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Context-Based Multi-Agent Recommender System, Supported on IoT, for Guiding the Occupants of a Building in Case of a Fire

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Abstract: The evacuation of buildings in case of fire is a sensitive issue for civil society that also motivates the academic community to develop and study solutions to improve the efficiency of evacuating these spaces. The study of human behavior in fire emergencies has been one of the areas that have deserved the attention of researchers. However, this modeling of human behavior is difficult and complex because it depends on factors that are difficult to know and that vary from country to country. In this paper, a paradigm shift is proposed which, instead of focusing on modeling the behavior of occupants, focuses on conditioning this behavior by providing real-time information on the most efficient evacuation routes. Making this information available to occupants is possible with a solution that takes advantage of the growing use of the IoT (Internet of Things) in buildings to help occupants adapt to the environment. Supported by the IoT, multi-agent recommender systems can help users to adapt to the environment and provide the occupants with the most efficient evacuation routes. This paradigm shift is achieved through a context-based multi-agent recommender system based on contextual data obtained from IoT devices, which recommends the most efficient evacuation routes at any given time. The obtained results suggest that the proposed solution can improve the efficiency of evacuating buildings in the event of a fire; for a scenario with two hundred people following the system recommendations, the time they take to reach a safe place decreases by 17.7%.

Keywords: multi-agent systems; recommender systems; context-based recommender systems; IoT—Internet of Things; fire building evacuation; ontologies; occupant behavior conditioning; building occupant guidance

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1. Introduction

The evacuation of buildings in case of fire is a widely studied problem. It is a sensitive thematic for society that has also motivated the growing interest of the academic community, with significant developments in recent decades concerning the modeling and simulation of occupants' movement. However, regarding the component of modeling related to people's behavior, there has been no corresponding development, mainly because this behavior depends on several factors that are difficult to know and vary from country to country. Even the use of artificial intelligence and so-called serious games [1] to create sufficiently immersive environments to allow potential "players" to have reactions that, in theory, will be identical to those they would have in a fire situation has not yet had results that allow obtaining the necessary knowledge to carry out this modeling with the desired rigor. On the other hand, in his doctoral thesis, Cordeiro [2] states that models that try to simulate people's behavior during evacuation do so in a simplified way and that they are very dependent on the sensitivity and knowledge of who uses the model. So, due to the lack of knowledge about people's behavior in a fire evacuation situation, more research still needs to be done, particularly about solutions capable of helping the occupants of these spaces, guiding them on their way until they are safe.

This difficulty in modeling occupants' behavior leaves the field of research open to approaches in which the focus is on solutions capable of transmitting real-time information to the occupants about the adequate evacuation routes given the fire reality. This type of solution makes people's behavior more predictable, reducing the uncertainty that this behavior introduces in the simulation of building evacuation. This solution represents a paradigm shift in building evacuation because instead of trying to model the behavior of occupants, the purpose is to condition this behavior by providing real-time information. This information allows the occupants to follow the most suitable paths from the beginning of the fire, thus avoiding the need to invert the direction of movement later when they are already in danger. By making it possible to provide timely information to occupants about the safest evacuation routes, a system such as the one mentioned may be able to reduce the time needed to evacuate a building safely, reducing the degree of uncertainty characteristic of human behavior.

The emergence and evolution of the IoT has led to significant developments in the manufacturing and production of sensors, allowing an immense range to be made available on the market at a low cost, leading to its increasing integration in buildings and other types of sensors of physical spaces. The installation of IoT devices in buildings, such as smoke, temperature, or heat detectors, can improve the well-being of those who move and live in them, allowing the production of information that occupants need in case of a fire. However, the diversity of devices and the heterogeneity of the data they produce requires that integration and dealing with interoperability problems be ensured. The paradigm of intelligent agents and multi-agent systems are suitable to help solve these problems of integration and interoperability because their architecture is suitable for the design and development of distributed systems and can respond to the requirements of the integration of things in the scope of the IoT. Furthermore, the architecture of agents and multi-agent systems is suitable for plug-and-play integration (connect and use), so this characteristic will also result in the advantages of its use as a technological basis to support the interaction between devices and people.

For Miranda et al. [3], the main objective in the development of applications for the IoT is the integration of technology in everyday life so that it results in a benefit for people as inhabitants or users of spaces. One of the possible benefits comes from creating applications or services that promote adaptability to the interests of the occupants and the environments in which they move. Recommender systems are systems that allow the users to adapt to the environment in which they are inserted, namely if they are supported on contextual information that is possible to obtain through the IoT.

Thus, by using recommender and multi-agent systems, this paper presents a solution to guide the occupants of a building in real time in the event of a fire. The solution proposed here consists of a multi-agent recommendation system based on contextual information obtained from IoT devices installed in the building. The herein presented system aims to recommend in real time the most efficient and safest evacuation routes to the occupants of a building. The proposed solution introduces a new paradigm in the evacuation of buildings in case of a fire, suggesting an approach that intends to condition occupants' behavior, providing them with real-time information on the evacuation routes they must follow to stay safe. In addition to the academic contribution to the research areas of multi-agent recommendation systems and fire building evacuation, the importance of this research work also resides in the fact that it addresses a fundamental problem for society related to security and safeguarding human lives. This paper contributes with the following novelty and main contributions:

- Development of a recommender solution based on a multi-agent system capable of improving efficiency in evacuating buildings in the event of a fire based on contextual information obtained through the IoT. The building evacuation solution provides real-time information to the occupants, contributing to conditioning the behavior of

the occupants, leading them to focus on tasks and movements that lead to their exit from the building;
- Development of a computational model for the dynamic graph representing the building, as well the development of models that, based on contextual factors, ensure the referred building graph is updated to reflect the environmental conditions of the building.

The importance of these contributions also lies in the fact that others can use them to support the development of other solutions in addition to the developed and herein presented prototype, thus contributing to the reinforcement of knowledge in the research areas addressed in this study, namely concerning multi-agent recommendation systems and the evacuation of buildings in case of fire. Furthermore, the contribution to the building evacuation domain is particularly significant in research related to the real-time orientation of occupants of a building in a fire emergency. Another important novelty that must be highlighted relates to the fact that the proposed solution, in addition to allowing future real implementation, can also be used to support the design of escape routes, even in the building design phase.

The remaining part of the paper is organized as follows: In Section 2, the theoretical concepts that support this work are introduced. Then, state-of-the-art multi-agent recommender systems and their use in the context of the IoT, as well as in the fire building evacuation domain, are presented. In Section 3, the multi-agent recommender system is presented in detail. In Section 4, the experimentation scenarios are described, and the results obtained are presented. Finally, in Section 5, a discussion of the obtained results is documented, and in Section 6, the conclusions and future work are presented.

2. Related Work

Considering that the research work presented here is based on the research areas of multi-agent recommender systems and fire building evacuation, this section summarizes the research work conducted to determine the state of the art in each research domain. Before presenting the referred state of the art for each research domain, the main theoretical concepts that support this research work are introduced.

2.1. Introducing Concepts

The concepts of an agent, a multi-agent system, a recommender system, and the IoT are introduced in the following subsections.

2.1.1. Multi-Agent Systems

According to Dorri et al. [4] it is possible to find in the literature multiple definitions for the concept of an agent, with no one being consensual [5], so different authors define an agent according to the use that each one makes of the term. For example, Maes [6] defines autonomous agents as computational systems that, inserted in complex and dynamic environments, perceive that environment and act autonomously to fulfill their designed purposes. Wooldridge [5] defines an agent as a computer system capable of acting autonomously in an environment to achieve its objectives. Franklin and Graesser [7] also define an autonomous agent as a system capable of perceiving the environment in which it operates and acting on it according to its objectives so that it subsequently senses the effects produced by its actions in that environment. In their survey, Dorri et al. [4], p. 28574 defines an agent as "An entity which is placed in an environment and senses different parameters that are used to make a decision based on the entity's goal. The entity performs the necessary action on the environment based on this decision".

Regardless of the agent definition, Morais et al. [8] define a multi-agent system (MAS) as a system composed of multiple intelligent agents that can work together to achieve goals that are more difficult to achieve by an individual agent. When integrated into a multi-agent system, agents can cooperate to achieve common goals or fulfill their purposes, negotiating to achieve the goals proposed by the system. Dorri et al. [4] define a multi-agent system as a set of multiple agents collaborating to solve a complex task. The same authors refer that features such as efficiency, flexibility, low cost, and reliability make MAS an effective solution for solving complex problems.

2.1.2. Recommender Systems

Recommender systems have been used in the most diverse application domains, including in the recommendation of pages on a website [9,10], in the recommendation of products in an online store [11], in the recommendation of learning resources in e-learning systems [12,13] or solutions within the scope of the IoT [14], in recommending tourist points of interest to visitors to a city [15], and in suggesting more efficient routes to drivers or recommending "things" to users. The different types of use make it possible to define a recommendation system as a system capable of recommending something to users. The term "item" can replace the term "something" in the previous definition in the recommender system's terminology, which refers to what the system recommends to users [16]. This definition fits that of Ricci et al. [16], for whom a recommendation system is a set of techniques and software tools that make items available for users. In line with the previous definitions is what Wei et al. [17] consider to be a recommendation: a reference to an item that is directed to the appropriate recipient. Compared with a traditional search system, Wei et al. [17] refer that recommender systems have the advantage of providing users with recommendations based on their previous preferences or the preferences of other users with similar interests. The definitions presented above allow us to state that the primary purpose of recommender systems is to support and encourage users in their decision making, providing them with items most aligned with their interests.

Recommender systems are usually classified according to how they generate recommendations, and traditionally, the following three types of approaches are identified [18]:

- Content-based approaches—the recommended items are those with similar content to past user preferences. This approach generates recommendations based on the attributes that characterize the items;
- Collaborative filtering approaches—where the recommended items are the ones that users with similar preferences to the active user liked in the past. Recommendations are generated based on user ratings;
- Hybrid approaches—in which the recommended items result from a combination of techniques used in collaborative and content-based approaches.

In addition to the approaches mentioned above, Burke [19] considers two more approach types:

- Knowledge-based approaches—recommendations are generated from inferences about users' preferences and needs. In this approach, the system knows how a specific item satisfies a user's particular need [20];
- Demographic-based approaches—in which the system generates its recommendations based on the user's demographic profile. This approach does not require a history of user ratings, as with collaborative and content-based approaches. [20].

Two other types of approaches are also commonly referred to in the literature regarding recommender systems:

- Approaches based on utility functions. Referred to by Akhtar e Agarwal [20] in their literature review, these approaches generate their recommendations from a utility function, which calculates the utility of a given item for a user;
- Context-based or context-aware approaches. This approach generates recommendations that consider the user context.

Considering the scope of the system presented in this paper, which proposes a multi-agent recommender system based on contextual information obtained from IoT devices, more attention is dedicated to context-based approaches.

Although traditional collaborative and content-based approaches continue to be the most used in recommender systems, those systems produce recommendations by only considering the item–user pair and not the user's context. For Jannach et al. [21], exploring the user's location—knowing who accompanies them and what nearby resources are available—increases the quality of recommendations. Rahman [22] also mentions that taking the context into account contributes to the improvement and reliability of recommendations. Thus, because they consider the contextual situation of the user, context-based recommender systems can generate more relevant recommendations [23]. Altulyan et al. [24] refer in their survey that the use of traditional approaches, which only consider the item–user pair, to generate recommendations tends to be inefficient when it comes to recommender systems for the IoT, which requires more contextual information. Haruna et al. [25] present the state-of-the-art context-based recommender systems, classifying the works according to the application domain, the type of approach in extracting contextual information, the type of approach in modeling this information, the type of filtering, and system evaluation techniques.

In 2005, Bazire and Brézillon [26] analyzed a corpus of 150 definitions for the term context, mainly obtained from the Web, and concluded that a consensual definition for the term is impossible. In general, authors assume the definition that best suits the context in which the term is used. However, in the scope of this work, it is important to understand what we are referring to when we talk about the use of context in recommender systems. In this sense, the classification used for the context in recommender systems is the one proposed by Adomavicius et al. [23], which is summarized in the 3×2 matrix reproduced in Table 1.

Table 1. Contextual Information Dimensions [23].

How Contextual Factors Change with Time	Knowledge of the Recommender Systems about Contextual Factors		
	Fully Observable	**Partially Observable**	**Unobservable**
Static	Everything Known about Context	Partial and Static Context Knowledge	Latent Knowledge of Context
Dynamic	Context Relevance Is Dynamic	Partial and Dynamic Context Knowledge	Nothing Is Known about Context

In their paper, Adomavicius et al. [23] present some recommender systems that fit into each matrix entry in Table 1. The system proposed in this paper fits into the first cell of the matrix, representing a situation in which everything is known about the context. The contextual factors are fully observable, and neither the contextual factors nor their structure change over time. According to Adomavicius et al. (2011), these types of systems are domain-specific, so the set of contextual factors relevant to generating recommendations must be specified as part of the recommendation system.

2.1.3. Internet of Things

The term Internet of Things (IoT) was first used in 1999 by Kevin Ashton in a presentation on the use of RFID technology at Procter & Gamble [27]. Since then, different authors have proposed different definitions. Atzori et al. [28] refer to the IoT as a new paradigm based on the idea that we are surrounded by various physical objects, such as RFID tags, sensors, actuators, smartphones, and wearables, that interact with each other to achieve common goals. Sri et al. [29] refer to the IoT as a confluence of wireless networks, the internet, and computing, which ensures the interconnection of physical objects by incorporating intelligent sensors and actuators, allowing these objects to collect and exchange information, thereby helping to communicate between them and between people and things.

The system proposed in this article falls within the scope of any of the aforementioned definitions, as it is based on data that result from the IoT ability to ensure the interconnection of physical objects installed or located in buildings, such as sensors, displays or smartphones, so that people occupying the building have access to real-time information about the most efficient evacuation routes.

As it is not within the scope of this research work to elaborate on the state of the art of the Internet of Things, it is of note here to refer to the research works developed by Atzori et al. [28], Sri et al. [29], and Laghari et al. [30]. Previous literature reviews give a perspective of the evolution of the IoT state of the art over a little more than a decade in areas such as (i) IoT architecture, which Laghari et al. [30] still consider worthy of further study to define a standard accepted by all types of application; (ii) data security and privacy; and (iii) supporting technologies, which Laghari et al. [30] also consider to be an open research area, namely concerning improving the reliability of sensors and communications to ensure their use in more critical application domains. Another area that Laghari et al. [30] consider worthy of attention from researchers refers to the need to consider in IoT applications the quality of experience (QoE) of users so that the applications and services provided are aligned with the actual needs of users

2.2. Multi-Agent-Based Recommender Systems

In his research work, Jennings [24] considers justifiable the use of multi-agent approaches for the development of complex and distributed systems. Thus, the inherent complexity of adapting and customizing websites and Web applications to the interests of their users is a complex problem, which justifies the use of multi-agent approaches in recommender systems. The problem related to the orientation of the occupants of a building during the process of evacuating a building in case of fire is also a complex problem that justifies the use of intelligent agents and multi-agent system technology. The very distributed nature of the IoT, which appears as a facilitating element of the solution proposed here, and the heterogeneity of the different IoT devices installed in a building also enhance the use of multi-agent systems.

Thus, considering the interest in combining recommender systems and multi-agent systems for the present research work, a systematic literature review on multi-agent recommender systems [31] was developed. The literature review was conducted in two phases: in the first phase, the research focused on identifying literature reviews on multi-agent recommender systems, while in the second phase, we focused on research works that propose recommendation solutions based on agent technology and multi-agent systems.

Regarding the search for literature reviews, no reviews specifically dedicated to multi-agent recommender systems were found. Concerning the literature reviews on recommender systems in general, many valuable contributions were found to be deserving of particular attention due to their impact on the literature reviews, namely those contributions developed by Adomavicius and Tuzhilin [32], Bobadilla et al. [33], Lu et al. [34], and Beel et al. [35]. The search also made it possible to identify a set of literature reviews oriented to specific application domains, such as e-learning [36] or tourism [37]. Further literature reviews on content-based recommendation approaches [38], collaborative filtering approaches [39], hybrid approaches [40], and context-based approaches [41] were also identified.

Regarding the search for research works that support solutions in multi-agent recommender systems, it is worth noting the growing adoption of this type of solution. After analyzing more than 150 papers, a set of research works were selected as representatives of recommender systems supported by multi-agent systems in the most diverse application domains, such as e-commerce, tourism, e-learning, social networks, financial markets, energy management, and IoT. Although most of these multi-agent solutions follow collaborative approaches, hybrid approaches are also significant, which is not surprising given the typical characteristics of multi-agent systems. Of additional note is the modularity of the systems provided by the distributed architecture of multi-agent systems, which enhances their use in the context of the IoT.

2.3. IoT Recommender Systems

According to Yao et al. [42], recommending things is a major step toward taking advantage of the IoT to benefit people and society, providing things of interest to users. However, for Forestiero [43], the interactions and relationships between people and things in the context of the IoT lack an adequate and efficient recommendation approach to serve users better. So, the suggestion or recommendation of things in this type of environment is an essential service in areas such as healthcare, smart cities, and smart spaces. Below are some research works that propose recommender systems in the context of the IoT supported by multi-agent systems.

One of these works is the one developed by Salman et al. [44], who propose a recommender system based on neural networks to make recommendations to users in the context of the IoT. As an innovative aspect, the authors refer to proactivity, achieved through the determination of the user's context and the recommendation of multiple types of items (gas stations, restaurants, and tourist attractions). Twardowski and Ryzko [14] propose a recommendation solution based on a multi-agent system and contextual information supported by the IoT to generate personalized recommendations on mobile devices. Digital signage (DS) is a technology used in the context of the IoT, particularly in public outdoor spaces, which allows for the provision of urban information and guidance to the residents of a city. Considering that, in most cases, these signaling systems do not incorporate a recommendation mechanism that considers the context, nor do they take interactivity into account, Tu et al. [45] present a context-aware recommender system to overcome these limitations. Taking advantage of the features that come from the IoT, Di Martino and Rossi [46] propose an architecture for a multi-agent recommendation system for mobility in smart cities. A multimodal solution is proposed, in which a user starts the journey in his car but can park in a car park and travel the rest of the way in public transport. The inclusion of parking in the recommendation system is one of the main contributions, given the little research in the area. According to the authors, the option for a multi-agent solution is due to its modularity and suitability for distributed approaches. Cha et al. [47] propose an IoT platform to support a context-based real-time recommender system, which relies on smartphone data to recommend new items to a user, using georeferencing to determine their location and, consequently, the context in which they are inserted. This location can be obtained in two ways: using the Google Location API to identify points of interest within a certain radius of action (used outside buildings) or using IoT devices whose radius of action depends on the signal coverage radius of that device. Another work is presented by Forouzandeh et al. [48], in which they propose a system whose purpose is to recommend things to users based on the similarity between users and the relationships between users, objects, and services. Finally, in their survey, Altulyan et al. [24] created a literature review on recommender systems for the IoT, presenting the works they considered most relevant in smart homes, smart health, car parking, or tourism. In their research work, the authors also propose a framework that, in addition to allowing the comparison of existing studies, aims to be a tool to support the development of new research projects.

2.4. Fire Building Evacuation

Considering that the system proposed here addresses the evacuation of buildings in case of fire, it is essential to present the related works in the area. Although the evacuation of buildings has been a problem studied over the last decades from different perspectives, such as the behavior of occupants, the identification of escape routes and their congestion, and the dangers arising from fire, the focus is mainly on the orientation of occupants during the building evacuation process.

In the first phase, the research work focused on the search for literature reviews regarding the evacuation of buildings. Most literature reviews focus on surveying evacuation models, systems, and algorithms for optimizing evacuation routes or evacuation simulation software. However, people's behavior in evacuation situations also deserves the attention of researchers as well. Regarding the occupants' guidance during the evacuation process, some literature reviews refer to research works that present solutions capable of guiding, in real-time, the occupants of the building to a safe place. Because they fall within the scope of the objectives of this research work, two of them are referred here. In the first one, Ibrahim et al. focus their research on intelligent evacuation management systems (IEMS). These systems must be able to suggest to occupants the routes that allow them to reach a safe place, helping them to avoid areas where congestion and route blocking occur, thus reducing the time to evacuate the building. The authors mention five methods of notifying occupants of evacuation routes: mobile applications, enlarged photos with indicative arrows, digital monitors, intelligent lighting, and sound signaling. In the other literature review, Bi and Gelenbe [49] present the state of the art in emergency evacuation and evacuation guidance, focusing on aspects related to algorithms and systems. The authors highlight the impacts of information and communication technologies (ICT) and IoT developments on disaster mitigation and prevention, identifying evacuation guidance and emergency search and rescue as lines of investigation. The authors define evacuation guidance as the process of guiding the occupants through safe zones with the help of algorithms or using pre-conceived static evacuation plans based on the prediction and analysis of occupant behavior models. Bi and Gelenbe [49] also identify possible future lines of research, such as the development of algorithms based on artificial intelligence to improve the determination of evacuation routes and resource allocation. The authors also suggest using multi-agent systems to model and develop better cooperation strategies.

In the second phase of the research, the focus was on research works addressing real-time occupant guidance during a building evacuation in case of fire. In their work, Wang et al. [50] propose integrating information from sensors in the form of a dynamic graph that evolves and translates the state of the sensors at each moment. The dynamic sensor graph propagates the state to an evacuation path graph. Based on both graphs, the authors propose an evacuation solution that considers the hazard inside the building. The proposed model was tested and evaluated through an agent-based simulation with the following parameters: (i) the number of successful evacuees; (ii) the average and maximum evacuation time. In their paper, J. Liu et al. [51] present a framework to calculate efficient evacuation paths to evacuate a building based on information obtained from a sensor network. A central server processes the information and calculates the evacuation routes in real time using the A* algorithm [52]. Finally, the evacuation routes are presented to the occupants through the existing signage in the building or through their smartphones. In their paper, Lujak et al. [53] present the architecture of a multi-agent system for optimizing evacuation routes in large smart spaces. The proposed model considers the safety aspects of the routes. Each occupant is represented in the system by an agent who runs on an app on their smartphone, from which they receive the shortest safe routes calculated by an agent specifically designed for this purpose. Shikhalev et al. [54] propose an algorithm that determines and presents occupants' safest path in a fire emergency. The proposed solution uses the Floyd–Warshall algorithm [55]. Instead of the edge weight being just its length, the authors consider a more complex criterion based on the square root of the sum of three criteria: a criterion called obstruction, which is related to the density of people in a specific area of the route; a timeliness criterion that is related to the hazards arising from fire (high temperature, large amount of smoke, low visibility, toxicity resulting from combustion); and a criterion related to the length of the route. Each criterion is subject to a weighting coefficient. Considering aspects related to route safety and the influence of stress on people's reactions to the emergency, Lujak and Ossowski [56] present the architecture for a solution to optimize evacuation routes based on a multi-agent system. Furthermore, the authors intend to provide recommendations of evacuation routes in real time through smartphones or smart displays. Developing sensor technology in the most diverse application domains enhances the implementation of building automation systems (BAS), which allow the management of these buildings. Based on these systems, Gokceli et al. [57] propose creating an emergency evacuation service that uses the IoT to integrate the typical functions of a building automation system (heating, ventilation, lighting, security, and energy management) with sensors, wearable devices, and smartphones. Lee et al. [58] propose an intelligent escape route system that combines sensors and digital signaling devices through a WSN. With the information obtained, the system perceives the conditions of the building, calculates the most appropriate evacuation route, then activates the respective digital signaling devices. In their study, Li and Zhu [59] present a model for optimizing evacuation routes that consider the distance to travel, the density of people, and the hazards arising from the fire, which depend on factors such as temperature, thermal radiation, and toxic gas concentration.

2.5. Summary

As a result of a systematic literature review conducted within the scope of our Ph.D. thesis, we present the state of the art in different research areas in which the solution proposed here fits. In addition, the study allowed knowledge consolidation about fire building evacuation and multi-agent recommendation systems. So, it was possible to identify the need to develop solutions capable of improving the efficiency of the evacuation of buildings in the event of a fire. Furthermore, concerning multi-agent recommender systems, the study allowed us to identify the potentiality and characteristics that justify adoption in the most varied application domains, namely in the context of the IoT, which explains their adoption in the solution presented here to guide occupants during the evacuation of a building in case of a fire.

3. The Proposed Solution: A Multi-Agent System for Recommending Fire Evacuation Routes in Buildings, Based on Context and IoT

This section presents the proposed solution to guide the building occupants to a safe place in case of fire. The solution uses a multi-agent recommendation system based on contextual information obtained from data collected by IoT devices installed in the building.

3.1. An Ontological Model as Support for the Recommender System

As seen from the literature reviews, the evacuation of buildings in the event of fire lacks solutions that can help the occupants in guiding them on their path until they are safe. The construction of such solutions requires a deep knowledge of the subject, which can be achieved through developing an ontological model to support the recommendation of evacuation routes in buildings under fire emergency. In this sense, an ontology for the evacuation of buildings under fire emergency [60] was created first, which allows us to clarify and consolidate the knowledge on the referred domain. In a second phase, based on the ontology mentioned above, an ontological model for the recommendation of evacuation routes in buildings under fire emergency [61] was developed, whose graphic representation is shown in Figure 1.

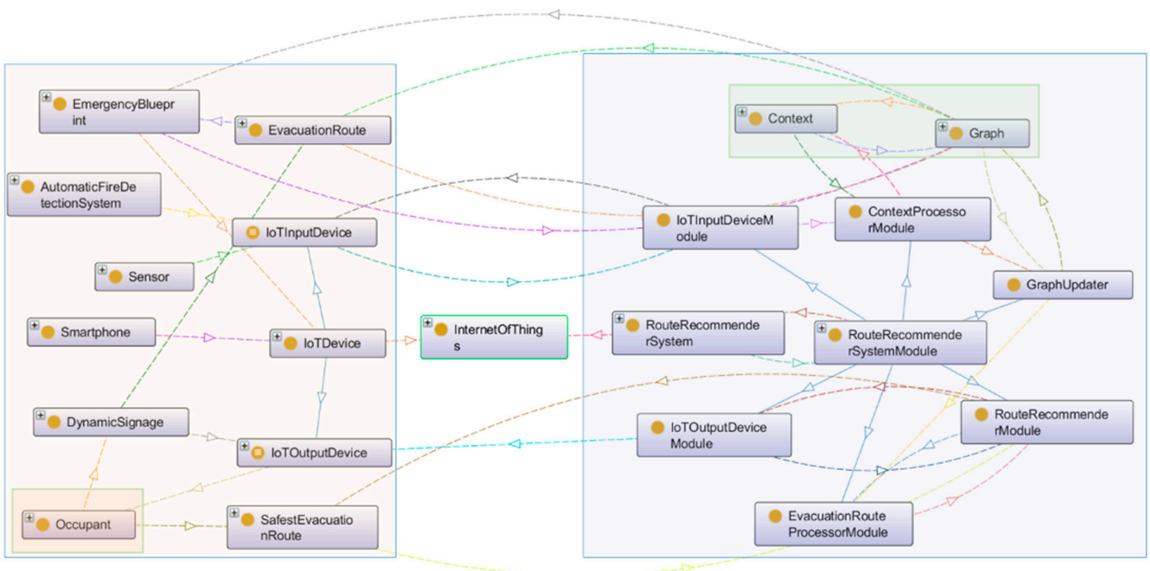


Figure 1. Graphical representation of the ontological model, highlighting two sets of terms that characterize this model, supported by the IoT. Obtained from Neto et al. [61].

The graphical representation of Figure 1 highlights two blocks of classes interconnected by the IoT. The left block of classes represents the building through its emergency blueprint, the evacuation routes, the different devices installed, and the occupants who move inside the building. In the right block of classes of the same figure, the classes that constitute the recommender system are shown, highlighting the context and graph classes, which serve as a basis for decision making in the recommender system.

Figure 2 presents the recommender system, its modules, and their relationships. The recommender system obtains data for processing through the **IoTInputDeviceModule**, which represents each IoT input device installed in the building that collects data to contribute to the recommender system's decision making. The data are sent to the **ContextProcessorModule**, which transforms it into contextual information. The **GraphUpdaterModule** uses that information to update the building graph in real time. The resulting graph is made available to the **EvacuationRouteProcessorModule**, which uses a graph theory algorithm to determine a set of safe paths made available to the **RouteRecommenderModule**. In possession of these safe routes, the **RouteRecommenderModule** generates recommendations that, through the **IoTOutputDeviceModule**, are sent to the respective IoT output devices, such as digital signs or smartphones, which present those recommendations to the building occupants.

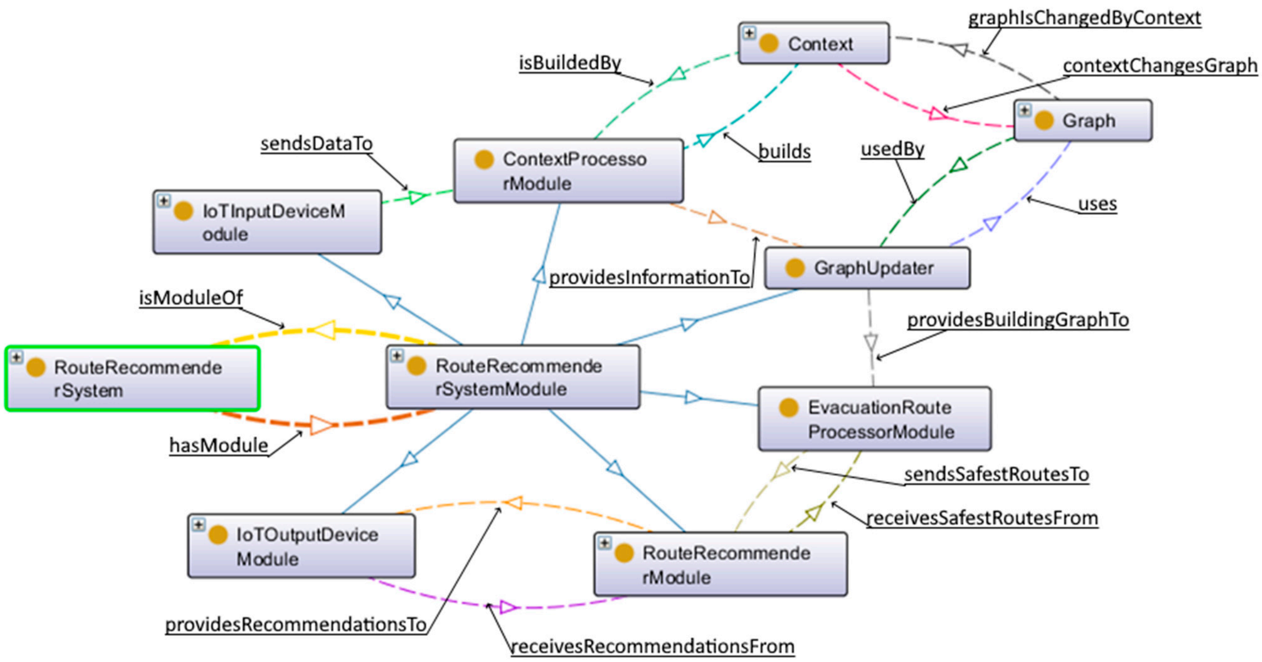


Figure 2. The recommender system, its modules, and their respective relationships. Obtained from Neto et al. [61].

3.2. The Recommender System

As mentioned before, the ontological model gives rise to a recommender system supported by the IoT. The recommender system recommends safe evacuation routes to the occupants of a building in a fire emergency, based on the building's contextual conditions, obtained through IoT devices. Figure 3 presents the global architecture of the solution.

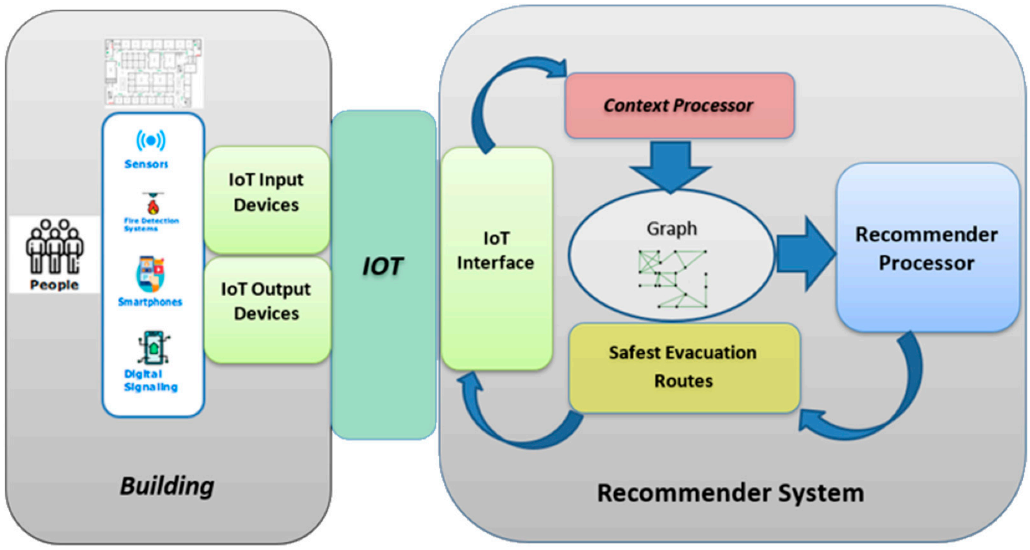


Figure 3. The global architecture of the recommendation solution.

It can be inferred from Figure 3 that contextual information is obtained through IoT input devices such as sensors, and that recommendations are made available to building occupants through IoT output devices such as digital signage. Furthermore, the architecture shows that the graph representing the building in the recommender system is updated in real time, based on that contextual information.

3.2.1. Contextual Factors to Consider

The contextual factors should allow the characterization of the evacuation routes used by the occupants to leave the building. The recommender system creates contextual information using the data obtained by the IoT input devices. These devices are sensors of different types capable of measuring different quantities and can be divided into two large groups. Firstly, the risk factor group (GFR) consists of devices that measure or detect quantities such as temperature, smoke, gas, or flame to reflect the risk to the occupants. Secondly, the congestion factor group (GFCg) reflects the congestion of routes resulting from the number of occupants in a section, which includes presence sensors and people counting. In addition to risk and congestion factors, the location factor must also be considered according to three aspects: the location of IoT input devices that allow the recommender system to be aware of the area of the evacuation route subject to restrictions; the location of IoT output devices used to indicate safe evacuation routes; and the location of the occupants in the building, to whom the recommendations are addressed.

3.2.2. The Recommender System Formulation

As its name suggests, the system presented here aims to recommend, in real time, the safest and most efficient evacuation routes so that the occupants of a building can reach a safe place. For the construction of this system, the following representations were considered:

- G is a graph representing the entire walkable area of a building and consists of vertices (V) and edges (A), which are pairs of vertices. A weight, w, associated with each edge represents the distance between the adjacent vertices or the time it takes an occupant to move between two adjacent vertices; thus, G can be written in the form:

$$G = (V;A,w) \tag{1}$$

- P represents the set of all paths in the graph G such that:

$$P = \{P_0, P_1, \ldots, P_N\} \tag{2}$$

- Each path P_i is a sequence of vertices $v \epsilon V$ such that:

$$P_i = \{v_{i0}, v_{i1}, \ldots, v_{iN}\} \tag{3}$$

- v_{ii} and v_{ii-1} are adjacent vertices;
- E represents a subset of P that contains all the evacuation routes that a building occupant must travel through to reach a safe place such that:

$$E_i = \{ve_{i0}, ve_{i1}, \ldots, ve_{iN}\} \tag{4}$$

where ve_{i0} to ve_{in-1} are vertices representing points inside the building, and ve_{iN} represents a safe place, be it inside (refuge zone) or outside of the building;
- W_i represents the length of P_i (or the time it takes to walk the path), such that:

$$W_i = \sum_{n=1}^{l} w_{in} \tag{5}$$

where w_{in} is the weight of the edge of the two adjacent vertices v_{ii} and v_{ii-1}.

The recommender system could use contextual information to update the graph. However, it has also become clear that contextual factors impact evacuation routes and, consequently, the conditioning of occupants' movement, namely due to the blocking of paths or the reduction in the speed of the occupants. So, the context, Cx, can be defined such that:

$$Cx = (GFR; GFCg) \tag{6}$$

where GFR and GFCg are the contextual risk and congestion factors referred to earlier.

The introduction of the contextual factors in the recommendation model considers that, in the recommender system, graph G represents the building. So, the edges (A) can be seen as parts of the evacuation path E. Therefore, the weight w, associated with each edge, changes its value depending on the context created by the fire ignition and perceived by the IoT input devices. Thus, G can be rewritten as a function of time:

$$G(t) = (V;A,w(Cx(t))) \tag{7}$$

G(t) and Cx(t) represent the graph and the context at time t.

Considering that the purpose of the recommender system is the recommendation of the safest and most efficient evacuation route so that the occupants leave the building safely, S(t,l) can be defined as the set of safer evacuation routes at time t, at location l, such that:

$$S(t,l) = \{S_0, S_1, \ldots, S_J\} \tag{8}$$

So, let RS be the recommender system; then:

$$RS: (G(t),t,l) \to S(t,l) \tag{9}$$

The above expression states that the recommender system recommends safe evacuation routes based on a dynamically updated graph based on the context. The context is built from data obtained by IoT input devices.

3.2.3. The Computational Representation of the Graph

In the herein-presented prototype, the graph representing the building is created based on the model developed by Neto et al. [62], which allows a building to be represented by a much lesser-dimensional graph, which directly impacts computing processing time since the Floyd–Warshall algorithm, used to solve all pairs' shortest path problems, has a time complexity of $\Theta(v^3)$, where v is the number of vertices of the graph.

To develop the prototype of the proposed system, it was considered that the graph consists of two matrices: an adjacent matrix (MA) and a distance matrix (MD). Both are square matrices in which the lines and columns represent the graph's vertices. In this way, the graph G at time t may be written in the form:

$$G(t) = (MA(t); MD(t)) \tag{10}$$

The above expression reflects the impact of contextual factors over time, thus translating into a graph that changes dynamically.

Additionally, considering MD_0, the initial distance matrix (at t = 0), and MFc, the matrix of contextual values that impact the paths between adjacent vertices, MD(t) can be rewritten in the form:

$$MD(t) = (MD_0; MFc(t)) \tag{11}$$

So, the dynamic graph, G(t), is represented with three square matrices such that:

$$G(t) = (MA(t); MD_0; MFc(t)) \tag{12}$$

where the values of MA(t), MFc(t), and MD_0 are calculated according to the following expressions:

- For MA(t), it must be considered that:

$$\begin{matrix} ma(i,j) = 1, \text{ if vertices i,j are adjacent} \\ ma(i,j) = 0, \text{ if vertices i,j are not adjacent} \end{matrix} \tag{13}$$

- Concerning the values of MD(t), which is a function of MD_0 and MFc(t), one must consider:

$$md((i,j),t) = (md_0(i,j) + mfc((i,j),t)) \tag{14}$$

  where:

  - $md_0(i,j)$ represents the values of MD_0 such that:

$$\begin{matrix} md_0(i,j) = d_{ij}, \text{ if vertices i,j are adjacent} \\ md_0(i,j) = \infty, \text{ if vertices i,j are not adjacent} \end{matrix} \tag{15}$$

  - d_{ij} is the distance between the adjacent vertices i,j;
  - mfc(i,j), with i and j being adjacent vertices, represents the values that MFc takes over time.

Our recommendation solution considers that contextual information is constructed from data gathered through IoT input devices installed in the building. In the model, two groups of contextual factors are defined: GFR and GFCg; the first relates to the hazard arising from the fire, and the second refers to route congestion. Further, as already mentioned, contextual factors impact evacuation routes, leading to blocking or congestion routes and slowing the occupants' movement. The following sections describe the models used to update the matrix of contextual factors as a function of route congestion and fire hazards.

3.2.4. Contextual Factors Matrix Update Model: Congestion

Congestion of evacuation routes results from the high density of people in a specific part of the route, particularly close to doorways and exit doors that, to a certain extent, strangle the way out, which can lead to situations of total blockage because people are unable to move [63]. Thus, one of the main objectives of the recommendation solution proposed here is to prevent possible blocking situations by recommending alternative safe evacuation routes. Those situations are prevented through IoT input devices equipped with the appropriate sensors and detectors, whose measurements are forwarded to the recommender system.

The information obtained by the IoT input devices regarding the number of people in a section of the evacuation route will determine the delay time in that section. To calculate this time, the concept of specific flow (Fe) is used, which Coelho [63] defines as the number of people passing through a given section of an escape route per unit of time and per unit of effective width of the evacuation element involved. The specific flow (F_e) can be given by the expression:

$$F_e = V * D \tag{16}$$

where V is the evacuation speed and D is the density, given in people per square meter.

According to the same author, the total flow (F) equals the product of the specific flow and the width (L) of the route section and is given by:

$$F = V * D * L \tag{17}$$

Thus, the time required for a group of people (P) to pass through a doorway of width L is given by the expression:

$$T = P/F = P/(V * D * L), \tag{18}$$

where time T corresponds to the delay time taken for the occupants to traverse in a segment, and it is used to update the matrix MFc(t) and, consequently, the graph. Thus, considering the segment of an evacuation route between two adjacent nodes i and j of graph G and considering T((i,j),t), the delay time of the occupants in that segment at instant t

$$mfc((i,j),t) = V_{NE} * T((i,j),t), \tag{19}$$

where $\boldsymbol{V_{NE}}$ is the speed at which an occupant travels in a fire emergency on an uncongested or low-occupancy-density route. Expression 19 is equivalent to saying that there is an increase in the distance between nodes i and j of graph G.

As for the value of VNE, the work of Coelho [63] and the PD 7974-6:2019 standard [64] were considered, which refer that for a density D < 0.54 (p/m^2,) the building occupants move without being affected by other occupants. Therefore, from the expressions of the occupants' movement speed presented in the referred research works, it is considered that, for the presented model, V_{NE} equals 1.2 m/s.

3.2.5. Contextual Factors Matrix Update Model: Risk

According to standard PD 7974-6:2019, smoke causes occupants to slow down due to reduced visibility and the presence of toxic and irritating gases. Table 2 shows the effects of smoke on occupants' visibility and speed.

Table 2. How the smoke effects influence occupants' visibility and speed. Adapted from standard PD 7974-6:2019 [64].

Smoke Density and Irritancy D.m^{-1} (Extinction Coefficient)	Approximate Visibility Diffuse Illumination	Reported Effects
None	Unaffected	Walking speed of 1.2 m/s
0.5 (1.15) non-irritant	2 m	Walking speed of 0.3 m/s
0.2 (0.5) irritant	Reduced	Walking speed of 0.3 m/s
0.33 (0.76) mixed	3 m approx.	30% of people turn back rather than enter the smoke area
Suggested tenability limits for buildings:		
small enclosures and travel distances: D.m^{-1} = 0.2 (visibilities of 5 m) large enclosures and travel distances: D.m^{-1} = 0.08 (visibilities of 10 m)		

According to standard PD 7974-6:2019, there is a relationship between the smoke density and the concentration of irritating gases, implying that for the proposed limit of D.m^{-1} = 0.2, most fires remain tolerable for 30 min concerning asphyxiating gases.

Another factor limiting the movement of occupants and their decision to continue along a specific route is heat, as temperatures resulting from a fire reach values that the human body cannot withstand. Standard PD 7974-6:2019 proposes tolerable limits for heat based on the time of pain resistance for unprotected skin, stating that in situations where there is a high percentage of water vapor in the air, as in fires in places with sprinklers, the maximum tolerable temperature is 60 °C.

Table 3 summarizes the impacts of smoke, toxic gases, and heat on the occupants' movement, whether in terms of the occupants' travel speed in the scenario where they are already in the smoke area, or if they decide not to enter the affected zone and to instead look for an alternative route.

Table 3. Impact of smoke, heat, and toxic and asphyxiating gases on occupants' movement.

Hazard Factor	Impact on Occupants' Movement
Smoke and toxic and asphyxiating gases	If there is smoke with density $D.m^{-1} \leq 0.2$, an occupant can move through it. However, the occupant's speed will tend to reduce to 0.3 m/s, so more time is needed to cover that section of the route affected by the smoke. As the speed in smoke-free conditions is 1.2 m/s (Table 2), an occupant will take four times longer to travel that section.
	If $D.m^{-1} > 0.2$, the model considers that there are no conditions allowing occupants to enter or travel through the area with smoke, especially as the probability of the existence of irritating or even asphyxiating gases is high, so the section must be considered prohibited.
Heat	The evacuation routes are traversable where the temperature in the cold layer is below 60 °C. For higher values, the presence of people is possible, but with low saturations and only in situations where people are already in the affected area, so people should avoid entering a section with temperatures above 60 °C.

Considering that the three mentioned factors tend to be present simultaneously in the same section, a model that considers five risk levels was considered for this study, as shown in Table 4.

3.2.6. Contextual Factors Matrix Update Model: Congestion and Risk

In the previous sections, separate models were presented for congestion and for the risk related to fire development and propagation. However, during a fire, both types of factors coexist. Hence, it is necessary to combine the values calculated for congestion and risk to determine the value of MFc((i,j),t) for each section of an evacuation route.

The methodology adopted is based on the levels of risk arising from the hazards related to smoke, toxic gases, and heat. Thus, in levels 4 and 5, considering that the sections are prohibited, the respective graph vertices are no longer adjacent, meaning there is an apparent infinite distance between those vertices. In the remaining risk levels, the value of the contextual factors matrix, mfc((i,j),t), results from the sum of the components related to congestion and risk presented in the previous sections, as shown in Expression 14. Table 5 shows the expressions to determine the values of the adjacency and distance matrices used in the recommender system.

3.3. The Multi-Agent Recommender System

In the previous sections, the recommendation approach was presented, as well as the theoretical formulation of the recommender system and the model for updating the graph of the building, depending on the change in environmental conditions. This section presents the referred recommender system's implementation using multi-agent system technology.

The use of multi-agent systems has already been justified and is in line with their growing presence as supports for recommender systems in the most diverse application domains and for using different approaches, as is the case of context-based approaches under IoT environments.

Table 4. Risk level table: Values of mfc((i,j),t) resulting from the impact of smoke, heat, and toxic and asphyxiating gases on occupants' movement.

Risk Level	Effects on Occupants' Movement	mfc((i,j),t) Values (Assumptions in the Developed Prototype)
0	The occupants move at normal speed. The graph is not affected.	**mfc((i,j),t) not affected**
1	It reflects the smoke in the area but with a reduced impact on the occupants' movement. This level of risk reflects in the graph by increasing the length of the section. However, a person will continue his way through the smoke.	The model assumes a 20% decrease in the occupants' speed, which is equivalent to an apparent 20% increase in the initial length of the route section, so: **mfc((i,j),t) = 0,2 * md_0(i,j)**
2	Both risk levels reflect that smoke density and heat are already noticeable. Therefore, those in the area will continue on their way if the bearable limits are ensured. However, the recommender system must penalize the routes that use the section in question; this fact will be reflected in the building graph, as shown in the column on the right.	A 50% speed decrease is assumed, which means an apparent doubling of the initial length of the section, so that: **mfc ((i,j),t) = 1,0 * md_0(i,j)**
3		The model assumes that the occupants' speed decreases from 1.2 m/s to 0.3 m/s, which means an apparent quadrupling in the initial length of the section, so: **mfc ((i,j),t) = 3,0 * md_0(i,j)**
4	Refers to route sections in which factor values exceed the bearable limits for people. The recommender system must consider these sections prohibited, so the graph must be updated accordingly.	The interdiction of the section is reflected either in the adjacency matrix—nodes i and j are no longer adjacent—or in the matrix of hazard factors, reflected in the following equations: **ma((i,j),t) = 0** **mfc((i,j),t) = ∞**
5		

Table 5. Conjugation of values related to congestion and risk.

Risk Level	Graph Matrix Values	Value Updates due to Risk	Value Updates due to Congestion
0	Mfc values	mfc((i,j),t) does not change	mfc((i,j),t) = V_{NE} * T((i,j),t)
	MD and MA values	md((i,j),t) = md_0 (i,j) + V_{NE} * T((i,j),t) ma((i,j),t) does not change	
1	Mfc values	mfc((i,j),t) = 0,2 * md_0 (i,j)	mfc((i,j),t) = V_{NE} * T((i,j),t)
	MD and MA values	md((i,j),t) = md_0 (i,j) + 0,2 * md_0 (i,j) + V_{NE} * T((i,j),t) ma((i,j),t) does not change	
2	Mfc values	mfc((i,j),t) = 1,0 * md_0 (i,j)	mfc((i,j),t) = V_{NE} * T((i,j),t)
	MD and MA values	md((i,j),t) = md_0 (i,j) + 1,0 * md_0 (i,j) + V_{NE} * T((i,j),t) ma((i,j),t) does not change	
3	Mfc values	mfc((i,j),t) = 3,0 * md_0 (i,j)	mfc((i,j),t) = V_{NE} * T((i,j),t)
	MD and MA values	md((i,j),t) = md_0 (i,j) + 3,0 * md_0 (i,j) + V_{NE} * T((i,j),t) ma((i,j),t) does not change	
4 and 5	Mfc values	mfc((i,j),t) = ∞	mfc((i,j),t) = V_{NE} * T((i,j),t)
	MD and MA values	mfc((i,j),t) = ∞ ma((i,j),t) = 0	

3.3.1. Multi-Agent Recommender System Architecture

Based on the global architecture represented in Figure 3, presented in Figure 4 is the architecture considering the Evacuation Route Multi-Agent Recommender System (ERMARSys), which highlights the role of the IoT and the context as a support for the recommender system in generating recommendations.

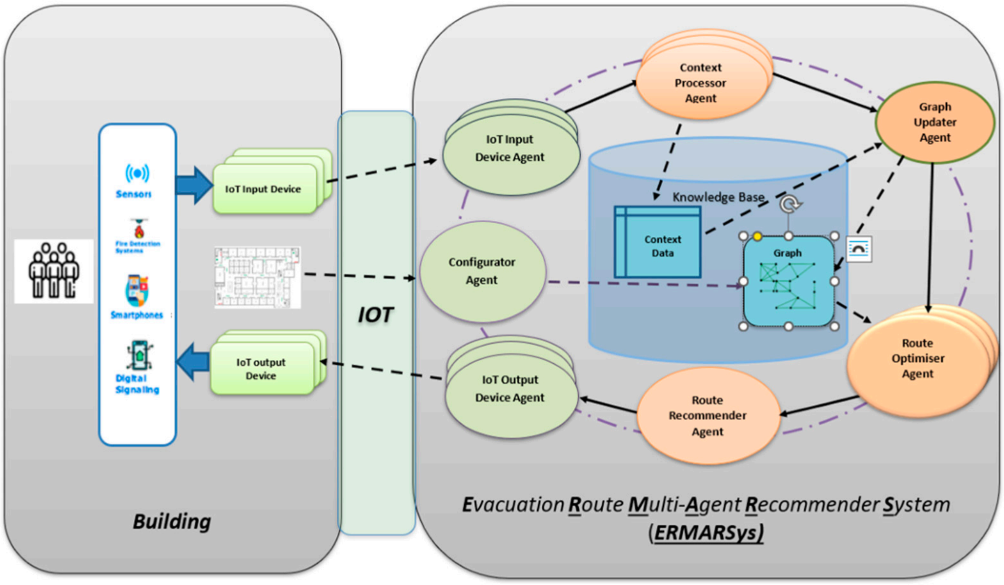


Figure 4. The architecture of the multi-agent-based recommender solution.

3.3.2. The Multi-Agent System

The multi-agent system considers seven different agent types, which can be divided into two groups. One group of agents interact with the building environment, and another group of agents are responsible for processing data and producing recommendations.

Concerning the first referred group, the model considers three types of agents. The **Configuration Agent** is the first of these agents. It is the system's starting point, to which all information related to the building is transmitted and whose primary function is to create the remaining agents. The second type is the **IoT Input Device Agent—**those agents that interact with the IoT input devices installed in the building, each of these devices having an agent with which it interacts in the multi-agent system. Finally, the third type of agent is the **IoT Output Device Agent**, and each agent interacts with an IoT output device installed in the building.

Regarding the group of agents responsible for processing data and producing recommendations, the model considers four different types of agents. One of the agents, called the **Context-Processor Agent**, receives data from IoT input devices, processes the data, and transforms the data into contextual information. Depending on the contextual factors involved, one or more agents of this type can exist. The second type of agent is the **Graph Updater Agent,** which uses the contextual information produced by the Context Processing Agent(s) to dynamically update the graph, reflecting the conditions of the building's evacuation paths in real time. Another type of agent, the **Evacuation Route-Optimizer Agent**, applies the shortest path search algorithm to the graph, and in this case, the "shortest path" refers to the path with the lowest sum of weights of the sections that make up its entirety. The fourth type of agent, the **Evacuation Route Recommender Agent**, in possession of the location of the IoT output devices in the building, uses the previous agent to determine the best routes to recommend to the occupants, sending them customized information to said IoT output devices.

In Figure 5, the architecture of the multi-agent system is presented in detail, highlighting the relationships between the different types of agents.

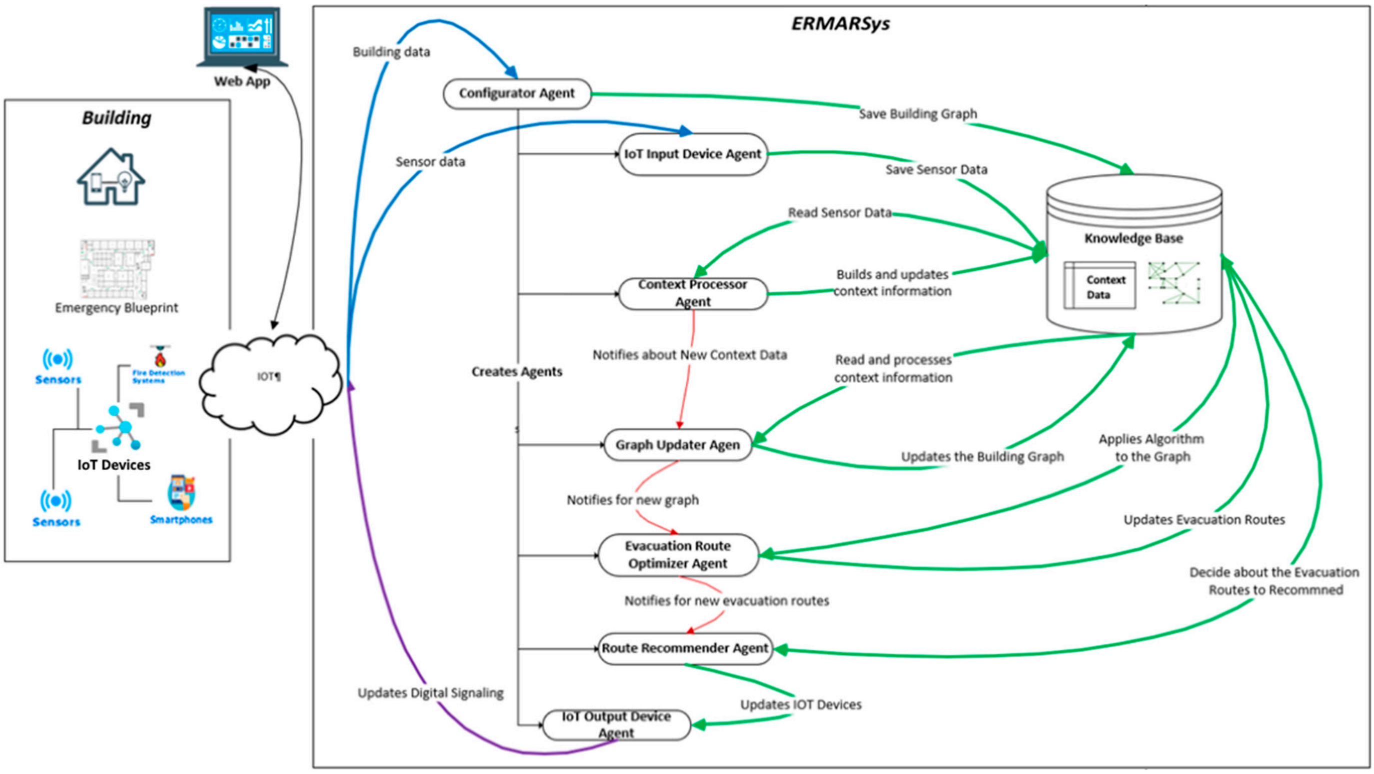


Figure 5. The architecture of the multi-agent system, highlighting the relationships between the different types of agents.

To evaluate the proposed recommender solution, a system prototype was implemented. The multi-agent system was implemented in Java, using the JADE (Java Agent Development Framework) (http://jade.tilab.com/, accessed on 2 April 2022), which facilitates the implementation of multi-agent systems and complies with the FIPA (http://www.fipa.org/, accessed on 2 April 2022) standard of the IEEE Computer Society. The prototype allows us to study the extent to which the proposed solution improves the efficiency of evacuating buildings in the event of a fire.

4. Experiments and Results

This section presents the experimental scenarios that allowed for the testing and evaluation of the prototype, as well as the results obtained. Firstly, the reason for choosing the platform used for the tests is justified. Then, the criteria used to evaluate the system are described, concluding with the description of the experimentation scenarios and the presentation of the test results.

4.1. The Test Platform

The recommender system was tested in a simulation environment using a Web simulation platform for building evacuation developed within the scope of our Ph.D. thesis. The Web platform is based on the Model for Analysis of Fire Safety Conditions in Buildings (MACSIE) presented by [65], which implements the models developed by [62] and considers 2D plans of the spaces that will be the basis of experimental scenarios.

The option to use the referred Web simulation platform instead of using a general-purpose simulation platform based on agents, such as NetLogo [66], GAMA [67], or AnyLogic (https://www.anylogic.com/#tab7, accessed on 4 May 2022), lies in the fact that more than the mere simulation of an evacuation process, it is necessary to develop and test a prototype (the presented multi-agent recommender system) with specific and very particular characteristics, namely concerning the paradigm shift in terms of the evacuation of buildings as mentioned above, in which the focus is no longer centered on the knowledge of people's behavior, but on the conditioning of that behavior through the provision of real-time information on the safest and most efficient evacuation routes.

4.2. Evaluation Criteria

The evaluation of the ERMARSys recommender system is conducted by comparing the evacuation times in the different simulated scenarios to assess the extent to which the impact of the multi-agent recommendation system is felt in the way occupants move until they are safe. The evaluation metric considers the overall objective of this research work, studying the extent to which the system can contribute to improving efficiency in the evacuation of buildings and recommending the most efficient, safe evacuation routes at any given time. Furthermore, these recommendations must help reduce the unpredictability of occupants' behavior, allowing them to move along paths that present adequate evacuation conditions, thus preventing occupants from moving along paths that lead to fire-blocked areas. Therefore, the ERMARSys assessment should focus on the movement time of the occupants, defined as the time the occupants take from the instant they start to leave the building to the moment they reach a safe place, comparing these times from tests and simulations, with and without ERMARSys and with and without a fire outbreak, for the different experimentation scenarios. Therefore, the basis of comparison is the occupants' reference movement time (TMRef), which can be defined as the maximum time that an occupant can take to reach a safe place in a situation where there are no blocked routes or congestion.

4.3. Experimental Scenarios

To conduct the tests, a building with a high density of people per square meter was considered, as is the case of the area referring to the LNEC congress center. It is a space of about 2000 m^2 with a capacity for about 300 people, including support staff. The space consists of the main room for about 200 seated people, five smaller rooms with an average capacity of 20 people, a technical room, six support offices, and a large hall, which, in general, is partially occupied by exhibitor stands. Figure 6 presents the space blueprint, designed with the Web simulation platform's Web component.

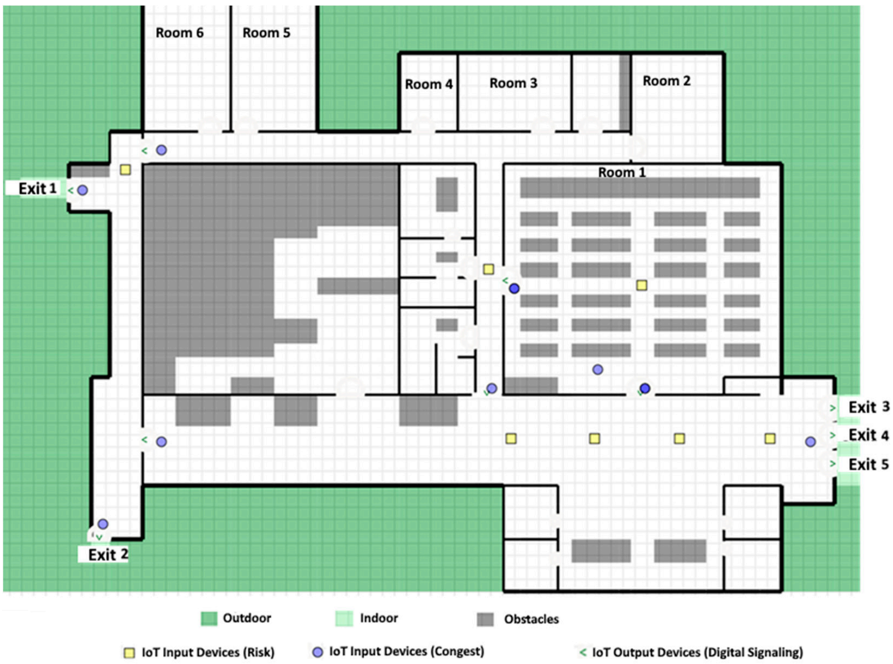


Figure 6. Simplified floor plan of the LNEC congress center, created with the Web component of the simulation platform.

The simulations were conducted with and without the ERMARSys active and with and without a fire outbreak. The following scenarios were considered:

- Scenario 1—Two occupants are positioned side by side in Room 2;
- Scenario 2—Group of 30 occupants positioned in Rooms 2 to 4;
- Scenario 3—Group of 200 occupants randomly positioned.

For each of the scenarios, the simulations considered two different situations related to the familiarity of the occupants with the building:

- Situation A—All occupants are familiar with the congress area and head towards the exit according to their knowledge of the space, so they do not follow the emergency signs;
- Situation B—None of the occupants know the space and continue to exit the building following the emergency signs.

The initial positioning of the occupants is the same for situations A and B.

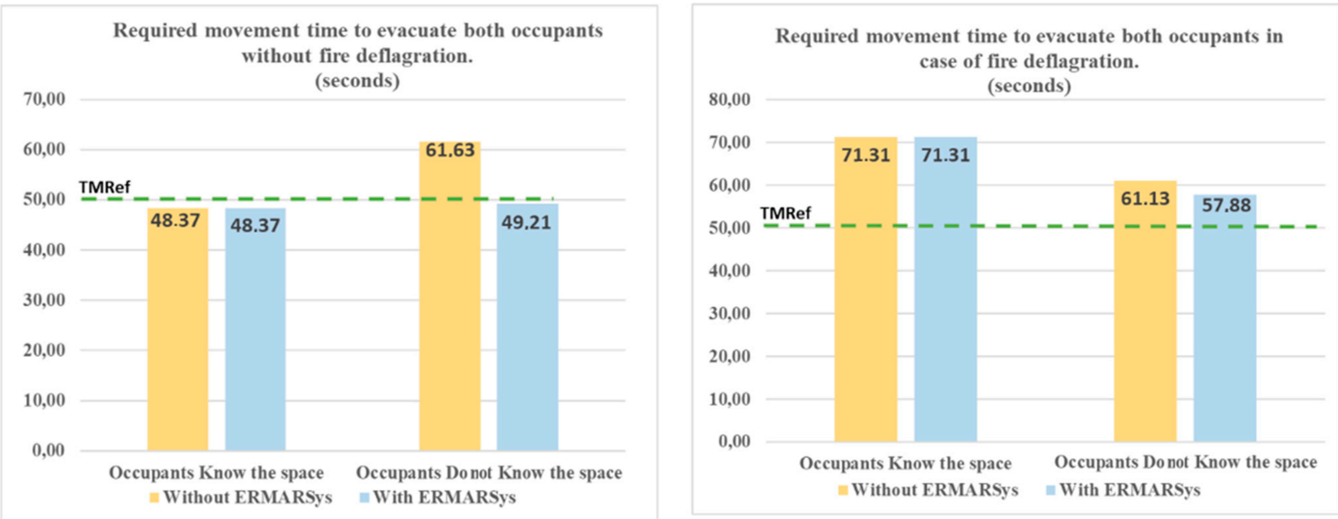
4.4. Results

This section presents the results obtained with the simulations for each scenario described. The results will be shown through bar graphs and images obtained from the simulation platform. The bar graphs show the results obtained for the movement time required to evacuate all occupants (or the movement time of the last occupant to leave the building) and for the number of occupants evacuated before reaching the movement time of reference (TMRef). The images from the Web simulation platform record the movement pattern of occupants during the evacuation process.

4.4.1. Results for Scenario 1—Two Occupants Are Positioned Side by Side in Room 2

The results obtained for this scenario show improvements in the evacuation process when EMARSys is active.

Without fire deflagration, the introduction of ERMARSys makes it possible for those occupants who do not know the building to leave the building within the TMRef (Figure 7a), leading to occupant behavior similar to that of those who know the building, as seen in the pattern of occupant movement shown in Figure 8a,c.



(**a**) (**b**)

Figure 7. Bar graph comparing movement time required to evacuate both occupants, without (**a**) and with (**b**) fire deflagration.

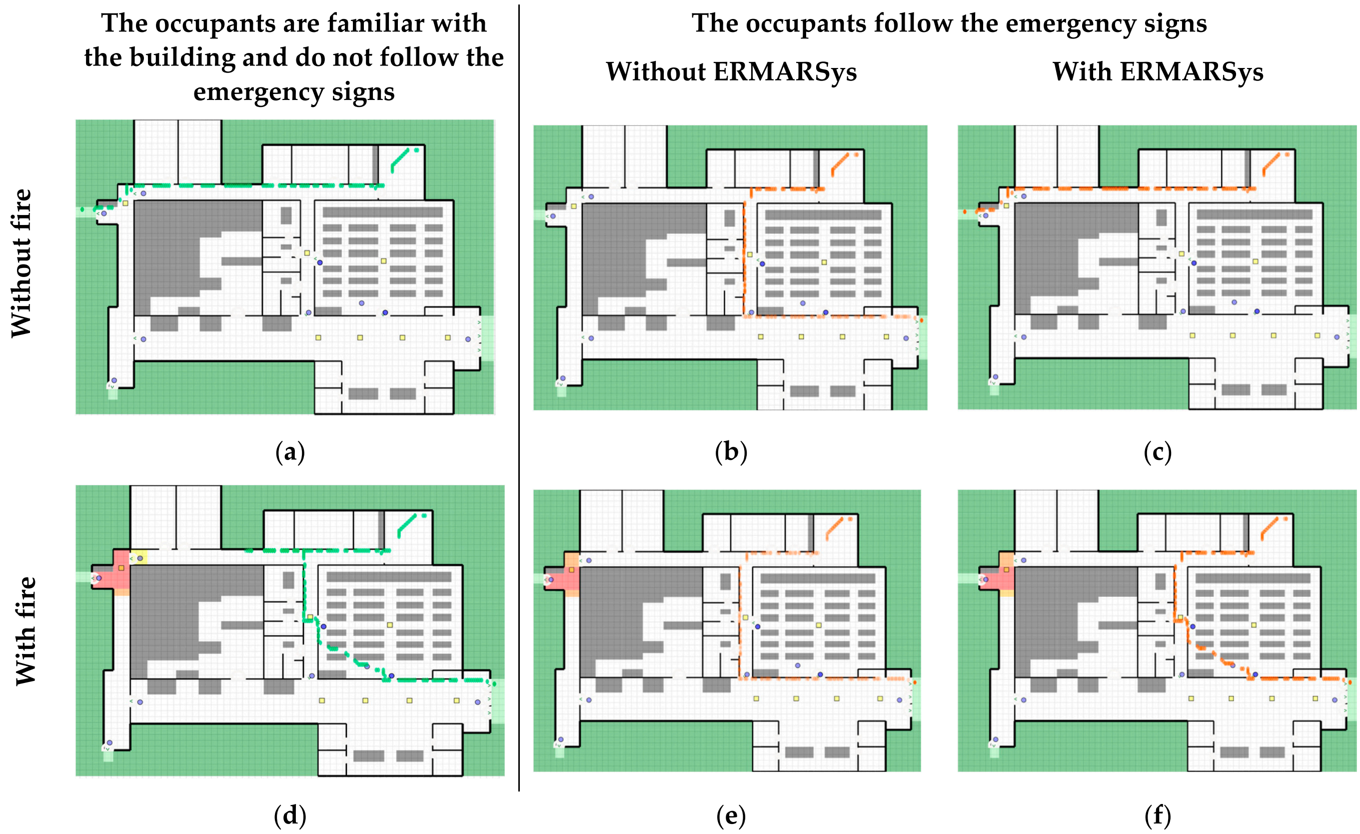


Figure 8. The evacuation routes followed by the two occupants in each simulated situation: (**a**) if occuppants are familiar with the space and without fire; (**b**) if the occupants follow static signaling with no fire; (**c**) if the occupants follow ERMARSys recommendations without fire; (**d**) if occuppants are familiar with the space in a fire situation; (**e**) if the occupants follow static signaling in a fire situation; (**f**) if the occupants follow ERMARSys recommendations in a fire situation.

4.4.2. Results for Scenario 2—Group of 30 Occupants Positioned in Rooms 2 to 4

As in previous scenario, the results obtained also show improvements in the evacuation process when ERMARSys is active.

Without fire, the introduction of ERMARSys makes it possible for those who do not know the building but follow the emergency signs to leave the building, taking a similar movement time as those familiar with the building (Figure 9a). This result is confirmed when comparing the occupants' movement pattern, shown in Figure 10a,c.

In case of a fire, the introduction of ERMARSys makes it possible to reduce the movement time required for occupants to leave the building (Figure 9b). As a result, the occupants unfamiliar with the building and following emergency signs need less time to leave the building: 60.30 instead of 88.78 s. This conclusion is corroborated by the images of the occupants' movement in Figure 10, showing that when the occupants are familiar with the building and do not follow the signs, they do not realize the fire location in time. This fact leads the occupant to return, which results in a longer movement time than when following the ERMARSys recommendations, as becomes apparent when comparing Figure 10f with Figure 10d,e.

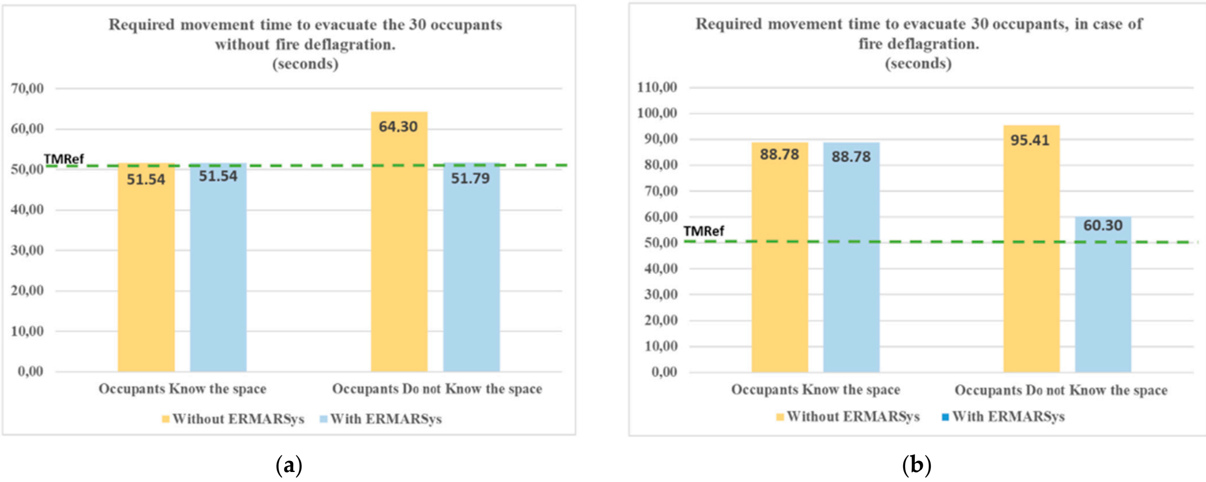


Figure 9. Bar graph comparing the movement time required to evacuate the 30 occupants without (**a**) and with (**b**) fire deflagration.

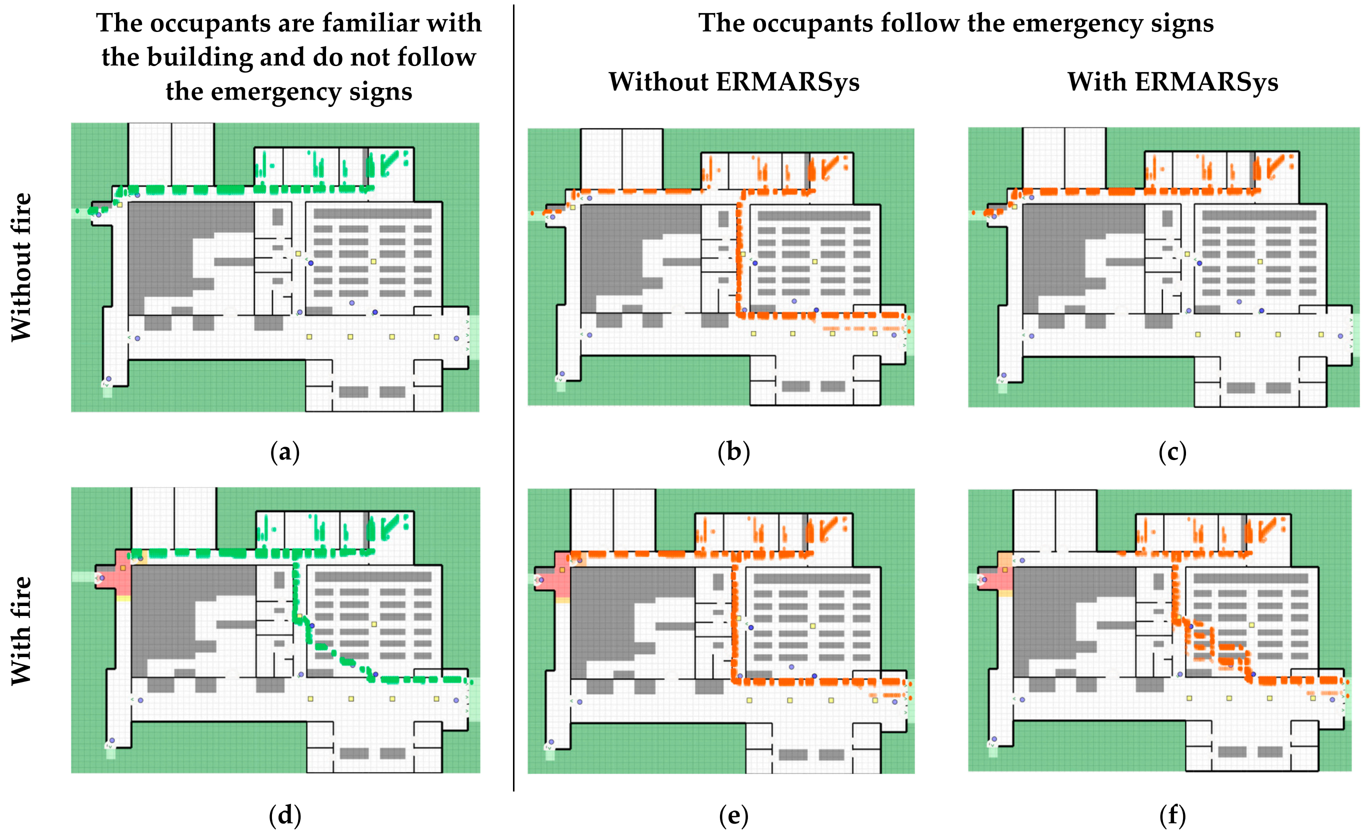


Figure 10. The evacuation routes followed by the 30 occupants for each simulated situation: (**a**) if occuppants are familiar with the space and without fire; (**b**) if the occupants follow static signaling with no fire; (**c**) if the occupants follow ERMARSys recommendations without fire; (**d**) if occuppants are familiar with the space in a fire situation; (**e**) if the occupants follow static signaling in a fire situation; (**f**) if the occupants follow ERMARSys recommendations in a fire situation.

4.4.3. Results for Scenario 3—Group of 200 Occupants Randomly Positioned

In this scenario, as shown in Figures 11 and 12, the results obtained also show improvements in the evacuation process when ERMARSys is active.

Figure 11. Bar graph comparing the movement time required to evacuate the 200 occupants: (**a**) without fire and (**b**) with fire.

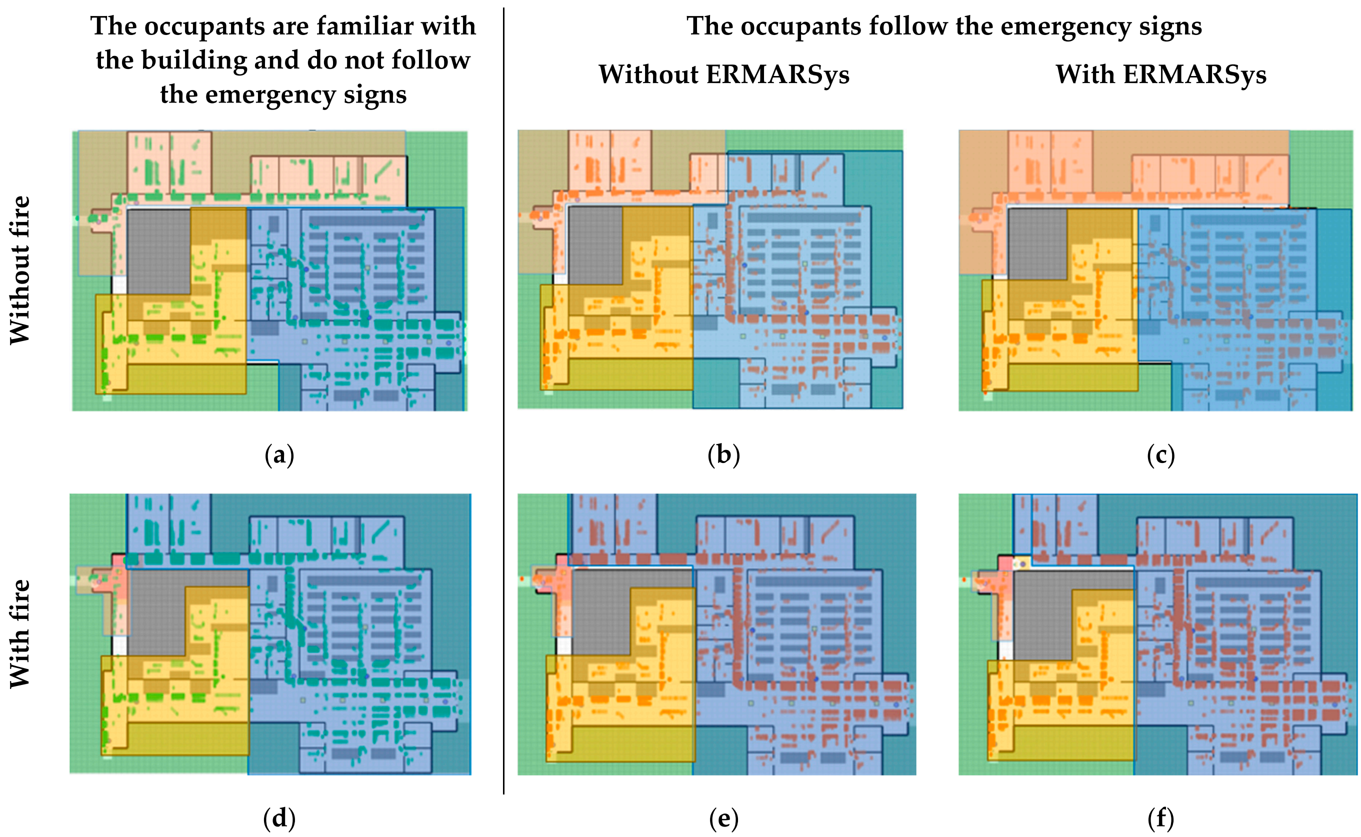


Figure 12. The evacuation routes followed by the 200 occupants for each simulated situation: (**a**) if occuppants are familiar with the space and without fire; (**b**) if the occupants follow static signaling with no fire; (**c**) if the occupants follow ERMARSys Recommendations without fire; (**d**) if occuppants are familiar with the space in a fire situation; (**e**) if the occupants follow static signaling in a fire situation; (**f**) if the occupants follow ERMARSys Recommendations in a fire situation.

When there is no fire outbreak, it is possible to verify that the introduction of ERMARSys allows those who do not know the building but follow the emergency signs to leave the building in a movement time similar to that of those familiar with the building

(Figure 11a). This result is confirmed when comparing the occupants' movement pattern shown in Figure 12a,c.

In case of fire, it is also possible to observe that the introduction of ERMARSys reduces the movement time required for occupants to leave the building (Figure 11b). For example, the occupants unfamiliar with the building but following the emergency signs need less time to leave the building: 80.53 s instead of 97.82 s. Additionally, the patterns of occupant movement shown in Figure 12 allow us to see, comparing Figure 12f with Figure 12d,e, that the occupants who initially moved to exit one reverse gear earlier, leading to the need for less time to evacuate all occupants.

5. Discussion

The results presented in the previous section immediately suggest that ERMARSys recommendations contribute to the fact that the occupants of a building need less time to leave it safely in the event of a fire alarm. Moreover, as is discussed in more detail in the following sections, this improvement in the evacuation process is observable in the scenarios with and without fire.

5.1. Scenarios without Fire Deflagration

For analyzing and evaluating the behavior of ERMARSys in scenarios where the fire alarm sounds but there is no obstruction of the building's evacuation routes, Figure 13 summarizes the results related to the movement time required for all occupants to leave the building.

Figure 13. Bar graph with movement times required for all occupants to leave the building in a situation where there are no restrictions on evacuation routes.

When a fire alarm is triggered but there is no obstruction of the escape routes, occupants familiar with the building tend to leave the building and continue along the path that leads to the nearest exit. Thus, it can be said that this is an efficient process of evacuating the building, so the results can be considered a reference point. So, considering that the simulation results for situations in which the occupants follow the ERMARSys recommendations are very similar to those obtained for cases in which the occupants are familiar with the building, we conclude that the introduction of ERMARSys makes the evacuation process more efficient for those who, being unfamiliar with the building, must follow the emergency signs. This improvement introduced by ERMARSys is due to the presented recommender system's solution by allowing the integration of dynamic emergency signs, through which information regarding the nearest safe exit is made available to occupants.

5.2. Scenarios with Fire Deflagration

Regarding the scenarios that consider the occurrence of a fire that impacts the paths used by the occupants, Figure 14 shows the results of the simulations referring to the movement time required for all occupants to reach a safe place.

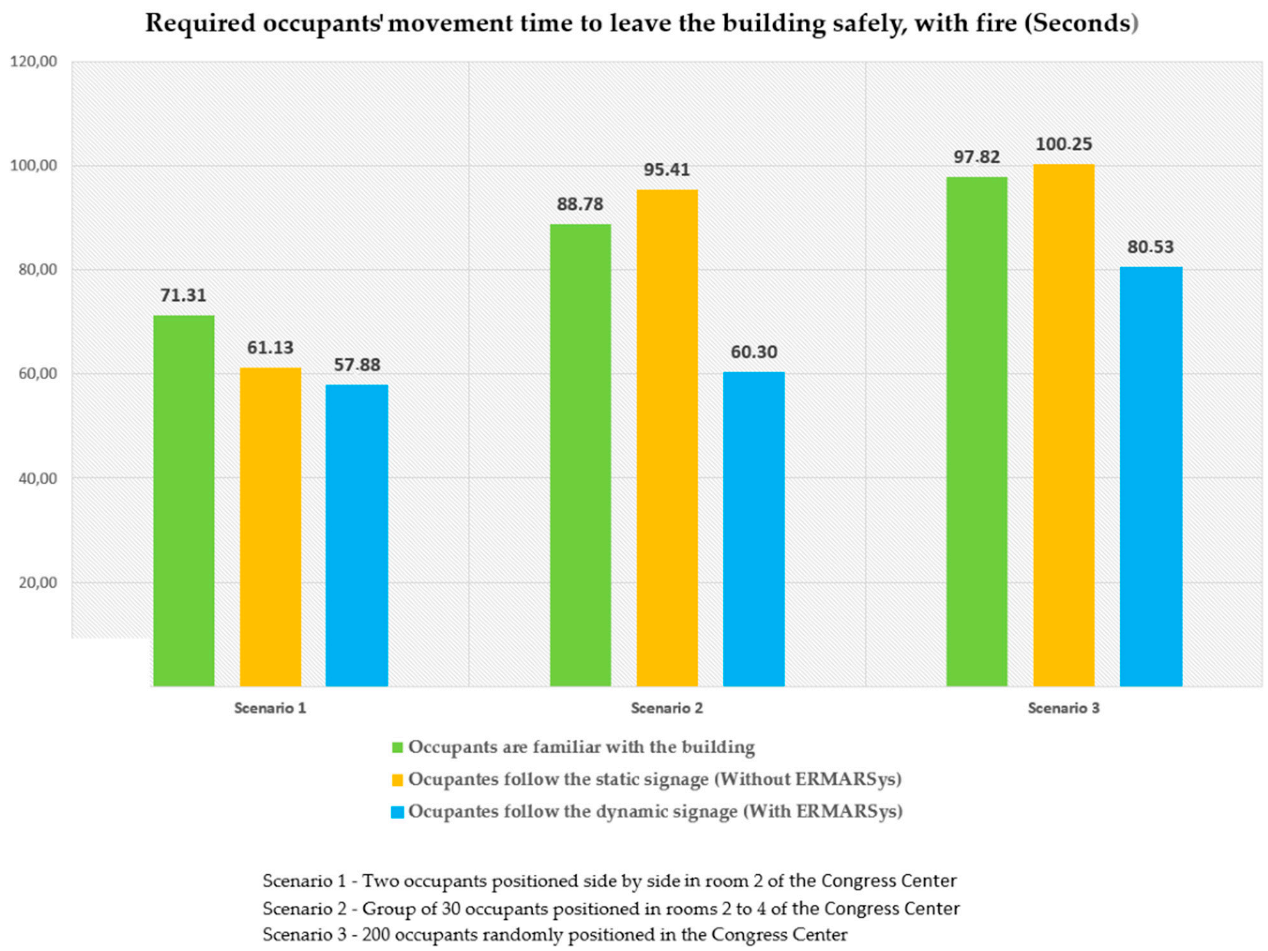


Figure 14. Bar graph with movement times required for all occupants to leave the building in a situation where the fire places restrictions on evacuation routes.

The impact of the fire on the evacuation routes means that knowledge of the building is not a necessary and sufficient condition to leave it most efficiently. Likewise, familiarity with the building does not translate to knowing the location of the fire nor the change in the environmental conditions it causes. The results suggest that introducing a system such as ERMARSys, capable of informing occupants in real time about the evacuation routes they must follow, makes the evacuation process more efficient, leading to less time needed for all occupants to leave the building.

The key results of the study are summarized in the Table 6.

Table 6. Key results of the study.

	ERMARSys Impact	
	Impact on Movement Time	**Impact on Evacuation Pattern**
The fire does not cause constraints or blockage of routes.	As seen from Figure 13, ERMARSys allows occupants who are unfamiliar with the building to leave the building as efficiently as those who are familiar with the building. When occupants follow ERMARSys recommendations, it takes about 20% less time for all occupants to be safe.	The images in Figures 8, 10 and 12 show that the evacuation pattern of those who follow EMARSys recommendations is similar to that of those who are familiar with the building.
The fire causes constraints or blockages of routes	As can be seen from Figure 14, ERMARSys allows occupants who are unfamiliar with the building to leave the building more efficiently than those who know the building or do not follow its recommendations. For example, in the case of the scenario with 200 occupants, it takes about 17.7% less time for all occupants to be safe.	The images in Figures 8, 10 and 12 show that when the occupants follow the recommendations of the ERMARSys system, they become aware of the fire constraints earlier, avoiding the need to reverse the direction of movement.

The improvement suggested by the simulation results is due to the fact that the ERMARSys recommender system uses contextual information obtained through IoT sensors, which detect changes in the environment and collect the data associated with these changes, transmitting them in real time to the system. In the case of the prototype developed and tested, the contextual data considered relate to two types of factors. One of the factors relates to the congestion of routes and results from the high density of people per square meter in a given area. The other type of factor is the risk factor, which results directly from the fire outbreak and leads to the constricting and blocking of evacuation routes. Considering that, for ERMARSys, the building is nothing more than a graph that changes depending on the contextual data it receives from the IoT input devices, it can be said that ERMARSys is the one who best knows the building evacuation routes at any given moment because it has information about the environmental changes that occur during the fire, which habilitates ERMARSys to help the occupants of the building reach a safe place.

It is also important to highlight another aspect that is not evident from the results obtained related to the occupants' behavior before they even decide to leave the building. In this regard, considering the work of Cordeiro [2], in which the author refers, based on simulation results with her developed behavioral model, that the time related to the occupants' decision making and the time consumed in conducting tasks influence the total evacuation time significantly. Therefore, the decisions or indecision mentioned by Cordeiro could be reduced or eliminated in buildings where it is possible to install systems identical to the one presented here because the occupants have information about the most efficient evacuation routes.

5.3. Limitations of the Study

The study's main limitations relate to the assumptions made for developing the recommender system prototype and for the experimental tests. Regarding the development of the prototype and considering the rules and constraints of the Web simulation platform, two types of generic contextual factors were considered (congestion and risk) without considering that in a real environment, different types of sensors are needed for a correct representation of the building environment. Thus, the following was assumed:

- In the case of congestion, a hypothetical sensor was considered that detects the number of occupants in a given section;
- In the case of the risk factor, a hypothetical risk sensor was considered, capable of reflecting the effects of the fire (smoke, temperature, and toxic gases) that could cause constraints in the evacuation routes. This assumption relates to the fire progression model incorporated into the Web simulation platform. However, it is important to note that the simplification mentioned does not harm the intended objectives, which

were to create constraints in the evacuation routes, simulating the change in context in the building.

Concerning the experimentation scenarios and strategies adopted in the simulated scenarios, the following limitations should be mentioned:

- Although preliminary tests were conducted for smaller buildings, it was considered that to address the study's objectives, the tests should be focused on a medium-sized building with a high density of people and typically used by people unfamiliar with the space;
- It was assumed that there was no contact between the occupants, each going his own way as if the others did not exist. For example, if an occupant turns back because they see a blocked route, the system does not warn nearby occupants;
- The simulations assumed that some occupants do not know anything about the building; however, with few exceptions, there is never a total lack of knowledge of the space; occupants generally register where they enter the building, so they tend to know at least that route of return.

6. Conclusions and Future Work

This research aims to study how a multi-agent recommender system, using contextual data obtained in real time through the IoT, can improve efficiency in evacuating buildings in the event of a fire. The results obtained suggest that a system such as ERMARSys can efficiently guide the occupants of a building to a safe place in case of fire by recommending the most appropriate and efficient safe evacuation routes at any moment.

Thus, it may be concluded that the future implementation of a system based on the recommender solution presented in this paper that occupants consider reliable may contribute to conditioning people's behavior, reducing the time between the emission of the alarm and effective commencement of building evacuation. In fact, by conditioning the individual behavior of the occupants, the system will minimize the actions they can conduct initially and that are not conducive to leaving the building, allowing the occupants to focus on exiting the building through the recommended safer evacuation routes.

For future work, the evaluation of other building typologies in terms of functionality, size, area, or capacity is of interest. Another area to explore is the deepening of the study of contextual factor models to consider diverse types of risk and their implications in the constraint of the evacuation routes and in the recommendations generated by the recommender system. Thus, regarding the impact of contextual factors related to constraints due to high occupancy densities (congestion), a line of future development and study is to incorporate in the model the use of information on the occupancy density in each building space at each moment to affect the redistribution of occupants to the exits to minimize congestion, thus introducing a new rule in conditioning. Furthermore, of interest is the test of other algorithms or heuristics for comparison with the Floyd–Warshall algorithm used. Finally, from the perspective of a future implementation of the proposed system, it is of interest to study whether people would be receptive to such a system and to what extent it would condition their behavior.

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