPU-SCC) to explore technological solutions for improving community fire safety. Initial discussions with key BFP personnel, including the municipal fire marshal and senior fire officers, revealed a critical gap: the BFP's existing community outreach, which relied on social media and occasional talks, was largely reactive and ineffective for a diverse population.

The BFP highlighted key challenges, such as engaging younger residents and the lack of a modern, interactive tool to help community members visualize and comprehend fire risks within their own homes. This collaborative problem-identification process, formalized through a memorandum of agreement, provided essential qualitative data. This data established the project's core mission: to transition fire safety measures from a reactive to a proactive approach.

Requirements Gathering and Benchmarking

Following the initial problem identification, a series of structured interviews and iterative consultation meetings were conducted with BFP personnel to gather detailed system requirements. During these sessions, the researchers presented a proposal for an AI-driven simulation tool, which was then collaboratively refined based on the operational expertise and needs of the fire officers. A requirement that emerged from these discussions was the need for an educational component tailored to children, with the BFP citing the platform sparky.org as an inspirational benchmark. This led to the requirement of creating a localized, BFP-standard educational hub that uses interactive games and modules to teach fundamental fire safety concepts. Furthermore, the researchers proposed a visual and interactive tool as part of the system, which the BFP supported due to its potential to help residents understand fire spread in layouts similar to their own homes. This direct, qualitative feedback from the end-users and domain experts was gathered throughout the development process in weekly meetings, ensuring that the system's features, particularly the visual simulation engine, were continuously aligned with their practical needs for a community-facing educational and risk assessment tool.

Technical Data Sourcing

The development of the system's AI components required two distinct types of technical data. For the AI Perception Model, whose purpose is to generate a digital twin from a floor plan image, a supervised learning approach was necessary. To this end, the researchers utilized the zimhe/pseudo-floor-plan-12k dataset, a large-scale, publicly available resource sourced from the Hugging Face online platform. This dataset, containing thousands of floor plan images and their corresponding pixel-level wall masks, provided the extensive, labeled data required to train the U-Net architecture for the semantic segmentation task.

In contrast, the AI Commander was developed using a reinforcement learning paradigm, which does not rely on a static, pre-existing dataset. The "data" for this model was generated dynamically through the process of trial-and-error interaction with the custom-built EvacuationEnv simulation environment. During training, the PPO agent gathered millions of "experience" tuples, each consisting of an observation of the environment, the action it took, the resulting reward, and the next observation. This experiential data, generated across thousands of simulated evacuation episodes, was the sole basis upon which the AI Commander learned and optimized its decision-making policy.

Data Model Generation

This study aims to design, develop, and evaluate a sophisticated AI-driven simulation engine. In order to achieve that, the researchers followed a systematic, step-by-step process of model generation. This process, illustrated in Figure 16, encompasses the entire pipeline from initial data collection through to model training and evaluation, ensuring a reproducible and technically sound methodology. The following sections detail each stage of this process.

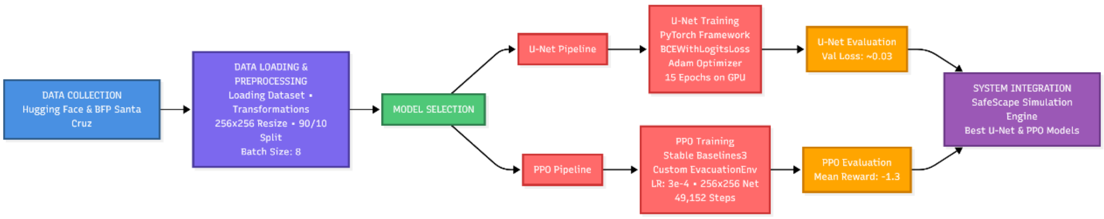

Figure 16. Data model generation process

Before the model training could commence, the raw data for the AI Perception Model was loaded and rigorously preprocessed. This foundational step is critical for ensuring the model learns from clean, standardized, and well-structured data, which directly impacts its final performance and accuracy.

Loading of Dataset

The study utilized the zimhe/pseudo-floor-plan-12k dataset. The data was loaded directly into the Google Colab environment using the load_dataset function from the Hugging Face datasets library. This method provided an efficient way to access the large-scale dataset without requiring a manual download and upload process. The loaded dataset contained paired images of floor plans and their corresponding wall masks.

Dataset Attributes

The zimhe/pseudo-floor-plan-12k dataset is composed of several columns, but the two essential for this study were the plans and walls columns, which represent the input image and the target mask, respectively. The attributes of this data are detailed in Table 1.

Table 1. Attributes of the Floor Plan Dataset.

Attribute	Description	Data Type / Format
plans	The input floor plan image.	PIL Image Object (RGB)
walls	The ground-truth segmentation mask showing the location of walls.	PIL Image Object (Grayscale)
image_id	A unique identifier for each image pair.	String

Transformations

To standardize the input for the U-Net model, a series of augmentations and transformations were applied to each image and mask using the torchvision.transforms library. The two primary transformations were:

- Resize: All images, regardless of their original dimensions, were resized to a uniform resolution of 256x256 pixels. This ensures that the input tensor for the neural network is always a consistent size.
- ToTensor: The images, initially loaded in the PIL (Pillow) image format, were converted into PyTorch tensors. This process also automatically scaled the image pixel values from the standard 0-255 range to a normalized range of 0.0 to 1.0, which is optimal for neural network training.

Splitting

To effectively monitor the model's performance and prevent overfitting, the full dataset was divided into a training set and a validation set. A 90/10 split was utilized, resulting in 90% of the data being allocated for training the model and the remaining 10% being held back as a validation set to evaluate the model's generalization capabilities on unseen data at the end of each epoch.

Dataloaders

Finally, the training and validation sets were wrapped in PyTorch's DataLoader class. The dataloaders were configured with a batch_size of 8, which was determined experimentally to be the optimal size that could be handled by the available GPU memory. For performance optimization, the dataloaders were also configured with num_workers=2 and pin_memory=True to enable multi-process data loading and faster data transfer to the GPU, ensuring that the GPU was never idle waiting for new data.

Model Selection

Following the preprocessing of the data, the next stage was to select the appropriate deep learning architectures for the two distinct AI components of the SafeScape engine. The goal was to choose state-of-the-art models that were purpose-built for each specific task, ensuring the highest potential for performance and accuracy. Based on the findings from the literature review and the specific requirements of the project, the researchers selected one specialized architecture for the perception task and one advanced algorithm for the decision-making task.

Perception Model: U-Net

For the task of generating a 2D digital twin from a floor plan image, a U-Net architecture was selected. As justified in the Algorithm Analysis section, the U-Net is a specialized convolutional neural network designed for semantic segmentation. Its unique encoder-decoder structure with skip connections makes it exceptionally effective at producing precise, pixel-level output masks, which was the primary requirement for creating an accurate wall grid for the simulation environment.

Decision-Making Model: Proximal Policy Optimization (PPO)

For the task of learning an optimal evacuation strategy, the Proximal Policy Optimization (PPO) algorithm was chosen. As a state-of-the-art reinforcement learning method, PPO is renowned for its stability and performance in complex, dynamic environments. Its capability to learn a robust decision-making policy through trial-and-error, combined with the availability of a professional-grade implementation in the Stable Baselines3 library, made it the ideal candidate for training the AI Commander to manage the sophisticated behaviors of the agent-based model.

Model Making and Training

This section details the specific implementation and training procedures for the two core AI models of the SafeScape engine: the U-Net for perception and the PPO agent for decision-making. The training for both models was conducted in the Google Colaboratory environment, leveraging its free-access T4 Graphics Processing Unit (GPU) to handle the computationally intensive tasks required for deep learning.

U-Net for Perception Model Training

The U-Net architecture, as defined in the "Algorithm Analysis" section, was implemented from scratch using the PyTorch deep learning framework. The model was built using the standard torch.nn modules to construct the convolutional layers, activation functions, and pooling layers that form the encoder-decoder structure.

The training of this model was executed as a supervised learning task. As shown in the code snippet in Figure [A], the training process iterates through the dataset for a total of 15 epochs. In each epoch, the model is presented with batches of floor plan images, for which it generates a predicted wall mask. The key components of the training loop are

- Loss Function: A BCEWithLogitsLoss function was used to calculate the pixel-wise error between the model's prediction and the ground-truth wall mask.
- Optimizer: An Adam optimizer with a learning rate of 1e-4 was employed to update the model's weights and minimize the loss.

- GPU Optimization: To maximize training speed on the T4 GPU, Automatic Mixed Precision was utilized. As seen in the figure, this was implemented using PyTorch's GradScaler and autocast to perform calculations in a faster, lower-precision format where possible without sacrificing numerical stability.

```
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
print(f"Using device: {device}")

# Initialize model, loss function, and optimizer
model = UNet().to(device)
criterion = nn.BCEWithLogitsLoss()
optimizer = torch.optim.Adam(model.parameters(), lr=config['learning_rate'])
scaler = torch.cuda.amp.GradScaler()

for epoch in range(config['epochs']):
    model.train()
    train_loss = 0.0

    train_iterator = tqdm(train_loader, desc=f"Epoch {epoch+1}/{config['epochs']} [Training]")

    for inputs, masks in train_iterator:
        inputs, masks = inputs.to(device), masks.to(device)

        optimizer.zero_grad()

        with torch.cuda.amp.autocast():
            outputs = model(inputs)
            loss = criterion(outputs, masks)

        scaler.scale(loss).backward()
        scaler.step(optimizer)
        scaler.update()

        current_loss = loss.item()
        train_loss += current_loss * inputs.size(0)

        train_iterator.set_postfix(loss=f"{current_loss:.6f}")

    # Validation phase
    model.eval()
    val_loss = 0.0

    val_iterator = tqdm(val_loader, desc=f"Epoch {epoch+1}/{config['epochs']} [Validation]")

    with torch.no_grad():
        for inputs, masks in val_iterator:
            inputs, masks = inputs.to(device), masks.to(device)
            with torch.cuda.amp.autocast():
                outputs = model(inputs)
                loss = criterion(outputs, masks)
            val_loss += loss.item() * inputs.size(0)

    train_loss = train_loss / len(train_dataset)
    val_loss = val_loss / len(val_dataset)

    print(f"\nEpoch {epoch+1} Summary: "
          f"Avg. Train loss: {train_loss:.6f}, "
          f"Avg. Validation loss: {val_loss:.6f}\n")

print("\n--- Training Complete ---")
```

Figure 17. Code snippet of the PyTorch training loop for the U-Net model.

This structured training process allowed the U-Net model to effectively learn the complex visual patterns of wall structures from the provided dataset, resulting in a highly accurate perception model.

PPO for Decision-Making Model Training

The AI Commander was trained using the Proximal Policy Optimization (PPO) algorithm, implemented via the Stable Baselines3 framework. The training was conducted in a specialized setup designed for performance and stability. To fully leverage the available computational resources, the training was configured to run on the T4 GPU while using the SubprocVecEnv class to create four parallel simulation environments on the CPU. This parallel architecture allowed the AI to gather training experiences much more rapidly than a single-threaded simulation would allow.

The PPO model was instantiated with a set of optimized hyperparameters, as detailed in Table 2. These parameters were chosen to enhance the model's learning capability and stability. Key choices include giving the AI a larger neural network (net_arch of [256, 256]) to handle the complexity of the environment, using a larger batch_size (256) for more efficient GPU computation, and setting a non-zero ent_coef (0.01) to encourage the agent to explore different strategies during training.

Table 2. Optimized Hyperparameters for the PPO Model.

Hyperparameter	**Value**	**Description**
learning_rate	3e-4	The step size for updating the model's weights.
n_steps	2048	Steps collected per environment before an update
batch_size	256	The number of samples per gradient update.

n_epochs	10	Number of Optimization epochs per update
gamma	0.99	Discount factor for future rewards
gae_lambda	0.95	Factor for the GAE advantage estimation.
clip_range	0.3	The clipping parameter for the PPO objective.
ent_coef	0.01	Entropy coefficient to encourage exploration.
policy_kwargs	net_arch=[256, 256]	Defines the size of the neural network.

The training process was conducted iteratively. The model was trained in sessions, with progress saved to a file (ppo_commander_v1.5.zip) at the end of each session. A CheckpointCallback was also used to automatically save backups during training to prevent data loss. As shown in the final training log in Figure [B], the model was trained for a total of 49,152 timesteps. The most critical metric, the mean episode reward (ep_rew_mean), showed a clear and consistent improvement throughout the training process, rising to a final value of -1.3. This demonstrates that the PPO agent successfully learned a highly effective and robust policy for managing the evacuation of agents with complex, human-like behaviors.

```
----------------------------------------
| rollout/                |            |
|    ep_len_mean          | 350        |
|    ep_rew_mean          | -1.3       |
| time/                   |            |
|    fps                  | 10         |
|    iterations           | 3          |
|    time_elapsed         | 2372       |
|    total_timesteps      | 49152      |
| train/                  |            |
|    approx_kl            | 0.012205137 |
|    clip_fraction        | 0.142      |
|    clip_range           | 0.2        |
|    entropy_loss         | -3.83      |
|    explained_variance   | 0.592      |
|    learning_rate        | 0.0003     |
|    loss                 | 3.15       |
|    n_updates            | 50         |
|    policy_gradient_loss | -0.0144    |
|    value_loss           | 10.1       |
----------------------------------------

--- 20000 timesteps of training complete ---

Upgraded AI Commander model saved to ppo_commander_v1.5.zip
Total timesteps trained so far: 49152
```

Figure 18. The final training log of the PPO agent after completing 49,152 timesteps.

Model Evaluation

Each of the two AI components of the SafeScape engine was evaluated using metrics appropriate for its specific task and learning paradigm. For the supervised learning-based Perception Model, the metrics focused on pixel-level classification accuracy. For the Reinforcement Learning-based Decision-Making Model, the metrics focused on the agent's ability to maximize its goal-oriented reward signal.

U-Net (Perception Model) Evaluation Metrics

To evaluate the performance of the trained U-Net model, three key metrics for semantic segmentation were utilized. These metrics were calculated on the held-out validation set to assess the model's ability to generalize to unseen data.

Pixel accuracy

This metric measures the overall percentage of pixels that were correctly classified as either “wall” or “non-wall.” It provides a general measure of the model’s correctness

$$Pixel\ Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Where TP, TN, FP, and FN represent the number of True Positive, True Negative, False Positive, and False Ngative pixel classifications, respectively.

Intersection over Union (IoU)

IoU is one of the most common and robust metrics for segmentation tasks. It measures the degree of overlap between the predicted wall mask and the ground-truth wall mask. It is a stricter metric than pixel accuracy as it penalizes incorrect localization.

$$IoU = \frac{TP}{TP + FP + FN}$$

Dice Coefficient (F1-Score)

The Dice Coefficient is conceptually similar to the F1-Score and provides a measure of similarity between the predicted and true masks. It is also widely used for evaluating segmentation performance.

$$Dice\ Coefficient = \frac{2 * TP}{2 * TP + FP + FN}$$

PPO (Decision-Making Model) Evaluation Metrics

The effectiveness of the PPO agent was not measured by classification accuracy, but by its performance in achieving the goals defined by the simulation's reward function. The following metrics, logged during the training process, were used to evaluate the agent's learning and final performance.

Mean Episodic Return (ep_rew_mean)

This is the primary metric for evaluating a reinforcement learning agent. It represents the average of the total cumulative rewards the agent received over a full simulation episode. A consistently increasing trend in this value is the key indicator that the agent is successfully learning an optimal policy to achieve its objective, which in this study is to maximize the number of survivors in the shortest time.

$$Reward = (Number\ of\ New\ Escapes * 10) - (Number\ of\ New\ Casualties * 10) - 0.01$$

Mean Episode Length (ep_len_mean)

This metric tracks the average number of steps the agent takes to complete a single episode. A decreasing trend in this value, while the reward is increasing, can indicate that the agent is learning to achieve its goal more efficiently.

Entropy (entropy_loss)

This metric measures the randomness or unpredictability of the agent's actions. It was monitored during training to ensure that the agent maintained a healthy level of exploration, preventing it from settling on a suboptimal strategy too early in the learning process.

System development methodology

For the development of the SafeScape platform, the study adopted the Agile methodology, specifically employing an Iterative and Incremental model of development. This approach was chosen over traditional waterfall models due to its flexibility and its capacity to accommodate evolving requirements, which is essential for a research-driven project involving stakeholder feedback and technical discovery (Sommerville, 2011). The core principle of this model, as illustrated in Figure [Z], is to develop the system through a series of repeated cycles (iterations), moving from an initial plan through to deployment, with each cycle producing a new, functional increment of the software.

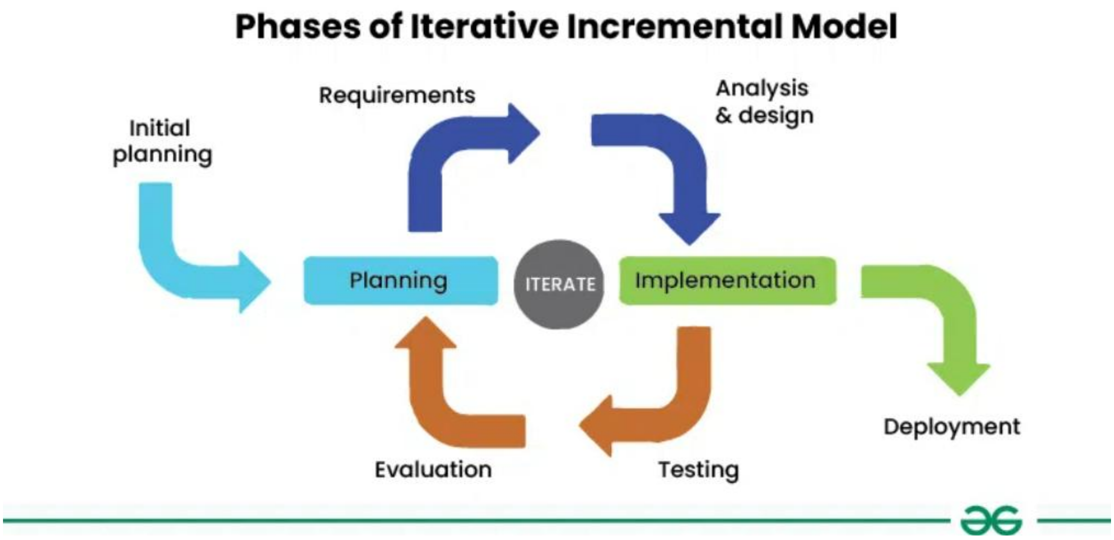

Figure 19. The Phases of the Iterative and Incremental Model. (*Iterative Incremental Model in Designing System*, 2024)

The application of this methodology in the project followed the structured phases shown in the figure for each development cycle. The process began with initial planning, where the overall project vision was established. Each subsequent iteration then involved a recurring loop of the following phases:

1. **Planning and Requirements:** Each cycle began with a detailed analysis of the core features required for the next increment of the system. This included the technical requirements for the AI models and the functional requirements for the user-facing platform, which were informed by the initial stakeholder consultations.
2. **Analysis, Design, and Implementation:** Based on the requirements, the necessary components were designed and coded. This included the development

of the AI architectures in Python and the implementation of user interface components in the web application framework.

3. **Testing:** The functional increments were rigorously tested. A key aspect of this phase was the use of prototyping, where the complete AI simulation engine was first developed and tested as a standalone prototype in a Google Colab environment to validate the core AI behaviors and measure performance.
4. **Evaluation:** Each increment was evaluated against the project's objectives. This stage included both quantitative evaluation and qualitative evaluation from stakeholders. The feedback from this phase was then used to inform the planning for the next iteration, creating the central feedback loop of the model.

This iterative process was applied to all major components, from the initial AI Perception Model to the fully trained AI Commander. Once all core features were developed and evaluated through multiple iterations, the project would proceed to the final deployment phase, involving the integration of the AI engine into the main web platform.

Software Tools

The development and training of the AI simulation engine were conducted entirely in a Python-based environment. Google Colaboratory was chosen as the primary platform due to its provision of free high-performance GPUs, which are essential for deep learning tasks. The specific frameworks and libraries, detailed in Table 3, were selected to implement the state-of-the-art algorithms required for the perception and decision-making models.

Table 3: Software Tools for AI Model Development

Software	Description
Google Colab	Colab notebooks allow you to combine executable code and rich text in a single document, along with images, HTML, LaTeX and more. When you create your own Colab notebooks, they are stored in your Google Drive account. You can easily share your Colab notebooks with co-workers or friends, allowing them to comment on your notebooks or even edit them.
Python	Python is an interpreted, object-oriented, high-level programming language with dynamic semantics. Its high-level built in data structures, combined with dynamic typing and dynamic binding, make it very attractive for Rapid Application Development, as well as for use as a scripting or glue language to connect existing components together.
PyTorch	PyTorch is an open source machine learning framework that accelerates the path from research prototyping to production deployment. Built to offer maximum flexibility and speed, PyTorch supports dynamic computation graphs, enabling researchers and developers to iterate quickly and intuitively. Its Pythonic design and deep integration with native Python tools make it an accessible and powerful platform for building and training deep learning models at scale.
Hugging Face datasets	Hugging Face is a company that maintains a huge open-

source community of the same name that builds tools, machine learning models and platforms for working with artificial intelligence, with a focus on data science, machine learning and natural language processing (NLP).

Stable Baselines3	Stable Baselines3 (SB3) is a set of reliable implementations of reinforcement learning algorithms in PyTorch. It is the next major version of Stable Baselines.
Gymnasium	Gymnasium is a maintained fork of OpenAI's Gym library. The Gymnasium interface is simple, pythonic, and capable of representing general RL problems, and has a migration guide for old Gym environments:
Numpy	NumPy is the fundamental package for scientific computing in Python. It is a Python library that provides a multidimensional array object, various derived objects (such as masked arrays and matrices), and an assortment of routines for fast operations on arrays, including mathematical, logical, shape manipulation, sorting, selecting, I/O, discrete Fourier transforms, basic linear algebra, basic statistical operations, random simulation and much more.
OpenCV	OpenCV (Open Source Computer Vision Library) is an open source computer vision and machine learning software library. OpenCV was built to provide a common infrastructure for computer vision applications and to

	accelerate the use of machine perception in the commercial products. Being an Apache 2 licensed product, OpenCV makes it easy for businesses to utilize and modify the code.
Pillow	Pillow is the friendly PIL fork, provides extensive file format support, an efficient internal representation, and fairly powerful image processing capabilities.
Matplotlib	Matplotlib is a comprehensive library for creating static, animated, and interactive visualizations in Python. Matplotlib makes easy things easy and hard things possible.

The main BFP E-Learning platform, which serves as the user-facing hub for the entire project, was developed as a modern web application. The tools listed in Table 4 were chosen to build a robust, scalable, and interactive frontend and a reliable backend for managing users and content. This architecture is designed to seamlessly integrate the AI simulation engine via API calls.

Table 4: Software Tools for System Development

Software	Description
Visual Studio Code	Visual Studio Code (VS Code) is a popular source code editor developed by Microsoft offering built-in support for JavaScript, TypeScript, HTML, CSS, and many other languages. It provides advanced features such as intelligent code completion (IntelliSense), debugging, code

	navigation, and extensibility with numerous plugins.
TypeScript	TypeScript is an open-source language maintained and developed by Microsoft. It adds additional syntax to JavaScript to support a tighter integration with your editor. Catch errors early in your editor or in your CI/CD pipeline, and write more maintainable code.
Python	Python is an interpreted, object-oriented, high-level programming language with dynamic semantics. Its high-level built in data structures, combined with dynamic typing and dynamic binding, make it very attractive for Rapid Application Development, as well as for use as a scripting or glue language to connect existing components together.
JavaScript	JavaScript is a lightweight, interpreted programming language widely used for web development. It supports multiple programming paradigms, including imperative, functional, and object-oriented styles.
HTML	(HyperText Markup Language) is the most basic building block of the Web. It defines the meaning and structure of web content. Other technologies besides HTML are generally used to describe a web page's appearance/presentation (CSS) or functionality/behavior (JavaScript).

CSS	Cascading Style Sheets (CSS) is a stylesheet language used to describe the presentation of a document written in HTML or XML (including XML dialects such as SVG, MathML or XHTML). CSS describes how elements should be rendered on screen, on paper, in speech, or on other media.
SQL	SQL (Structured Query Language) is a domain-specific language used for managing and manipulating relational databases. It allows querying, updating, and managing data within databases through statements such as SELECT, INSERT, UPDATE, and DELETE.
React	React is a declarative, component-based JavaScript library for building user interfaces. It enables the creation of reusable UI components with a virtual DOM for efficient rendering and supports hooks for managing state and side effects. React powers a vast ecosystem for web and mobile application development.
Tailwind CSS	Tailwind CSS is a utility-first CSS framework that enables developers to style web applications by composing utility classes directly in the HTML. It promotes rapid UI development with low-level, customizable CSS utilities without writing custom stylesheets.
Radix UI	Radix UI is a library of unstyled, accessible UI primitives

	for building high-quality design systems and web applications. It focuses on providing accessible and flexible components that can be styled and composed according to project needs.
Lucide React	Lucide React is a React component library for Lucide icons, offering a collection of simple, customizable, and accessible SVG icons designed to work seamlessly with React applications.
Recharts	Recharts is a composable charting library built on React components using D3 under the hood. It provides declarative chart building blocks that enable developers to create responsive, reusable charts with minimal configuration. It supports various chart types like line, bar, pie, and area charts, making it popular for React data visualization.
Sonner	Sonner is a modern React notification library focusing on simplicity and accessibility. It provides customizable toast notifications with animation support and easy integration for alerting users in React apps.
Next.js	Next.js is a React framework used to build fast and scalable web applications. It supports hybrid static and server rendering, automatic code splitting, optimized performance, and API routes, making it a popular choice

	for production React apps.
Prisma	Prisma is a next-generation open-source ORM (Object-Relational Mapper) designed to simplify database management and interactions for Node.js and TypeScript applications. It provides an intuitive data modeling language via its Prisma schema, type-safe database queries through Prisma Client, and automated migrations to manage database schema changes.
SQLite	SQLite is a lightweight, serverless, self-contained SQL database engine often embedded in applications for local data storage. It stores the entire database in a single file and is frequently used for development, testing, and small to medium web or mobile apps where simplicity and minimal configuration are key.
Node.Js	Node.js is a powerful, open-source JavaScript runtime built on Chrome's V8 engine that allows developers to run JavaScript code outside the browser. It enables server-side and networking applications with an event-driven, non-blocking I/O model designed for scalable, high-performance applications
Facebook SDK	The Facebook Software Development Kit (SDK) is a collection of tools and libraries provided by Meta (Facebook) to help developers integrate Facebook's

services into their apps.

To satisfy the project's objective of creating engaging, age-appropriate educational content, a dedicated set of tools was used to develop the interactive games for the platform's "Kids Section." The libraries and frameworks detailed in Table 5 were selected for their capabilities in creating interactive, browser-based experiences that align with the educational goals of the BFP.

Table 5: Software Tools for Game Development

Software	Description
Game Maker	GameMaker is a complete development tool for making 2D games, used by indie developers, professional studios, and educators worldwide. Create games for Windows, Mac, Linux, Android, iOS, HTML5, Xbox Series X|S, PlayStation 5, and Nintendo Switch.
GIMP	GIMP is a cross-platform image editor available for GNU/Linux, macOS, Windows and more operating systems. It is free software, you can change its source code and distribute your changes.
Blender	Blender is a fully integrated 3D content creation suite, offering a broad range of essential tools, including Modeling, Rendering, Animation & Rigging, Video Editing, VFX, Compositing, Texturing, and many types of

	Simulations.
RenPy	Ren'Py is a visual novel engine used by thousands of creators from around the world that helps you use words, images, and sounds to tell interactive stories that run on computers and mobile devices. These can be both visual novels and life simulation games.

System Architecture

The researchers designed a comprehensive system architecture that outlines the logical structure of the BFP E-Learning platform and the data flow between its various components. This architecture, illustrated in Figure [Z], employs a modern, multi-layered approach to separate concerns and ensure the system is scalable, maintainable, and secure. The diagram distinguishes between frontend components (responsible for user interaction), backend components (responsible for core logic and data management), and components that serve both.

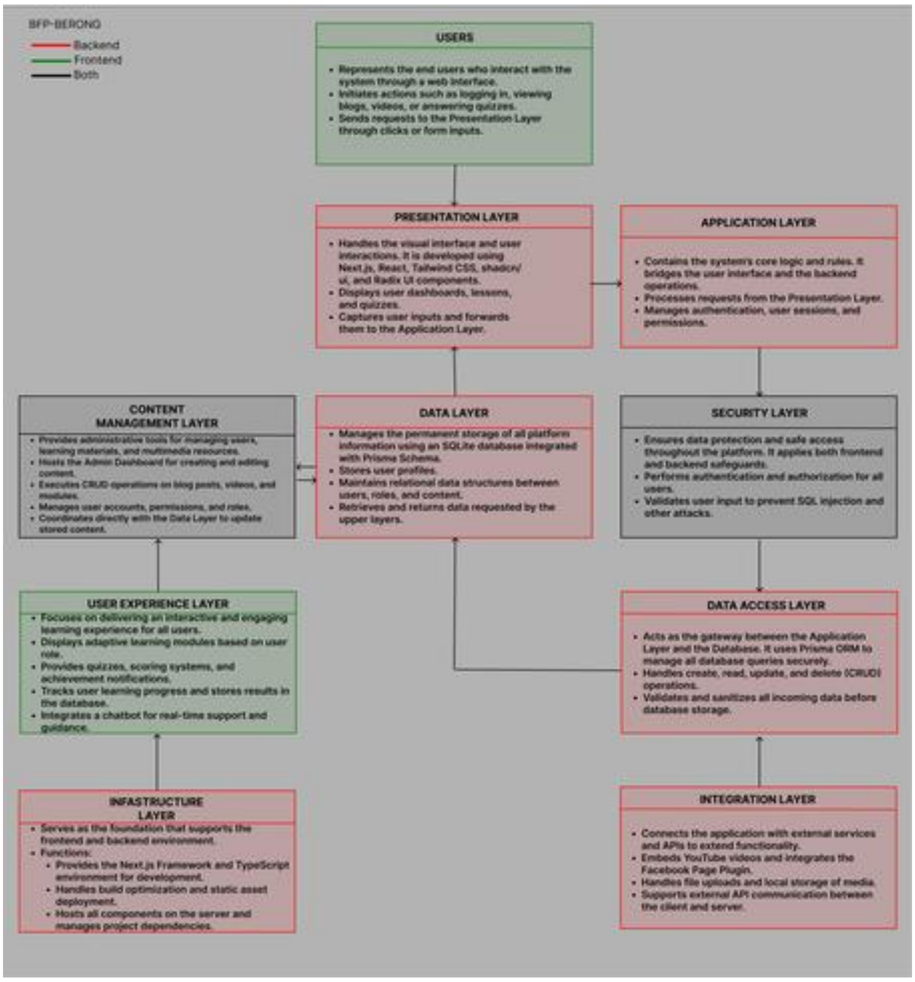

Figure 19. The System Architecture of the SafeScape Platform.

The architectural flow begins with the Users, who interact with the system through the Presentation Layer. This layer, which constitutes the visual interface built with Next.js and Shadcn/UI, captures all user inputs and forwards them to the Application Layer. The Application Layer acts as the central processing hub, containing the system's core business logic, managing user sessions, and directing requests. For data-related operations, it communicates with the Data Access Layer, which uses the Prisma ORM to securely perform CRUD (Create, Read, Update, Delete) operations on the SQLite database, managed by the Data Layer. All interactions are protected by a Security Layer that handles authentication and authorization. The system's functionality is extended via an Integration Layer, which connects to external services and, most critically, facilitates the API communication with the separate Python-based AI Simulation Engine. The final output and user experience are delivered back through the Presentation and User Experience Layers, completing the data flow.

Software Testing

To fully assess the overall study and ensure the reliability, functionality, and correctness of the SafeScape platform, the researchers defined a multi-layered testing strategy. This strategy encompasses different testing methods, from verifying the smallest individual components to validating the complete end-to-end user experience. The testing process is designed to ensure that the AI models are accurate, the system architecture is robust, and the final application meets the needs of its target users.

Model and Simulation Testing

The primary evaluation of the study's core technical contribution involved the thorough testing of the AI models and the simulation environment itself. This testing was designed to quantitatively measure the performance of each AI component against its specific objective.

Perception Model Testing: The trained U-Net model was evaluated on a held-out validation set (10% of the total dataset) that was not used during training. The model's performance was measured using standard semantic segmentation metrics, including Pixel Accuracy, Intersection over Union (IoU), and the Dice Coefficient. These metrics provide a quantitative assessment of the model's ability to accurately generate a digital twin from an unseen floor plan image.

Decision-Making Model Testing: The performance of the trained PPO (AI Commander) model was evaluated by analyzing the metrics logged during its final training and validation runs. The primary metric was the Mean Episodic Return (ep_rew_mean), which measures the agent's effectiveness in achieving the goal of maximizing survivor count. The evaluation focused on the clear, positive trend of this metric over the course of the training, which serves as empirical evidence of successful learning.

Simulation Behavior Testing: Before final training, the integrated EvacuationEnv was subjected to qualitative testing using a random agent. This "Test Drive" was used to visually verify that all the implemented mechanics of the agent-based model—such as the state transitions (Calm to Panicked), speed modifications, and the "tripping" behavior—were functioning as designed within the simulation loop.

Unit Testing

Unit testing forms the first layer of the testing strategy, focusing on the smallest individual components or "units" of the software in isolation. The purpose of unit testing is to validate that each function or module behaves exactly as expected. For the Python-based AI backend, unit tests are to be written using the Pytest framework to verify critical utility functions and ensure the core simulation logic is mathematically correct. For the Next.js frontend, the Jest testing framework will be utilized to test individual React components, ensuring they render correctly and manage their state properly given a set of inputs.

Integration Testing

Integration testing is the phase where individual software modules are combined and tested as a group. The primary goal is to expose faults in the interaction between integrated units. For the SafeScape project, the most critical integration point is the API communication between the Next.js frontend and the FastAPI backend. An integration test would, for example, involve the frontend making a live API call to the /api/process-image endpoint and asserting that the backend returns a valid JSON response with the expected data structure, thereby verifying that the two separate services can communicate effectively.

End-to-End Testing

End-to-end testing is a comprehensive methodology used to test the application's workflow from beginning to end, simulating a complete user journey. This study plans to employ an automated E2E testing framework, such as Cypress or Playwright, to validate the entire simulation pipeline. A typical E2E test script would automate the process of launching the web application, uploading a floor plan image, programmatically interacting with the "Simulation Setup Wizard" to define parameters, triggering the simulation, and finally, asserting that the animation and dashboard results are correctly displayed on the page. This ensures that all components function together seamlessly from the user's perspective.

User Testing

User Acceptance Testing is the final and most critical phase of the testing process, where the system is validated by its intended end-users and stakeholders. To determine the usability and effectiveness of the SafeScape platform, the developed system will be presented to personnel from the BFP Santa Cruz and a sample of target users (e.g., adult residents, educators). Feedback will be collected through structured surveys and direct interviews. This qualitative data, focusing on the accuracy of the simulation's predictions, the responsiveness of the website, and the overall user-friendliness of the platform is essential for identifying the system's strengths and areas for future improvement.

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