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HurricaneLog: A Serious Game for Data Collection and Analysis of Hurricane Preparedness and Response Operations

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Abstract. Hurricanes are destructive natural disasters that frequently cause significant damage and disrupt communities. Effective response relies on the swift actions of government and humanitarian organizations, with logistics playing a crucial role in ensuring timely aid delivery. However, the complexity and unpredictability of disaster management can hinder decision-making, often resulting in unintended outcomes. Data collection during emergency operations is challenging, and post-event surveys are prone to recall bias, creating barriers to obtaining valuable data for improving decision-making. To address these challenges, we introduce HurricaneLog, a serious game that simulates disaster preparedness and response in a hurricane-prone region. By replicating realistic hurricane scenarios based on historical data, HurricaneLog provides a simulated environment for practicing decision-making and collecting granular data, enhancing training for humanitarian logistics professionals and apprentices. This study contributes by introducing a publicly available game and proposing a methodological framework for analyzing participants' decisions and evaluating strategy effectiveness. Findings from an experiment involving 76 participants reveal decision-making patterns and offer further insights into disaster management

Keywords: Humanitarian logistics, serious games, data collection and analysis, disaster operations management, preparedness, response

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1. Introduction

Hurricanes are among the most devastating natural disasters, causing widespread destruction when they strike populated areas. In the United States alone, hurricanes have resulted in financial losses exceeding $1.3 trillion and have been responsible for the highest number of fatalities among weather-related disasters since 1980, with a total of 6,890 lives lost [1]. The annual Atlantic hurricane season presents recurring challenges for governments and communities, compounded by the inherent unpredictability of these events.

In the wake of such crises, the responsibility for immediate response often falls heavily on non-governmental organizations (NGOs) that strive tirelessly to aid affected populations. For instance, the World Food Programme (WFP) provided assistance to an astounding 160 million individuals in 2022 alone [2]. Central to these relief efforts is humanitarian logistics, a critical component that constitutes nearly 80% of operational costs [3]. Logistics, as defined by Thomas and Mizushima [4], involves the strategic coordination of tasks related to the efficient management, transportation, and oversight of goods and information from their origin to their intended recipients. Given the scale and complexity of these operations, effective training and preparedness are imperative [5].

Humanitarian logistics professionals operate in chaotic and high-pressure environments [5], where rapid decision-making is crucial, and lives depend on timely actions [6]. These decisions are often made under uncertainty, as responders must determine where people in need are located, what their specific needs are, how to access them, and what resources are available [7]. Additionally, they must navigate limited resources and logistical constraints. The complexity of these tasks can lead to suboptimal decisions, resulting in resource losses and adverse impacts on affected populations [8]. Therefore, diversified and frequent training is essential to keep professionals prepared for future disasters [4, 7].

Understanding the decision-making processes and the impact of associated strategies in humanitarian logistics is critical for improving training and operational effectiveness. However, collecting data on decision-making during actual operations presents significant challenges. The chaotic nature of disaster response makes it impractical for decision-makers to record every action without hindering the response effort and potentially risking lives. Retrospective data collection methods, such as post-operation surveys, often suffer from recall biases and inaccuracies [9, 10]. Moreover, existing information systems in humanitarian operations primarily focus on aggregating data from diverse sources to support informed decisions and efficient planning [11, 12], but they lack the capability to capture detailed data on specific decisions and their operational impacts.

To address these gaps, we propose an innovative solution that leverages serious gaming to simulate disaster preparedness and response operations in a multi-region context. Our work introduces *HurricaneLog*, a serious game designed to facilitate comprehensive data collection and analysis of decision-making processes in humanitarian logistics. By simulating realistic disaster scenarios using data from past events, *HurricaneLog* recreates meaningful environments that mirror the challenges faced by humanitarian decision-makers. The engaging nature of the game allows for the collection of detailed decision-making data without the ethical and practical constraints present in real disaster situations.

Unlike existing games in the humanitarian logistics field, which often focus on single-region scenarios or lack data collection capabilities, *HurricaneLog* uniquely combines a multi-region context with both preparedness and response phases of disaster management. Additionally, it captures granular data on players' decisions, enabling the analysis of different strategies and their outcomes. This approach not only enhances training initiatives by providing an interactive learning platform but also contributes to research by offering insights into decision-making dynamics in humanitarian operations.

The objectives of this article are threefold: (i) to present *HurricaneLog*, a publicly available game (`https://thiagocorreiap.github.io/HurricaneLog/`) that facilitates training and data collection; (ii) to propose a data analysis methodology that characterizes decision-makers (players) and evaluates the performance of different disaster management strategies implemented within the game; and (iii) to provide insights from an experiment involving participants using the game, highlighting observations from the data analysis.

The design and development of *HurricaneLog* were informed by comprehensive analysis of disaster management literature and consultations with professionals in the field, ensuring the game's relevance to real-world scenarios. By bridging the gap between theoretical research and practical application, our work aims to advance the understanding of decision-making in humanitarian logistics and contribute to more effective disaster preparedness and response strategies.

The rest of this article is organized as follows. Section 2 discusses related works. Section 3 presents the *HurricaneLog* game and its components. Section 4 describes the data collection process facilitated by the game, followed by analyses of participant strategies and their implications. Finally, Section 5 concludes the article with remarks and future directions.

2. Related works

Understanding and improving decision-making processes in humanitarian logistics is crucial for enhancing operational effectiveness and saving lives during disasters. In this section, we examine existing literature to identify gaps and support our claims regarding the need for innovative solutions like *HurricaneLog*. We begin by exploring current information systems used in humanitarian operations, highlighting their roles in enhancing situational awareness and supporting decision-making. We discuss how these systems, while valuable, fall short in capturing detailed data on the specific decisions made by logistics professionals and their operational impacts. Next, we introduce serious games as a potent tool recognized by the scientific community for simulating decision-making scenarios and facilitating data collection. We review how games have been employed across various domains for education, training, and data collection, demonstrating their versatility and effectiveness. Moving closer to our focus, we delve into serious games developed specifically for humanitarian logistics, analyzing their features and limitations, particularly regarding data collection on decision-making processes. By identifying these gaps, we underscore the necessity for solutions like *HurricaneLog* that can fill these voids by providing comprehensive data collection and realistic simulation of disaster scenarios.

The criticality of data utilization in humanitarian logistics has been underlined by Shalash et al. [13], emphasizing its indispensable role in evidence-based planning and decision-making in operational contexts. During operations, humanitarian decision-makers seek to enhance situational awareness by accessing data from governmental, non-governmental, and institutional sources to understand the crisis at hand. Consequently, numerous information systems have been developed to aggregate and disseminate data, providing comprehensive situational awareness and facilitating informed decision-making [11].

Notable examples include platforms like *ReliefWeb*, the *Humanitarian Data Exchange (HDX)*, the *Logistics Information Exchange (LogIE)*, and *HELIOS*. *ReliefWeb*, provided by the United Nations Office for the Coordination of Humanitarian Affairs (OCHA), offers practitioners timely information on complex emergencies and natural disasters worldwide by consolidating reports, maps, and analyses from over 4,000 key organizations [14]. Similarly, the *HDX*, managed by OCHA's Centre for Humanitarian Data, aims to make humanitarian data easy to find and use for analysis, hosting a growing collection of datasets accessed globally [15]. The *LogIE*, developed by the Logistics Cluster, enhances operational planning by providing a customizable view of logistics data, supporting both emergency response and preparedness efforts [16]. Additionally, *HELIOS* is a supply chain-focused information system collaboratively built by several humanitarian organizations, including Oxfam-GB and World Vision International, to track expenditures, manage inventories, and improve supply chain efficiency during humanitarian operations [17].

Academic research has also contributed to this field. For instance, Yagci Sokat et al. [18] discuss the use of real-time data for improving decision-making in humanitarian logistics. They present a framework for integrating near real-time data into logistical models, aiming to enhance situational awareness during disaster response. Their case study on Typhoon Haiyan illustrates how data from governmental agencies, digital humanitarian networks, and geospatial mapping tools can inform operational planning.

Similarly, Timperio et al. [19] propose a beneficiary-centric decision support framework that integrates data analytics, network optimization, and simulation to identify logistics bottlenecks and support inventory management. Their framework aims to enhance resource coordination in humanitarian logistics, demonstrating the critical role of information systems in operational efficiency.

While these information systems and research initiatives significantly improve situational awareness and support evidence-based planning, they predominantly focus on aggregating and disseminating data rather than capturing the specific decisions made by logistics agents and their operational impacts. For example, platforms like *HDX* and *LogIE* provide valuable data for decision-making but do not record the rationale behind individual decisions or the outcomes of those decisions in operational contexts. Similarly, *HELIOS* enhances supply chain management by tracking transactions and inventories but does not capture the decision-making processes of logistics personnel during crises.

The article by Yagci Sokat et al. [18] highlights this gap by demonstrating that while real-time data can inform decision-making, the systems in use do not document the specific decisions or analyze their impact on operational outcomes. This limitation restricts opportunities for comprehensive analysis of decision-making behaviors and the evaluation of different strategies' effectiveness. Therefore, the limitations of current information systems in capturing decision-making data *during* humanitarian operations emphasize the necessity for innovative solutions. Given these limitations, there is a need for approaches that can effectively capture detailed decision-making data during humanitarian operations. One promising avenue is the use of serious games.

Games present themselves as a promising avenue for addressing these data collection challenges. Recognized for their unparalleled engagement capabilities, games captivate millions of users worldwide. Leveraging this inherent engagement power, the scientific community has increasingly turned to games as potent tools for engagement, data collection, and analysis. One notable application of games is in the context of *serious games*, where the primary focus shifts from entertainment to learning [20, 21]. Serious games have found application across diverse fields, including education [22], training [23], advertising [24], and healthcare [25].

Regarding data collection, games offer a unique opportunity to gather valuable insights from players. Researchers have employed various games to collect data on cognitive functions, spatial skills, creativity, problem-solving, and social interactions. For example, studies by Iyadurai et al. [26] and Lau-Zhu et al. [27] utilized *Tetris* to gather data on cognitive functions and spatial skills. Similarly, Simons et al. [28] and Lee and Probert [29] employed *Civilization* to study player creativity and problem-solving. Additionally, the game *World of Warcraft* has been used for collecting data on player behavior, social interactions, and decision-making processes [30, 31]. These examples highlight the versatility of games as effective tools for data collection and analysis in various research domains.

Building on these successes, serious games have been increasingly adopted in the field of humanitarian logistics, becoming valuable tools for training and educating logistics professionals, volunteers, and students. Harteveld and Suarez [32] highlight the significant role that serious games can play in the humanitarian context, underscoring their ability to simulate real-world challenges and facilitate understanding through interactive experiences. These games simulate various aspects of humanitarian logistics operations, such as disaster response, supply chain management, and coordination of goods and personnel, providing immersive experiences that enhance learning and understanding.

One notable example is the *Disaster Response Game* developed by Klein et al. [33], which simulates disaster response operations in disaster-prone areas. In this multiplayer game, players act as humanitarian agents who must coordinate limited supplies and logistics to meet the needs of affected populations. The game allows players to rebuild infrastructure, distribute relief items, and manage resources under time pressure, reflecting realistic challenges faced in the field. To assess the game's effectiveness, the authors collected data through short surveys administered to participants after gameplay. Additionally, they conducted debriefing sessions to facilitate discussions about the learning outcomes. While the game received positive feedback, highlighting its realistic aspects and the importance of collaboration, it lacks a distinct preparedness phase and does not have built-in mechanisms to collect detailed data on decision-making processes during gameplay.

Similarly, *THINKLog*, created by Abdul Rahim et al. [34], is designed to teach supply chain management within humanitarian operations, focusing on warehouse location decisions and response logistics. The game consists of two stages: a preparedness phase where players select warehouse locations based on multiple criteria, and a response phase where they deliver relief items while handling disruptions. The authors used a software application to collect data on players' decisions during the preparedness phase, specifically the weights assigned to decision criteria and the selected warehouse locations. This data was further analyzed to assist in building simulation models for improving warehouse locations in real-world scenarios. However, data collection during the response phase was not implemented, and the game does not capture detailed decision-making data throughout the entire gameplay experience.

Another significant contribution is the *Humanitarian Aid and Relief Distribution (HARD) Game* by Alaswad and Salman [35], a multiplayer turn-based game that simulates the humanitarian supply chain from suppliers or donors to affected populations. Players manage inventory levels, order and ship relief supplies, and coordinate with other supply chain nodes to fulfill demands. The authors utilized pre- and post-surveys to assess the game's effectiveness as a teaching tool and to gather feedback on participants' learning experiences. While the game emphasizes resource management and coordination, it does not include built-in data collection mechanisms to capture players' decision-making processes during gameplay. Additionally, it lacks a clear separation between preparedness and response phases.

Logistics to the Rescue [36] focuses on highlighting the use of social media to detect populations in need after a natural disaster. In this game, players act as emergency dispatchers, assessing demand locations and planning rescue routes based on both reliable (e.g., 911 calls) and unreliable (e.g., social media posts) information sources. The game provides insights into integrating social media data into disaster response. To evaluate its educational impact, the authors conducted post-gameplay surveys with secondary school students, confirming positive feedback regarding the game's ability to educate about social media use in emergencies. However, the game offers limited strategic depth in preparedness, does not simulate real-time disaster evolution, and lacks built-in data collection on decision-making processes during gameplay.

Other games, such as *Food Force* [37] and *Inside Haiti Earthquake* [38], contribute to raising awareness and educating players about the complexities of humanitarian operations. *Food Force* immerses players in the challenges of humanitarian food distribution in conflict and disaster-affected areas, involving missions like food procurement and distribution logistics. *Inside Haiti Earthquake* allows players to experience scenarios from different perspectives—survivors, humanitarian agents, and journalists—making choices that affect outcomes. These games primarily use post-gameplay reflections or discussions to assess learning outcomes but do not incorporate built-in data collection mechanisms to capture detailed decision-making data. Moreover, they lack a multi-phase disaster management approach and do not provide strategic depth in logistics planning.

In the realm of disaster preparedness, games like *Disaster Detector* [39] and *Stop Disasters!* [40] teach players about disaster risk reduction strategies. Players make infrastructure improvements to mitigate disaster impacts, receiving hints about imminent disasters. These games offer insights into disaster mitigation but provide limited real-time event simulation and do not delve into the complexities of multi-phase disaster management. Data collection in these games is minimal, often limited to tracking scores or levels achieved, without capturing detailed information on players' decision-making processes. Any assessment of learning outcomes typically relies on external surveys or evaluations.

In addition to digital serious games, simulation-based training exercises have been extensively utilized in humanitarian logistics to enhance the preparedness and response capabilities of practitioners. These simulations replicate realistic disaster scenarios, allowing logistics professionals to practice and refine their skills in controlled environments. For example, Gralla et al. [5] detail a simulation exercise aimed at training logistics response teams. Participants engage in a seven-day disaster simulation where they are evaluated on their decision-making and actions by experienced professionals. Daily feedback sessions provide insights into their performance regarding critical aspects such as time management, information sharing, and priority setting.

Similarly, Stuns and Heaslip [41] evaluate the effectiveness of a Logistics Emergency Response Unit training exercise organized by the Finnish Red Cross. Through interviews and observations, they assess the training outcomes across multiple dimensions, noting significant improvements in participants' practical skills and knowledge application. The *Logistics Cluster* also conducts simulation-based training programs that immerse skilled logistics professionals in realistic emergency scenarios over a week-long period [42]. These programs focus on enhancing competencies in emergency response, project management, and leadership within field-like conditions.

While these simulations are instrumental in improving operational readiness, they often rely on qualitative assessments and lack mechanisms for capturing detailed data on the decision-making processes of participants. Evaluations are typically based on observations, debriefings, and self-reported feedback, which may not capture all aspects of decision-making dynamics. This limitation presents an opportunity to enhance these training methods by integrating data collection tools that can record and analyze decisions made by participants in real-time.

Despite the valuable contributions of existing games, significant gaps remain. Many of these games focus primarily on a single phase of the disaster management cycle—mitigation, preparedness, response, or recovery—often without a clear separation between these phases. This approach limits the strategic depth that players can explore, especially in the pre-disaster phases. Additionally, the lack of built-in data collection mechanisms means that researchers and educators must rely on external methods, such as surveys or interviews, to gather insights into players' decision-making processes. These methods can be limited by self-report biases and may not capture the nuances of in-game decisions. Furthermore, most games do not simulate real-time evolution of natural events, depriving players of the opportunity to track and respond to dynamic disaster scenarios. The absence of detailed data on how players interact with evolving situations limits the potential for comprehensive analysis of decision-making strategies and their effectiveness.

To address these gaps, we introduce *HurricaneLog*, a serious game designed to provide a multifaceted platform for both education and research in humanitarian logistics. *HurricaneLog* distinguishes itself by offering a multi-region context with clear separation between the preparedness and response phases, enabling players to explore complex strategies and understand the impact of their decisions over time. The game incorporates real-time simulations of hurricanes with stochastic behavior, requiring players to make decisions under uncertainty and adapt to evolving scenarios.

A significant advancement of *HurricaneLog* is its comprehensive built-in data collection capability. Unlike existing games that rely on post-game surveys or external assessments, *HurricaneLog* captures detailed data on players' decisions during both preparedness and response phases. This includes investment choices, resource allocations, timing of actions, and response strategies. By recording these data points in real-time, the game enables in-depth analysis of decision-making processes and strategies. Researchers can evaluate the effectiveness of different approaches, identify patterns in decision-making, and gain insights into common challenges faced by players.

By combining multi-region management, clear disaster phase separation, real-time event simulation, and detailed data collection, *HurricaneLog* advances both the practice and research of humanitarian logistics. It not only enhances training initiatives by providing an interactive learning platform but also contributes to research by offering insights into effective strategies and common pitfalls in disaster preparedness and response. This comprehensive approach allows for a deeper understanding of players' behavior and decision-making dynamics, which was previously unexplored in this context.

3. Game structure

HurricaneLog is designed around the core principles of realism and interactivity. Players assume the role of logistics coordinators tasked with preparing for and responding to hurricane events across multiple regions. The game integrates real historical data [43–45], weather patterns [46–49] and information extracted from the scientific literature [50–55] to simulate scenarios, challenging players to allocate resources, manage supply chains, and coordinate relief efforts effectively.

Building upon this foundation, this section provides a comprehensive overview of the structure and mechanics of *HurricaneLog*, outlining its gameplay elements, core components, and the metrics used to evaluate player performance. We begin by describing the gameplay, introducing the strategic operational area and the roles players assume in coordinating logistics across multiple islands. Next, we delve into the game components, detailing the preparedness investments and response actions available to players, as well as the game mechanics that simulate real-world disaster scenarios through stochastic storms and forecasts. Finally, we discuss the metrics and scoring system, explaining how key performance indicators (KPIs) are used to assess players' effectiveness in managing disaster response efforts.

3.1. Gameplay

The game introduces players to a strategic operational area comprising four islands, each representing a nation under the player's logistical coordination. These islands, situated in a hurricane-prone area, face seasonal hurricane threats, adding a layer of complexity to the logistic challenges. Alongside these, a fifth element symbolizes international suppliers, offering crucial support throughout the game. This setting is depicted in Figure 1, which illustrates the islands within the player's logistical responsibilities and a continental area where the international suppliers are located. The player role is to coordinate the logistic activities in these islands, preparing them for the upcoming hurricane season, then responding to eventual hurricane-related disasters.

The player performance is evaluated based on three key performance indicators: the efficiency of response operations as measured by average response time to assist affected populations (to minimize), the economic efficiency reflected in the total operational costs (to minimize), and the effectiveness in meeting the needs of those affected, quantified by the proportion of needs met relative to the total number of people impacted by the hurricane (to maximize). These metrics collectively indicate the player's success in managing disaster response efforts, emphasizing speed, cost-effectiveness, and the capacity to address humanitarian needs. The game concludes with the end of the hurricane season, at which point players are presented with an operations report. This report summarizes their performance across the region, breaking down the KPIs both collectively and by individual island. Designed to facilitate reflective learning, this final report encourages players to evaluate their strategic approaches, offering insights into the trade-offs among different KPIs.

The gameplay of *HurricaneLog* is structured into two primary phases: preparedness and response. In the preparedness phase, the focus is on strategizing for the forthcoming hurricane season. Players assess the needs of each island,

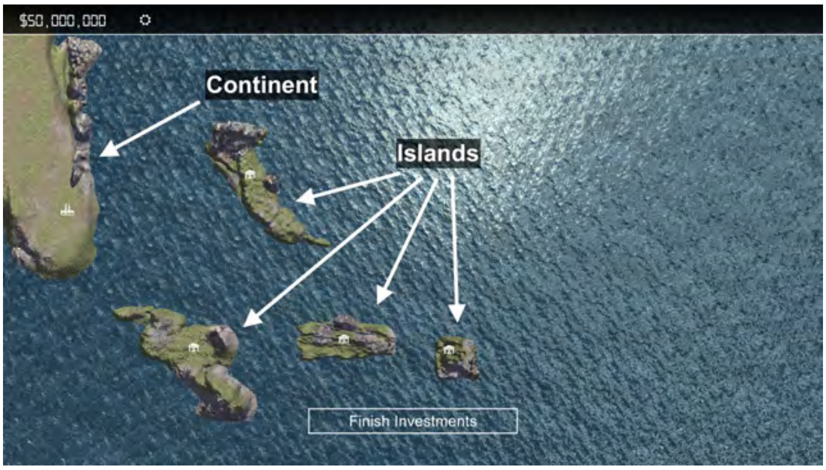


Figure 1: Region simulated in the game.

considering economic conditions, risk exposure, population size, and logistics performance. These assessments inform investment decisions aimed at enhancing the islands' resilience to hurricanes. The economic condition reflects the island's structure strength regarding potential future disasters. Risk exposure assesses the likelihood of facing such disasters. Population size gives an insight into the potential impact on residents, guiding the scale of logistical support needed. Logistics performance evaluates the infrastructure and supply chain's efficiency, critical for effective disaster response. Islands with lower logistics performance require strategic investments to bolster transportation networks and supply chain resilience. Figure 2 provides an overview of the islands' profiles, presented to players at the start of the game. During the preparedness phase, players make decisions about the investments each island will receive, ranging from increased prepositioning of resources to agreements with international suppliers and improvements in distribution capacity. These investment decisions will be further detailed in Section 3.2.1.

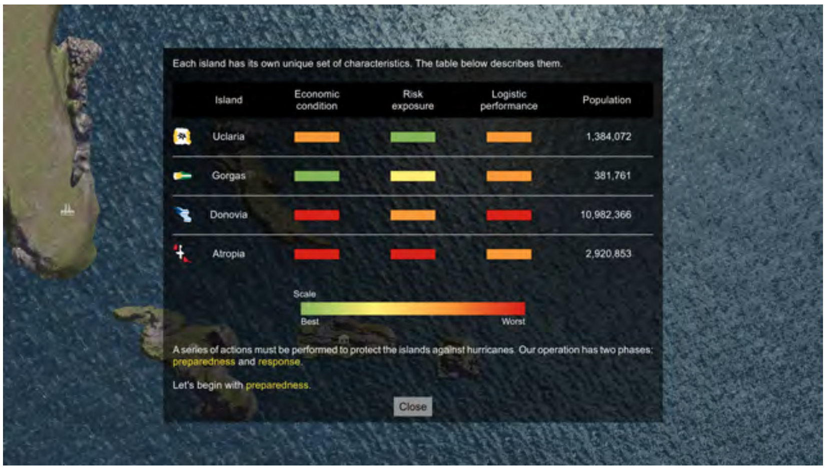


Figure 2: Characteristics of the islands simulated in the game.

In the response phase, players are tasked with managing the aftermath of hurricanes, an effort found in real-life operations by organizations like the International Federation of Red Cross and Red Crescent Societies (IFRC), known for distributing Family Kits with essential survival items in the Caribbean [50]. This phase challenges players to distribute similar relief items to meet the critical needs of the affected populations (e.g. shelter, food, water, sanitation, hygiene products, medication), which are critical to effective disaster response [56, 57]. Players' decisions in this phase involve allocating and distributing Family Kits across the managed islands. The details and complexities of these decisions are discussed further in Section 3.2.2. The game simulates the distribution of these items through an interactive interface, enabling players to see the direct impact of their preparedness investments and decisions. This gameplay structure facilitates the collection of decision-making data, providing valuable insights into the efficacy of various strategies.

3.2. Game components

3.2.1. Preparedness investments

Preparedness is a fundamental component of effective disaster management. Careful preparation significantly enhances response efficiency, playing a major role in disaster response operations [3, 58]. As defined by Cozzolino [59], preparedness involves all actions taken in anticipation of a disaster.

In *HurricaneLog*, the essence of successful disaster management is captured in the strategic investments made by players during the game's preparedness phase. This proactive approach not only leads players to improve the islands' resilience but also exemplifies the essential nature of preparedness in the context of real-world disaster management operations.

Players encounter seven distinct investment options, each aimed at strengthening the region against forthcoming hurricanes. Each option is available in multiple discrete levels, with higher levels representing greater enhancements and incurring higher costs. This tiered structure allows for gradual improvements across areas such as relief distribution, information accuracy, and operational efficiency. Because the preparedness budget is limited, players must strategically choose investment levels that best align with the specific needs of each island. The available investment categories include:

- *Preposition (# of relief items in each warehouse)*: This involves the advanced purchase and storage of family kits in local warehouses, ensuring immediate availability when disasters strike.
- *Warehouse Capacity (warehouse size and resilience)*: This option enhances the physical structure and operational efficiency of warehouses, increasing their resilience to hurricane damage, storage capacity, and handling capabilities.
- *Distribution Capacity (distribution speed)*: This investment improves the logistics of distributing family kits by upgrading vehicles, handling equipment, and training for drivers, thereby accelerating the delivery rate.
- *Communication and Information Sharing (information accuracy)*: This improves the effectiveness of communication systems and protocols, ensuring accurate and timely information about the availability and status of family kits in warehouses and its manipulation.
- *Supplier Agreements (supplier responsiveness and supply availability)*: These agreements secure a reliable supply of family kits from international suppliers, ensuring rapid availability in emergencies.
- *Regional Transportation Agreements (timely availability of ships and planes)*: This involves contracts with transportation providers to ensure timely access to shipping options. It distinguishes between ships, which offer cost-effective but slower delivery, and planes, which provide quicker but more expensive transportation.
- *Customs Clearance and Sharing Agreements (reduced border processing time)*: This investment focuses on trade facilitation and customs management to expedite the customs clearance process for family kits, reducing delays in emergency situations.

Figure 3 provides a visual representation of this decision-making interface, showing the options available to players and the corresponding budget constraints. The preparedness phase is not timed, allowing players to explore the impacts of each investment option and strategize accordingly.

The preparedness investment options are categorized into two distinct groups: (i) local investments, affecting only the island where the investment is made, and (ii) regional investments, benefiting every island in the game's region. For instance, local investments target specific vulnerabilities of an island, such as fortifying a warehouse against storm damage, whereas regional investments, like establishing broader transportation agreements, improve the collective response capability across all islands. The effectiveness of these investments can be assessed in several ways, e.g., the

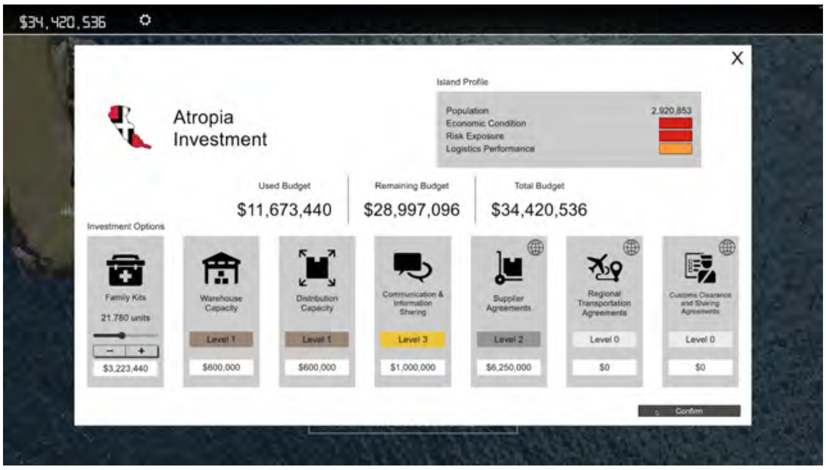


Figure 3: Player's view of an island's characteristics and the available investment options in *HurricaneLog*.

extent of infrastructure damage and consequent loss of family kits, efficiency in handling operations, and the speed of the distribution process. These factors collectively influence the players' KPIs evaluated throughout the game, stressing the important role of strategic investment in disaster preparedness and its direct impact on the game's outcomes. Such a structured approach emphasizes the significance of meticulous planning and resource allocation in enhancing disaster management capabilities. The selection and costing of these investment options were informed by comprehensive analysis and consultation of disaster management literature, as well as by interviews with professionals, ensuring their relevance to real-world scenarios.

3.2.2. Response actions

During the hurricane season, players enter the critical response phase, tasked with managing emergencies caused by the hurricanes. The primary mechanism for emergency relief within the game involves the distribution of family kits to affected populations. While this task may appear straightforward, it requires players to devise and implement thoughtful strategies to effectively address the needs of those impacted. A successful humanitarian operation not only meets the immediate needs of a population but also aims for a sustainable reduction of vulnerability, accomplishing these goals efficiently and ensuring timely intervention [60].

Players are thus faced with several key decisions: determining the necessary quantities of family kits, sourcing these kits, deciding on the timing of dispatch, and selecting the appropriate mode of transportation. Optimizing these decisions demands a comprehensive analysis comprising various factors — the costs associated with acquiring and shipping the kits, the time each transportation process takes, and the potential for delays that could hinder timely delivery. This complex decision-making process reinforces the game's objective to simulate the multifaceted challenges of real-world disaster response efforts, encouraging players to critically assess resource allocation, logistical planning, and the impact of their actions on recovery outcomes.

Furthermore, the efficacy of response actions is closely connected to prior preparedness investments. Players will immediately experience how earlier strategic decisions impact the ease and effectiveness of their response efforts. Investments in infrastructure, logistics, and agreements made during the preparedness phase directly influence the operational capacity to deliver family kits and manage emergencies, showcasing the critical importance of foresight and planning in disaster management.

3.2.3. Game mechanics

The main goal of the game is twofold: to generate valuable data on decision-making processes and outcomes related to humanitarian logistics operations, and to enhance players' understanding of the critical importance of both preparation and efficient response in humanitarian logistics, emphasizing strategic investment, resource allocation, and logistical planning.

Preparedness budget: In the preparedness phase, players' investments are constrained by a budget, requiring them to carefully assess the islands' needs and make informed decisions to optimize hurricane season preparation. This constrained resource environment simulates the budget limitations commonly faced by humanitarian organizations in the real world, promoting strategic planning and prioritization. Such careful allocation of resources is designed to help players recognize the value of strategic investments in reducing vulnerabilities before disasters strike. This aspect of the game illustrates a principle supported by the findings of Stumpf et al. [61]: investing in preparedness not only mitigates immediate vulnerabilities but also results in substantial economic savings post-disaster.

Damage assessment: Following each hurricane event, players are provided with a detailed impact assessment on the island's population. This report includes the number of family kits required to address the population's immediate needs, the inventory of family kits available in local warehouses, and the extent of kit losses due to hurricane damage. Additionally, the report offers insights into how the players' preparatory investments influenced the effectiveness of the response operations. This feedback mechanism is designed to help players understand the outcomes of their strategic choices, offering a clear view of the consequences of their preparedness and response efforts. Figure 4 provides an example of a damage report that a player would receive following a hurricane event.

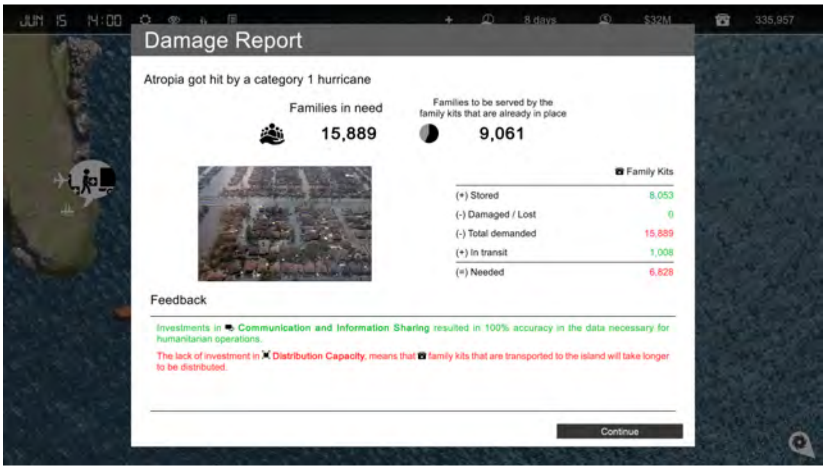


Figure 4: Example of a damage report in *HurricaneLog*, showing the impact on the island and required resources.

Storms with stochastic behavior: The game simulates storms that are modeled according to actual hurricanes from previous seasons, thereby incorporating their inherent stochastic nature. This design choice introduces a realistic element of uncertainty into the gameplay, compelling players to strategize and make decisions under conditions of unpredictability. Such a setup closely mirrors the challenges faced by disaster management professionals, who must often plan and respond without the certainty of future outcomes.

Forecasts: In conjunction with the game's simulated storms, players are provided with forecasts that predict the movements and intensity changes of these storms. This feature is designed to help players assess the potential need for assistance on various islands in the foreseeable future, encouraging them to adapt their strategies accordingly. Mirroring the practices of real-world forecast agencies, such as the NOAA's Hurricane Center in the Atlantic Ocean [62], these game-based forecasts add an extra layer of realism to the simulation, requiring players to incorporate predictive information into their disaster management planning. Figure 5 illustrates how these forecasts are presented to the game players in *HurricaneLog*.

Stochastic processes: The game models the logistics of transferring family kits between islands or from an international supplier to an island through a series of steps that mirror those typically involved in real humanitarian operations, including preparing, shipping, receiving, and distributing relief items. To maintain focus on strategic decision-making while offering a realistic representation of logistical challenges, the game abstracts these processes, introducing challenges and uncertainties characteristic of such operations, primarily in the form of stochastic delays. This approach introduces an element of unpredictability, accurately reflecting the often uncertain timings of logistics in disaster relief efforts.

International suppliers: During the response phase, players can procure additional family kits from international

Figure 5: View of hurricane forecasts and storm trajectories during the hurricane season in *HurricaneLog*.

suppliers, beyond those pre-positioned in the preparedness phase. These suppliers offer an unlimited supply within the game, presenting a strategic option for augmenting resources in times of need. However, acquiring these extra kits incurs higher costs, influenced by the level of investment in supplier agreements. Such agreements can result in either pre-agreed or escalated costs, alongside potential reductions in shipment times. This mechanic introduces strategic flexibility, allowing players to choose between focusing on pre-positioning kits as a proactive measure or relying more heavily on international suppliers, a decision reflective of strategy variations commonly observed in real-world relief supply chains [63].

3.3. Metrics and scoring

Player performance in preparedness and response operations is evaluated based on the core objectives of logistics operations: timeliness, coverage, and cost-efficiency. A successful humanitarian operations aim to reach the maximum number of vulnerable individuals promptly and cost-effectively [60]. Accordingly, *HurricaneLog* assesses player performance through three key performance indicators, reflecting these critical dimensions of logistics success. Figure 6 shows where the KPIs are displayed to the players in the game's main view. Region A in the figure displays a summary of KPIs across all islands, including average and total values, while Region B details the KPIs for each individual island. This setup allows players to assess their strategy's effectiveness in real-time and make necessary adjustments. Descriptions of these indicators and the methods used for their calculation are provided below.

3.3.1. Average response time

The game evaluates the timeliness of players' operations through KPI *average response time*, which specifically measures the efficiency in addressing the needs of disaster-affected families. For each family that receives aid in the form of family kits after a hurricane, the game records the time elapsed from the request for aid to the delivery of the kits. The average response time is calculated only for families that have received aid, excluding any unmet demands from the calculation. Consequently, if a player fails to meet any demands, their average response time would be recorded as zero, reflecting an unfulfilled response effort.

The formula for calculating the average response time (ART) is as follows:

$$ART = \frac{\sum_{i=1}^{n} T_i}{N}, \tag{1}$$

where T_i represents the response time for each family i that received aid, and N is the total number of families that received aid. This formula ensures a comprehensive assessment of how efficiently players are able to respond to emergencies, reflecting the critical importance of prompt aid delivery in humanitarian operations. To calculate the number of families affected in the event of a hurricane, the game employs a methodology inspired by the approach proposed by [50]. This method takes into account two key data points for each nation represented by the islands in

Figure 6: Display of game key performance indicators during the response phase.

the game: the highest percentage of the population historically affected by a hurricane (L) and the current population of the nation (P). Given that the game's islands are modeled after real locations in the Caribbean, these parameters are derived from accessible online databases. The calculation incorporates a random variable (h_f) influenced by the storm's category (f), which reflects the varying intensity and potential impact of hurricanes. The formula for estimating the population affected (d_f) is as follows:

$$d_f = h_f \times P \times L,$$

where:

$$h_f = \begin{cases} [0.5, 1.0], & \text{for } 4 \leq f \leq 5; \\ [0.2, 0.5], & \text{for } f = 3; \\ [0, 0.2], & \text{otherwise.} \end{cases} \tag{2}$$

The hurricane category (f) is determined according to the *Saffir-Simpson Hurricane Wind Scale*, with higher categories indicating more severe storms that can cause catastrophic damage and affect a larger portion of the population [64]. This scale, as detailed by the National Hurricane Center (NHC), helps to contextualize the potential severity of the hurricanes simulated in the game, ensuring that the impact on the virtual population aligns with realistic expectations of damage based on the storm's intensity.

3.3.2. Active demands ratio

The game assesses the effectiveness of player responses to disaster scenarios through the KPI *active demands ratio*. This KPI quantitatively evaluates the extent to which players' response operations meet the needs of the population affected by hurricanes. Lower percentages indicate a higher coverage of needs, suggesting effective operational reach where fewer individuals lack necessary assistance. Conversely, higher percentages signal a significant portion of the affected population remains unassisted, highlighting areas for operational improvement.

The calculation of this KPI involves determining the ratio of families in need, i.e., those that have not yet received aid, denoted by I, divided by the total number of families impacted by a hurricane, i.e., those that have been assisted (A) plus those that have not (I). The formula is represented as follows:

$$U = \frac{I}{A + I}. \tag{3}$$

3.3.3. Total operational cost

The third and last KPI evaluates players' operational efficiency by measuring the *total operational cost* incurred during both the preparedness and response phases of the game. This KPI includes the costs associated with investments made during the preparedness phase, the expenses related to securing family kits in warehouses, the transportation of kits between islands, and the acquisition of additional kits from international suppliers during the response phase. The methodology for calculating these costs is informed by insights from disaster risk management professionals and relevant literature, reflecting real-world financial considerations in disaster response logistics. Specifically, costs include a yearly percentage for warehouse storage, derived shipping rates for family kit transportation based on actual data, and a premium for kits acquired from international suppliers to simulate handling and preparation expenses.

At the conclusion of the hurricane season, players receive a final operation report, as illustrated in Figure 7, that summarizes their obtained KPIs for the entire region and by individual island. This report also includes details on their levels of investment in preparedness, providing a holistic view of their overall performance. The report is divided into three key areas: A, which presents an overall summary of the player's KPIs; B, which displays the evolution of the KPIs over time; and C, which provides a detailed breakdown of the KPIs per each individual island.

Figure 7: Operation report provided to players at the end of the hurricane season.

4. Results and discussions

This section presents the results of our study and discusses the findings related to players' decision-making and performance in *HurricaneLog*. We begin by detailing the data collection process, on Section 4.1, where 86 participants with diverse backgrounds engaged with the game. Following this, we evaluate the participants' performance using key performance indicators recorded during their first game session to minimize the influence of prior experience. In the Section 4.3, we delve deeper into the strategic approaches adopted by players. This analysis is organized into subsections that examine the relationship between preparedness investments and island profiles, assess the impact of these investments on KPIs, and evaluate the performance of different response strategies during the game's response phase. By clustering players based on their investment decisions and response actions, we identify patterns and correlations that highlight effective strategies and common challenges faced within the game.

4.1. Data collection

The data collection performed for our study aimed to capture the decision-making processes of participants during simulated hurricane disaster management operations in the *HurricaneLog* game. The study involved 86 participants, recruited through the data mining course at Polytechnique Montreal, social media outreach, and an online workshop session at the EURO Humanitarian Operations Summer School on Humanitarian Logistics, held from June 26 to 28, 2023 at the University of Bath, UK. To ensure consistency in understanding the game's objectives and mechanics, all participants received a detailed tutorial before engaging with the game. This preparation standardized participants' interaction with the game, enhancing the reliability of the data collected.

At the start of the game sessions, participants were prompted to fill out an in-game questionnaire assessing their educational level, background expertise in humanitarian logistics, and prior gaming experience. The participant pool was predominantly students (80%), reflecting the game's primary exposure to academic environments. The demographic distribution also included professionals from various sectors: 9% from science, technology, engineering and mathematics fields, 4% from Transportation, Distribution, and Logistics, and smaller percentages from other sectors such as Education, Health Science, Information Technology, and Law, Public Safety, Corrections, and Security. Notably, despite the majority being students, 29 participants had a background in logistics. Table 1 presents a detailed breakdown of participants' professional experiences and their specific involvement in logistics, operations management, and the humanitarian sector. The data highlights the range of experience levels among the participants, from novices to those with over a decade of professional experience. Regarding their gaming experience, 28 participants identified as non-gamers, 25 as casual gamers, 24 as mid-core gamers, and 9 as hardcore gamers.

Experience Area	None	<1 month	1-3 months	3-12 months	1-3 years	3-6 years	6-10 years	10+ years
Overall professional experience	15%	5%	7%	36%	18%	14%	4%	1%
Experience in logistics and operations management	68%	5%	6%	2%	6%	10%	0%	3%
Experience in the humanitarian sector	80%	5%	2%	9%	3%	0%	0%	1%

Table 1: Participants' experience levels in professional work, logistics and operations management, and the in humanitarian sector (N = 86).

4.2. Participants performance

We collected players in-game actions to evaluate their decision-making and performance. We evaluated the effectiveness of participants' strategies through the key performance indicators recorded during their first game session. This approach was chosen to avoid the influence of prior experience and iterative learning from multiple players sessions.

The KPIs reflect the primary objectives of the game: to provide timely assistance to the largest number of people while minimizing costs. Ideally, players should aim for low average response times, a minimal percentage of unsatisfied demands, and reduced operational costs. Achieving excellent scores across these indicators simultaneously is challenging due to their interdependent nature. For example, a player might achieve a minimal operational cost, which could result in higher average response times and a greater active demands ratio. This relationship between the KPIs shows the complexity of decision-making within the game and illustrates the trade-offs players must navigate.

To ensure the validity of our analysis, players who scored above 80% on the KPI *active demands ratio* are excluded from further analysis. This exclusion is based on our observation that such high active demands ratio may indicate a misunderstanding of the game objectives, leading to skewed performance results. A total of 14 players were removed from the analysis based on this criterion.

Table 2 summarizes the boxplot values for each KPI from the participants first session, where an outlier is defined as a data point that significantly deviates from the rest of the distribution; in this case, outliers were determined as those falling beyond 1.5 times the interquartile range above the upper quartile or below the lower quartile. This data reflects a wide range of strategies, from prioritizing low average response times to minimizing costs. To enrich our analysis, the *total operational cost* KPI is split into the costs related to preparedness and those related to response operations.

KPI	Min.	Q1	Median	Q3	Max.	Outliers
Avg. response time (days)	4	14.75	20.5	31.12	52.5	56.5, 57.5, 62.5, 64, 64.5, 67, 69.5, 80
Active demands ratio (%)	0	0	1.5	20	48	68, 69, 77, 78, 79
Preparedness cost ($M)	29.33	41.19	49.51	49.99	49.99	0, 7.31, 18.57, 21.37, 25.23, 25.62
Response cost ($M)	32.96	79.14	96.91	113.14	152.41	0.57, 3.95, 9.04, 11.46, 192.54

Table 2: Summary of key performance indicators for game players.

The average response time indicator shows a significant range, with some players achieving a remarkable average of 4 days. This suggests that some strategies were very efficient in meeting demands promptly. Conversely, the high maximum values indicate that some players struggled with timely fulfillment of demands, possibly due to delayed actions or prioritizing other aspects of the game, such as costs. The outliers in this KPI further highlight the variability in player strategies and their effectiveness.

The active demands ratio illustrates skewed performance. Most players, about 50%, were able to successfully fulfill almost all demands, with the median score being 1.5%. However, the presence of outliers scoring up to 79% indicates that some players failed to meet most of the demands, either by focusing excessively on cost minimization rather than effective response, or by waiting too long to act upon the emergency, resulting in the game ending without their major intervention. This wide spread demonstrates the variety of players' strategies and their outcomes, highlighting the challenge of balancing cost and timely aid delivery.

In terms of preparedness cost, the data indicates strategic investment in preparedness, with most players, almost 75%, utilizing their full budget, as evidenced by the concentration of median, third quartile, and maximum values around the budget cap of \$50M. This suggests that players recognized the importance of thorough preparation. The response cost KPI presents a wide range of values, from \$32.96M to \$152.41M, with significant outliers. These outliers suggest that while some players managed to keep response costs low, others faced considerable expenses, likely due to insufficient preparedness investments or inefficient response strategies.

4.3. Data analysis of players actions

Besides assessing players' performance through their KPIs, we analyzed players' decision-making. We further explore the strategic approaches adopted by players during the game, aiming to uncover patterns and correlations between different strategies and performance outcomes. Thus, we seek to identify which strategies were most effective and why, as well as areas where players commonly faced challenges in the game.

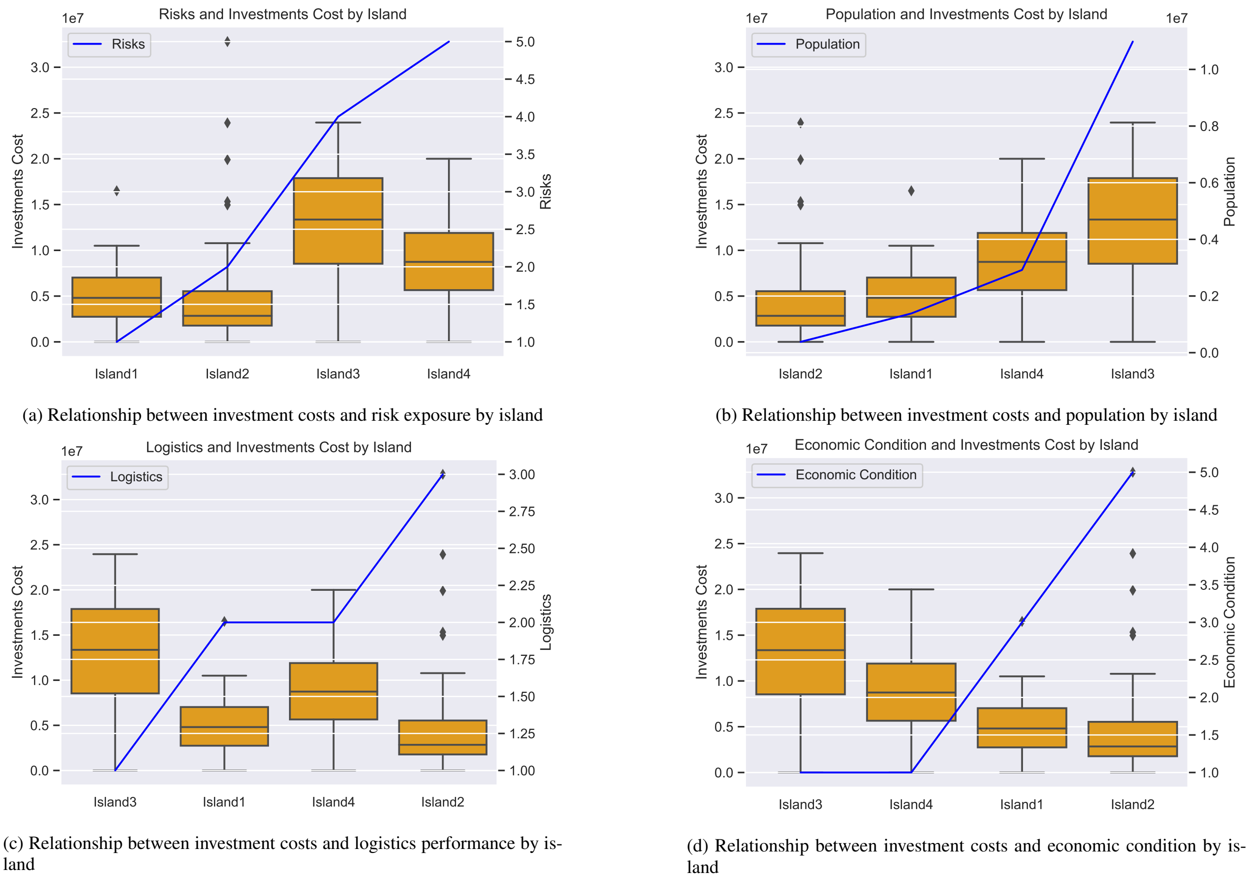
4.3.1. Relationship between preparedness investments and island profiles

We analyzed the impact of the islands' profile indices on the preparedness investments made by the players. The players investment decisions showed a significant relationship with the islands' risk exposure ($r = 0.40, p < 0.001$) and population size ($r = 0.52, p < 0.001$). Players invested significantly more in islands with higher risk exposure and larger populations, with the latter showing stronger evidence. Similarly, a significant relationship was found between investment spending and the islands' economic condition ($r = -0.44, p < 0.001$) and logistics performance ($r = -0.47, p < 0.001$) indexes. In these cases, players invested significantly less in islands with better economic indices and better logistics infrastructure. Evidence of these behaviors are shown in Figure 8.

The observed behaviors can be partially attributed to the costs associated with prepositioning family kits, which, on average, account for 68.41% of the budget spent by players during the preparedness phase in our experiment. We observed that the islands with higher risk exposure and larger populations (i.e., Islands 3 and 4) had 2.3 times more prepositioned family kits than the other islands. This observation indicates that players preferred to adopt strategies focused on prepositioning family kits on islands which are more likely to be affected by hurricanes, seeking to provide quick assistance to the maximum number of affected people. Our analysis shows that this strategy proved to be more effective than strategies that did not prioritize high-risk islands, as will be further discussed in Section 4.3.2. These findings highlight the complexity of players' decision-making and suggest that players prioritized immediate accessibility to aid for higher-risk and more populous islands.

4.3.2. Impact of preparedness investments on KPIs

We examined the relationship between the preparedness investments and the game KPIs, aiming to understand how different investment strategies can influence the effectiveness and efficiency of disaster response. To achieve this, we performed a clustering analysis of the investment decisions made by the players in our experiment. The goal was to identify clusters representing distinct investment strategies, allowing us to observe the players preparedness approaches within the game. For each player p, we collected the level of investment selected for each investment category and the amount of family kits prepositioned, creating an investment matrix INV^p. In this matrix, each row $i = 1, 2, 3, 4$ corresponds to a targeted island, and each column to an investment type. Thus, $INV^p(i, j)$ stores the investment level of option j allocated by player p to island i. The fifth row of the matrix INV^p, refers to investment levels selected for regional preparedness investments. The INV^p matrices were standardized to prevent variables with larger value ranges (such as the number of prepositioned family kits) from dominating the clustering process. The matrices were then clustered using the k-means algorithm [65] with the Frobenius distance as dissimilarity measure.



(a) Relationship between investment costs and risk exposure by island

(b) Relationship between investment costs and population by island

(c) Relationship between investment costs and logistics performance by island

(d) Relationship between investment costs and economic condition by island

Figure 8: Relationships between investment costs and island profile indices.

We performed clustering for $k = 5$ clusters, which maximizes the silhouette score [66]. Table 3 reports the mean values of the investment matrices found within each cluster. These values correspond to the clusters' centroids, representing the central tendencies found in each cluster.

Disaster preparedness strategies

We present next an interpretation of the clustering structures found:

Cluster 1: This cluster is composed by players who focus on prepositioning family kits on vulnerable islands, allocating more family kits on Islands 3 and 4 when compared to the other clusters. Their strategy included significant investments in warehouse capacity and distribution capacity on these islands. In contrast, they invested minimally on the less vulnerable islands, and on regional options.

Cluster 2: Similar to cluster 1, the players in this cluster prioritize prepositioning family kits on vulnerable islands, although they preposition significantly fewer kits than those in cluster 1. The players in cluster 2 invested the most overall, prioritizing the vulnerable islands and communication infrastructure, with increased investments in regional options as well.

Cluster 3: This cluster exhibits a combination of strategies from cluster 1 and cluster 2. Players in this cluster allocated more family kits to Islands 3 and 4, thereby prioritizing more vulnerable regions. In addition, they invested more in warehouse capacity, distribution capacity, and communication infrastructure on these islands. They also allocated some investments to regional options, demonstrating a balanced approach between investment on more vulnerable islands and broader regional preparedness.

Cluster 4: Players in this cluster adopted a strategy focusing on the less vulnerable islands, aiming to safeguard resources and promptly send them to affected populations in case of disaster. They prepositioned more family kits on the least vulnerable island (Island 2) and concentrated local investments there. Additionally, these players heavily

Cluster		Preposition	Warehouse Capacity	Dist. Capacity	Comm.	Supplier Ag.	Regional Transp.	Customs Cl.
1	Island 1	24,577.00	1.00	0.38	0.50	-	-	-
	Island 2	24,577.50	0.88	0.38	0.50	-	-	-
	Island 3	109,923.25	2.50	1.75	1.00	-	-	-
	Island 4	79,187.50	2.00	1.75	0.75	-	-	-
	Regional	-	-	-	-	0.38	0.38	0.13
2	Island 1	14,740.50	1.50	1.14	2.50	-	-	-
	Island 2	10,291.14	1.07	0.93	2.36	-	-	-
	Island 3	54,383.29	2.36	1.86	2.79	-	-	-
	Island 4	25,317.29	2.21	2.00	2.86	-	-	-
	Regional	-	-	-	-	2.43	1.00	2.21
3	Island 1	24,312.73	0.97	1.07	0.93	-	-	-
	Island 2	11,152.70	0.67	0.77	0.63	-	-	-
	Island 3	77,239.27	2.27	2.30	1.87	-	-	-
	Island 4	42,133.33	1.67	1.67	1.47	-	-	-
	Regional	-	-	-	-	1.77	0.97	2.03
4	Island 1	11,704.20	1.20	0.60	0.60	-	-	-
	Island 2	105,818.60	3.00	2.00	1.80	-	-	-
	Island 3	7,544.40	1.00	0.20	0.20	-	-	-
	Island 4	10,331.60	1.00	0.80	1.00	-	-	-
	Regional	-	-	-	-	2.80	1.00	1.60
5	Island 1	29,512.60	0.87	0.40	0.60	-	-	-
	Island 2	22,551.93	0.73	0.40	0.67	-	-	-
	Island 3	35,249.73	1.27	0.67	0.73	-	-	-
	Island 4	32,424.40	1.27	0.47	0.73	-	-	-
	Regional	-	-	-	-	0.93	0.87	0.93

Table 3: Average investment matrices for the 5 clusters obtained clusters of preparedness investments.

invested in supplier agreements, creating a backup family kit provider in case local capacities were exceeded.

Cluster 5: The players in this cluster invested the least overall on region preparedness.

To evaluate the impact of the various strategies represented by each identified cluster, we calculated the average KPIs achieved by the players whose INV^p matrices are clustered together. These cluster-level KPIs are presented in Table 4. Based on these scores, we remark the following for every strategy.

Cluster	Avg. response time	Active demand ratio	Preparedness cost	Response cost
1	23.44	0.39	45,872,632.00	55,009,145.00
2	23.61	0.09	47,107,510.57	95,330,505.71
3	16.73	0.05	47,484,362.27	103,769,041.67
4	58.80	0.03	49,049,022.40	123,208,834.00
5	38.93	0.25	30,057,989.33	83,958,088.27

Table 4: Mean KPIs for the players associated to the clustered investments matrices.

Strategies performance analysis

Players in **Cluster 1** focused heavily on prepositioning family kits on vulnerable islands, investing significantly in warehouse and distribution capacity. Despite these efforts, this strategy resulted in the highest active demand ratio, indicating the worst demand satisfaction among all clusters. The critical issue of the preparedness strategy adopted by the players in Cluster 1 lays in the lack of investment in supplier agreements, which delayed the shipment of additional family kits from international suppliers once local stocks were exhausted. As a result, players in Cluster 1 were unable to meet the full demand promptly, leading to high unmet needs. Interestingly, Cluster 1 achieved the lowest response cost, suggesting that the reliance on local capacities minimized operational expenses. However, this cost-saving approach likely contributed to the high active demand ratio, as players may have tried to conserve their budget, impacting their overall coverage and the ability to assist all affected populations. While the reduced response cost reflects financial efficiency, it came at the expense of timely and comprehensive assistance.

Players in **Cluster 2** also prioritized vulnerable islands but took a more diversified approach, spreading their investments across regional infrastructure and communication systems. The investment in communication and information sharing likely played a significant role in the strategy's success, providing players with more accurate information about the availability of family kits and the specific needs of the affected populations. This allowed them to make more informed decisions, contributing to the lower active demand ratio, with only 9% of demands left unsatisfied. However, this focus on fulfilling demands led to a high response cost. The reliance on external resources, accessed through supplier agreements, helped players meet the needs but increased their overall expenses. This higher cost reflects the players' priority on meeting demands, even if it meant incurring additional expenses. Ultimately, the increased cost was justified by the strategy's effectiveness in reducing unmet needs, though the heavy dependence on external suppliers made this approach more expensive overall.

Cluster 3 demonstrated the best overall performance, balancing speed, efficiency, and cost management. Players in this cluster adopted a combination of strategies seen in Clusters 1 and 2. They prioritized vulnerable islands, allocating more family kits to Islands 3 and 4, and invested significantly in warehouse capacity, distribution capacity, and communication infrastructure on these islands. Additionally, they made some investments in regional preparedness, allowing them to mobilize resources more efficiently across the region. This balanced approach led to the lowest average response time among all clusters, indicating that players were able to meet demands promptly. The focus on vulnerable islands, combined with moderate investments in supplier agreements, helped to achieve a small active demand ratio, leaving only 5% of demands unsatisfied. Although this strategy resulted in a relatively high response cost, it was not the highest among the clusters. The combination of rapid response and low unmet demand outweighed the moderate preparedness and response costs, demonstrating that focusing on vulnerable islands and balancing regional investments provide a highly effective strategy overall.

Cluster 4 adopted the most distinct preparedness strategy, focusing on prepositioning family kits and investments on a less vulnerable island, likely with the intention of creating a safe hub for distribution. This approach was supplemented by heavy investments in supplier agreements, which players saw as a robust backup for meeting demands. Initially, this strategy appeared effective, as Cluster 4 achieved the lowest active demand ratio, covering almost all demands. However, this success in coverage came at the cost of the highest average response time by far. The delay in response can be attributed to two key factors: first, the lack of significant investment in distribution capacity on the vulnerable islands meant that once family kits arrived, they took longer to reach the affected populations. Second, by focusing prepositioning efforts on less vulnerable islands, players introduced additional delays in shipping kits to areas directly impacted by hurricanes. The elevated response and preparedness costs are also explained by this strategy. Not only did players need to acquire more family kits from international suppliers to meet the demands, but they also faced higher transportation costs in shipping the kits from their "safe hub" to the affected regions. While this strategy provided comprehensive coverage, it proved less efficient in terms of both response time and cost.

Players in **Cluster 5** invested the least in preparedness efforts, which led to poor performance in both average response time and active demand ratio. Their frugal approach minimized preparedness costs, but the lack of substantial investment during the preparedness phase led to higher operational inefficiencies during the response phase. This strategy demonstrates the risks of under-investing in key areas, as it resulted in significant delays and unmet demands.

In general, none of the clusters achieved a zero active demand ratio, indicating that all players struggled to fully meet the needs of the affected population. However, Clusters 2, 3, and 4 showed stronger performance in this area, with lower active demand ratios, suggesting that their investment strategies were more effective in addressing the demands of disaster response.

In summary, our analysis demonstrates that the diverse preparedness investment strategies employed by players in the *HurricaneLog* game significantly influence the KPIs. This underscores the critical role of investment decisions in shaping disaster management outcomes within the game.

4.3.3. Performance Evaluation of Response Strategies

We also analyzed the operational decisions made during the response phase of the game. This analysis consisted of examining the relationship between the family kits transfer decisions made by the players during the disaster response phase and the resulting performance indicators, focusing on understanding how response strategies may influence the performance of the humanitarian operation.

For this purpose, we performed a second clustering of the players, this time based on their response strategies during the game's response phase. This analysis involved creating a transfer matrix, T, to summarize the players' transfer decisions. Each row of T corresponds to a player, and each column represents one of the following features related to a player's behavior:

- Frequency: The total number of performed transfers;
- Days between transfers: The average number of days between transfers;
- Mean transfers by plane: The average number of family kits transferred by plane;
- SD transfer by plane: The standard deviation of family kits transferred by plane;
- Mean transfers by ship: The average number of family kits transferred by ship;
- SD transfer by ship: The standard deviation of family kits transferred by ship;
- Recency: The number of days between the player's last transfer and the end of the hurricane season;
- Preventive transfers: The number of transfers made to the islands before there were struck by a hurricane;
- Reactive transfers: The number of transfers made to the islands after there were struck by a hurricane.

These features were adapted from the cluster analysis of financial transactions from [67]. The first seven features can be directly extracted from players' transfer decisions collected from the game. However, the last two features (i.e., preventive and reactive transfers) required the definition of a hyper-parameter that defines a threshold to classify a transfer as preventive or reactive.

To define this hyper-parameter we identified the scenarios that could trigger a reactive behavior from a player. Three unique scenarios were recognized: (i) the formation of a forecast uncertainty cone over the island, suggesting a possible yet uncertain hurricane impact with a lower chance; (ii) the appearance of a projected hurricane path over the island, suggesting a higher probability of a direct impact; and (iii) the actual landfall of the hurricane on the island. An illustrative example of these scenarios is shown in Figure 9. In the example, the hurricane forecast cone appeared over the island 5.7 days before the hurricane hit, and the forecasted hurricane track appeared over the island 4.7 days before the hurricane actual hit. By analyzing the entire set of hurricane simulated in the game, we concluded that a threshold value of 5.5 days was able to capture the reactive behaviour of a player. Thus, transfers made to an island before or after 5.5 days of a hurricane hit were classified as reactive, whereas transfers made to an island out of this window were classified as preventive.

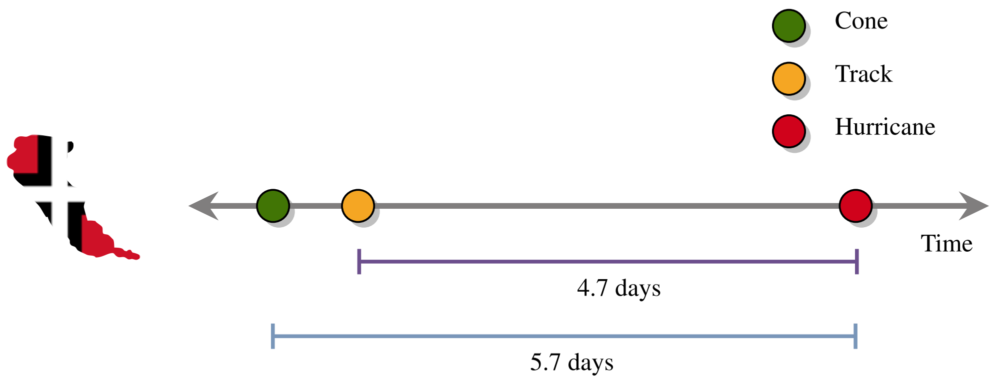


Figure 9: Example of scenarios that can trigger a player reaction.

A correlation analysis between the nine aforementioned features with the KPIs obtained by the players in our experiment revealed that four of the features were not correlated to any of the performance metrics. Thus, we retained for our clustering analysis of T the following five features: Frequency, Mean transfers by plane, SD transfer by plane, and Preventive transfers. The lines of T, each associated to a player, were then clustered by k-means with $k = 4$

clusters, which was defined by the maxmium silhouette score among various values of k. Finally, T was standardized in order to make sure that each feature played an equal part in the clustering analysis.

The resulting clusters represent distinct types of strategies identified among players. Table 5 presents the average behavior of each cluster, represented by the cluster centroid. The last row of the table indicates the number of players in each cluster. Overall, we can observe that all identified strategies showed a higher proportion of reactive transfers compared to preventive transfers. A detailed examination of the strategy employed by each cluster follows.

Cluster	Frequency	Mean transfers by plane	SD transfer by plane	Preventive transfers	# of players
1	4.50	142,955.86	120,373.04	0.85	20
2	11.25	61,281.55	74,193.70	4.18	28
3	5.42	65,973.72	40,441.75	0.84	19
4	2.20	276,538.00	14,538.40	0.20	5

Table 5: Mean response strategies for each of the 5 identified cluster.

Disaster response strategies

Players in **Cluster 1** performed an average of 4.5 transfers, which is below the overall clusters average of 5.84 transfers. These players sent a high average number of family kits per transfer using planes. However, the high standard deviation in the number of kits transferred suggests significant variability in their transfer decisions. This could imply that players in this cluster were inconsistent in their response strategy—alternating between large-scale and smaller-scale transfers. Such variability might reflect uncertainty or a lack of a clear strategy, leading players to either overreact in some cases or under-respond in others.

Cluster 2 strategy was the most commonly adopted by players and involves performing more transfers with a lower average number of family kits per transfer. The high standard deviation, however, indicates significant variability in the number of family kits being transferred–suggesting that while players frequently sent aid, the amount sent each time varied widely. This implies that players adjusted the size of their transfers based on evolving situations or specific needs rather than distributing resources evenly. Additionally, this strategy had the highest proportion of preventive transfers ($4.18/11.25 \approx 37\%$), indicating that players were often reactive to the hurricane track predictions.

Cluster 3 strategy represents a more balanced approach compared to those adopted in the other clusters. Players in this group performed an average number of transfers slightly above the overall average, with a moderate amount of family kits per transfer. The standard deviation in the number of family kits per transfer was lower than those observed in Clusters 1 and 2, suggesting more consistency in the number of kits dispatched each time. However, the strategy was still primarily reactive, with preventive transfers accounting for only a small portion of the total. This suggests that players in this cluster aimed to maintain a steady and reliable flow of aid without overcommitting resources too early, but without the high variability seen in Cluster 2. The moderate number of transfers, combined with consistent family kit transferred quantities, indicates a strategy that balanced between risk and resource efficiency, potentially leading to more timely yet controlled responses to disaster events.

Cluster 4 strategy was the least adopted by players and is characterized by the fewest amount of transfers, exhibiting a highly reactive behaviour. Players following this strategy likely waited for hurricane damage events to occur before dispatching family kits, which explains the high concentration of kits per transfer—an average of 276,000 per plane transfer. By waiting for the damage reports, these players were able to send the exact amount of family kits needed, resulting in fewer but larger and more targeted relief efforts. While this approach minimizes unnecessary transfers, it also risks delayed response times, potentially leaving affected populations without immediate aid in the initial aftermath of a disaster.

To gain further insights into how the identified response strategies impacted the KPIs, we assessed the cluster-level KPIs by averaging the KPIs scored by each player within each cluster. The results of this analysis are displayed in Table 6. We remark from this table that three out four cluster obtained good active demand ratios showing that they were able to meet most of the demands for family kits.

Strategies performance analysis

Cluster 1 achieved the best active demand ratio, successfully meeting the highest proportion of demands. However, this led to a higher average response time and the greatest response cost among all clusters. The higher response time suggests that while players were focused on meeting all demands, they may have faced delays due to the vari-

Cluster	Avg. response time	Active demand ratio	Preparedness cost	Response cost
1	30.25	0.05	45,368,011.40	107,723,755.00
2	27.39	0.09	42,016,375.86	106,150,504.61
3	20.16	0.30	45,924,851.37	61,702,929.21
4	28.60	0.10	38,148,219.20	92,828,420.00

Table 6: Mean KPIs of the response strategies clusters.

ability in their transfer sizes. The high standard deviation in the number of kits transferred reflects this inconsistency, as players alternated between large-scale and smaller-scale transfers. This inconsistency likely led to a strategy that, while thorough in demand fulfillment, was less efficient in terms of time and cost management.

Cluster 2 performed well across all KPIs, with a small active demand ratio, leaving only 9% of demands unsatisfied, and relatively low preparedness and response costs. This cluster had a slightly higher average response time than Cluster 3, but its cost efficiency and demand fulfillment were well-balanced. The high number of preventive transfers and the significant variability in the number of family kits per transfer suggest that players frequently sent aid but adjusted the size of their transfers based on evolving situations or specific needs. This flexible and proactive approach likely helped manage costs effectively while still responding to demands in a timely manner.

Cluster 3 excelled in achieving the lowest average response time, indicating a quick and efficient response strategy. However, this came at the expense of the active demand ratio, with 30% of demands left unsatisfied, the worst among all clusters. The focus on speed over comprehensive demand fulfillment likely led to lower overall response costs, as players prioritized quick responses without fully meeting all needs. The consistent transfer sizes suggest that players maintained a steady flow of aid, but the trade-off between speed and completeness is evident in the cluster's KPI outcomes.

Cluster 4 had the lowest preparedness cost, indicating a frugal approach to pre-disaster investments. However, the strategy's reliance on reactive measures led to a higher average response time, ranking third among the clusters. Despite this, the cluster managed a decent active demand ratio, with 10% of demands unsatisfied, while keeping response costs lower than players in Clusters 1 and 2. The strategy's reliance on post-damage assessments allowed players to send large, targeted transfers, as reflected in the high number of family kits per transfer. While this approach minimized unnecessary pre-disaster spending, it also resulted in delayed responses, highlighting the trade-offs between cost efficiency and timeliness in disaster response.

In conclusion, our analysis demonstrates that the response strategies employed by players significantly influence the game's KPIs, with particular effects observed in average response time and response cost. The findings reveal that while some strategies prioritize rapid response at the expense of resource efficiency, others focus on cost-effectiveness but risk leaving demands unmet. The variability in outcomes highlights the complexity of disaster management decisions, where the timing, scale, and consistency of transfers play important roles in determining overall effectiveness. These insights show the importance of strategic planning in disaster management scenarios, suggesting that a balanced approach, which optimizes both preparedness and responsiveness, may lead to more favorable outcomes. Future studies could explore how these strategies might be adjusted or improved to enhance performance further, both within the game and in real-world applications.

5. Conclusions

This study introduces *HurricaneLog*, a serious game that addresses a significant gap in humanitarian logistics by providing a comprehensive tool for analyzing decision-making processes in disaster preparedness and response, specifically within multi-country regions (represented as islands). Unlike previous humanitarian games, which have not fully explored the complex interplay between preparedness and response phases, *HurricaneLog* offers a detailed simulation environment that captures granular data on strategic preparedness decisions, resource allocations, and operational logistics response decisions.

Our primary objective was to design a game that not only facilitates training but also enables effective collection of decision-making data in humanitarian operations. By aligning *HurricaneLog*'s design with real-world data and insights from existing literature, we provide players with an immersive experience that reflects the challenges logistics managers face in disaster scenario management. Through this setup, *HurricaneLog* offers valuable insights into the nuanced and interdependent decisions involved in disaster preparedness and response, highlighting critical trade-offs between cost, speed, and demand satisfaction.

Building on this, a secondary objective of our study was to propose a methodological framework for analyzing the data collected during gameplay. This framework includes both descriptive statistics and advanced clustering analyses, enabling us to categorize decision-makers and gain deeper insights into their disaster management strategies and performance.

Through an empirical study involving 72 participants, our analysis identified five distinct preparedness strategies, with a balanced approach (Cluster 3) proving most effective. This strategy involved prioritizing investments in vulnerable islands by prepositioning resources and enhancing critical infrastructure, resulting in the lowest response times and highest demand satisfaction, meeting 95% of demand with a manageable increase in costs. The response phase analysis revealed four primary strategies, each reflecting different priorities in balancing cost, speed, and demand fulfillment. For instance, one cluster adopted frequent, smaller shipments that achieved a balance between responsiveness and cost-efficiency, while a reactive approach focused on addressing needs as they arose, leading to longer response times but reduced costs. A rapid-response strategy achieved the lowest response times but struggled with comprehensive demand coverage, underscoring the trade-offs inherent in disaster logistics.

These findings underscore the complex, interconnected nature of humanitarian operations performance, where achieving one objective often requires compromising another. *HurricaneLog* thus provides a unique educational and analytical platform that enables both students and practitioners to understand and navigate these trade-offs, deepening their understanding of decision-making dynamics in disaster management. By equipping players with insights into the effectiveness of various preparedness and response strategies, this game has the potential to inform both real-world logistics operations and future research.

HurricaneLog serves as an educational tool within disaster management curricula, offering a simulated environment where participants can experiment with different approaches to disaster preparedness and response. This interactive experience fosters a deeper understanding of strategic investment in preparedness and the need for flexibility in response, ultimately enhancing the ability to make informed and effective logistics decisions.

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