



Risk assessment methodologies, models and algorithms



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ABBREVIATIONS

ABBREVIATION	Full Name
ABM	Agent-based Model
CDF	Collaborative Digital Framework
CFD	Computational Fluid Dynamics
RA	Risk Assessment
UML	Unified Modeling Language
TR	Transmission risk







PUBLISHABLE SUMMARY

Cruise ships are unique closed environments that blend private and public areas, where diverse populations come together and travel for extended periods. These conditions create an ideal setting for the spread of infectious diseases, both airborne and waterborne, due to the close proximity of passengers and the shared facilities on board. To address these challenges, this task developed risk assessment mathematical models and software components for assessing health hazards on ships and achieve the functionality of the Collaborative Digital Framework (CDF) proposed in the scope of the HS4U project.

This task included analyses and modelling of accessible areas such as public spaces, and cabins using data from HS4U use cases and existing information. Data from pilot partners, including ship schematics, air filtration, ventilation systems, and sewage systems, was retrieved, and rooms and equipment were categorized based on their impact on various diseases. A mapping between ship components and disease spread was defined.

Based on these, a biomedical model was developed to simulate infection transmission in passenger ships, both indoors and outdoors, estimating and predicting infection risks for short time spans at a micro-scale. The model integrated various types of equipment—including thermal cameras, audio sensors, and pathogen detection systems—to monitor early indicators of infectious diseases and assess real-time risk through a fuzzy inference system. Computational tools were used to model and predict the spread of microbes through air and water, accounting for real-world measurements of air-flow characteristics and piping system parameters. These methods simulated infection spread at a micro-scale, capturing the impact of human interactions and environmental factors on disease transmission, while enhancing the risk assessment process of the developed biomedical model.

The biomedical model was evaluated through experiments in multiple scenarios of air-, water- and surface-mediated disease transmission for different infrastructural components of cruise ships. The results of these experiments demonstrated that the proposed biomedical risk assessment model effectively and accurately estimates disease transmission risks, while also providing actionable risk mitigation recommendations to the crew. An additional merit of the model is its modular design that allows for adaptability to different ship configurations and sensor setups. Consequently, the technologies developed in this task can be effectively integrated into the CDF framework in accord with the aim of the HS4U project, while its adaptability ensures that it can be utilized in future maritime health initiatives.





FOREWORD

In the context of the research conducted for the implementation of Task 3.2, a biomedical risk assessment framework for assessing health hazards on ships was developed. This task included (a) analyses and modelling of accessible areas such as public areas, cabins, and self-checking docks using evidence-based data from HS4U use cases and existing information, (b) biomedical modelling in passenger ships to facilitate simulation-based analyses of infection transmission (for indoor and outdoor areas), and (c) computational modelling, simulation, analysis, and assessment of airborne and waterborne bacterial and virus spreads through surfaces for their design implications in evidence-based naval architecture and marine engineering plans. The results of this research have been published in several peer-reviewed scientific journals and conferences, where more details on the literature, models, and methods investigated can be found.

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1. INTRODUCTION

Cruise ships are closed environments that combine private and public areas, where diverse populations travel together for several days. Such conditions are considered ideal for the spread of both airborne and waterborne diseases. A recent example is the Diamond Princess cruise ship, where after a passenger was tested positive for COVID-19 (SARS-CoV-2), the passengers and the crew were instructed to quarantine for two weeks. During that period, there was an extensive spread of the virus throughout the ship, counting 651 cases over 3,711 passengers and crew (Batista et al., 2020). After almost one month, all passengers and crew disembarked. Notably, 712 (19.2%) were tested positive for COVID-19, and among them, 331 (46.5%) were found asymptomatic (Moriarty et al., 2020).

In general, disease outbreaks are relatively common in closed environments, such as cruise ships, nursing homes, hospitals, and college dormitories (Mouchtouri et al., 2020). In the case of cruise ships, outbreaks are associated with either airborne diseases, *e.g.*, COVID-19 or waterborne diseases, *e.g.*, gastrointestinal (GI) diseases. These are usually attributed to organisms, such as Salmonella, Shigella, enterotoxigenic Escherichia coli, influenza virus, and Legionella pneumophila, and, more recently, norovirus and COVID-19 (Hill, 2019; McCarter, 2009). During such outbreaks, cruises often go into quarantine until the source is isolated and the spread is mitigated. Therefore, modeling and predicting the progress of disease outbreak in closed environments is of paramount importance for their mitigation. The success of a modeling approach depends highly on the parameters taken into consideration, such as social and behavioral factors, as well as parameters related to the transmission pathways. For the latter, accurate data regarding the transmission through the air, water, and surfaces are key to the effectiveness and fidelity of a simulation.

Diseases can spread via different transmission modes, including airborne, droplet, contact, and fecal-oral transmissions (Delikhooon et al., 2021). The most common disease transmission pathway among individuals is air. An infectious disease, such as COVID-19 can be spread when contact is established between an infected host and a susceptible one. Peer-to-peer contact modes involve complex interactions of a pathogen with a fluid phase, *e.g.*, isolated complex fluid droplets or a multiphase cloud of droplets. When an individual exhales, including coughing or sneezing, micron-sized droplets are formed, which can transfer airborne pathogens, such as viruses (~10–100 nm), bacteria (~1 µm), and spores (~1–10 µm) (Bourouiba, 2021). Fine and ultrafine particles (airborne transmission) can stay suspended for an extended period of time (≥ 2 h) and be transported through simple diffusion and convection mechanisms as far as 8 m (Delikhooon et al., 2021). These can be either transmitted directly to other people or be deposited on surfaces and transmitted indirectly through contact.

Another but less frequent transmission pathway is water. A direct source of infection is infected potable water, while premise plumbing with non-potable water, *e.g.*, showers, toilets, and sink faucets, and the water systems associated with it, are common indirect sources of infection transmission (Carlson et al., 2020). Nevertheless, nowadays extensive



measures are taken to minimize or even eliminate the occurrence of such cases (Leslie et al., 2021; Muli et al., 2020). Air bubbles are ubiquitous on water surfaces and are common in facilities of cruise ships, such as pools and toilets. Bubbles can also cause public health concerns, since droplets generated from contaminated water may carry infectious payloads that can lead to airborne disease transmission. Contaminated droplets can be easily transported over short and long distances by drafts, such as those generated by the heating ventilation and air-conditioning (HVAC) system. Inhalation of droplets or droplet nuclei containing bacteria is a recognized route of infectious disease transmission, e.g., outbreaks of *Legionella* (Prussin II et al., 2017), which are attributed to aerosolization from bursting bubbles. Another source for the waterborne transmission of diseases is the development of biofilm in the piping systems, especially those with warm water (<50°C). Biofilms develop on most surfaces in contact with non-sterile water. Pathogens in biofilms do not usually spread from person-to-person or through direct consumption of the water, but there is considerable evidence that individuals become ill when exposed to airborne water droplets that have been seeded by those pathogens. Activities that can lead to their aspiration include showering and hand washing.

Although viruses, such as SARS-CoV-2, are principally transmitted through person-to-person contact through droplets produced while talking, coughing, or sneezing, transmission may also occur through other routes, such as contaminated surfaces. However, the role that surfaces play on the spread of the disease remains contested. For example, infective coronavirus has been found to persist on surfaces from 3 h to 28 days, depending on different environmental factors, e.g., surface material, humidity, and temperature. Viruses can be transferred from contaminated surfaces to the hand upon contact and from the hand to the mucous membranes on the face. Nevertheless, experimental findings reported in the literature support the current perception that contaminated surfaces are not a primary mode of transmission, at least as regards SARS-CoV-2 (T. Chen, 2021; Pitol & Julian, 2021).

Monitoring and controlling the spread of a disease in a cruise ship is a complex problem, requiring information about the ship (e.g., accessible areas, ventilation, and water supply network), the passengers (e.g., demographic and health data), and possible diseases, including their symptoms and treatments, the respective pathogens and epidemiology. To this end, several guidelines and protocols have been developed ((WHO) & others, n.d.; Organization & others, n.d.); however, their application is mainly based on decisions and interventions performed by the vessel's crew. Therefore, managing a crisis, such as an epidemic, on board is currently prone to human errors, which can be life-threatening in the case of severe infectious diseases. The frequency of such errors depends on several parameters, including the number of the crew members, their training and experience, the size of the vessel, and the number of passengers on board. Furthermore, the interaction of crew members with diseased passengers can contribute to further spreading of the disease and affect its operational capacity.

It is therefore evident that an automatic system for disease spread monitoring and control in cruise ships would contribute to limiting the dependencies on the human factor,





and consequently to passengers' safety. Towards this direction, this chapter presents a conceptual model integrating technologies that could be used for disease monitoring and spread control. This model integrates sensors, actuators, artificial intelligence, mathematical, numerical and/or other simulation models to predict the risk of disease spread in cruise ships, and to support decision making regarding possible mitigation measures.

The remainder of this chapter is organized as follows: Section 2 presents ship related data including provided ship schematics, empirical risk levels gathered for each compartment and a summary of disease monitoring approaches and equipment focusing on ships and enclosed spaces, Section 3 introduces the biomedical risk assessment (RA) model developed, including an extensive review of related methodologies for epidemic-related RA and simulation of disease spread, as well as an overview of the simulated scenarios examined in this deliverable; Section 4 presents the computational modeling, simulation, analysis, and assessment conducted; Section 5 presents the experiments and results; Section 6 discusses key outcomes and conclusions derived.

2. SHIP RELATED DATA

2.1 Ship Schematics

In the context of the HS4U project, ship schematics of two representative cruise ships, *i.e.*, World Dream and Celestyal Discovery, were provided by the partners. These schematics were utilized to identify different areas of the ship and probable disease transmission scenarios that were used to create the biomedical RA model. These schematics include detailed information about the ship areas for each deck, including passenger cabins, eating areas, recreational spaces such as bars and casinos, swimming pool areas and public toilets. Information regarding the structure (surface area and height) and the capacity of these areas were used to adjust the biomedical RA model for each scenario and area. The schematics for several decks of the ship can be observed in Figures 1 & 2. Additional information that is available in these ship schematics is the furniture arrangement of the depicted spaces, such as the position of furniture in each area. These data were further utilized for simulation purposes, *i.e.*, modeling of areas, and to assist in the decision-making process of the biomedical RA model.



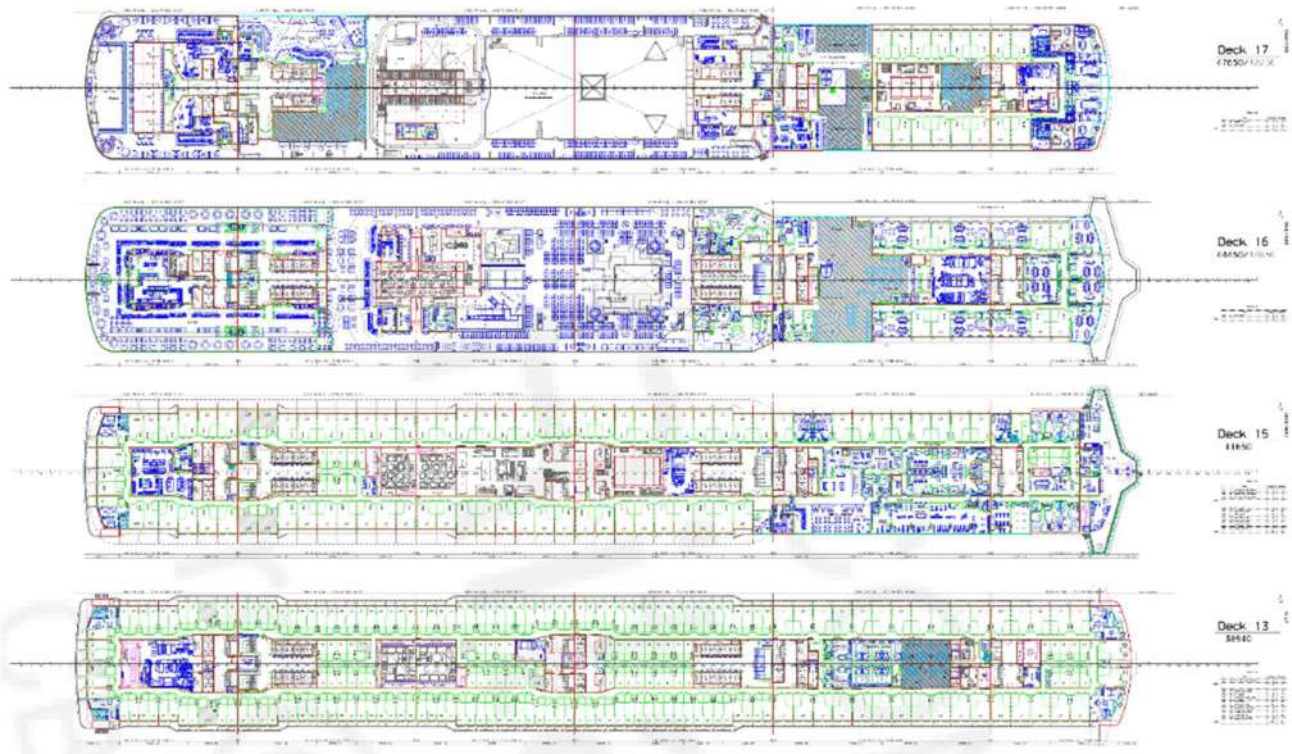


Figure 1. Ship schematics for Deck 13,15,16,17 of the World Dream cruise ship.

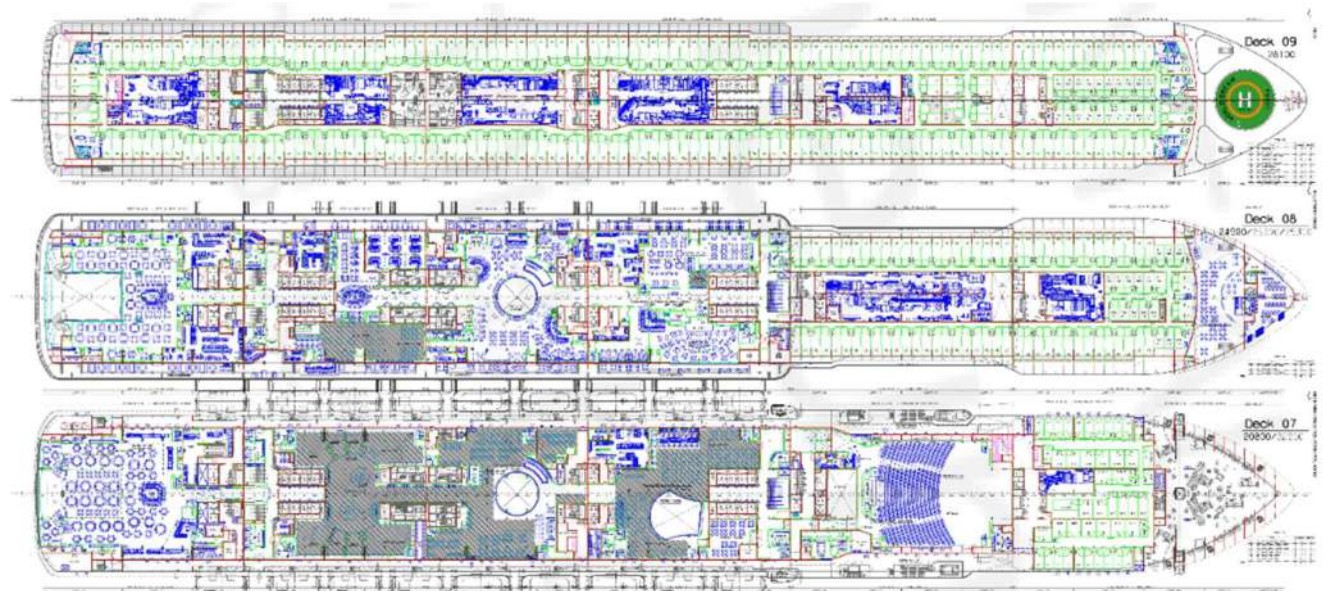


Figure 2: Ship schematics for Deck 7-9 of the World Dream cruise ship.

The public areas of the World Dream cruise ship are denoted in blue and the cabins green. As observed in Figures 1 & 2, the schematics provide more details regarding the space configuration of the public areas, which enable the computational modelling of these rooms for simulation purposes. Additionally, detailed schematics for several decks of the Celestyal Discovery can be observed in Figures 3-6. In these schematics, cabins are denoted with green, orange, cyan and purple depending

on the type of the cabin (Figures 5 & 6). Public areas are denoted with blue, orange or black (Figure 6). The overview of this cruise ship can be observed in Figure 3. This cruise ship comprises 11 Decks.

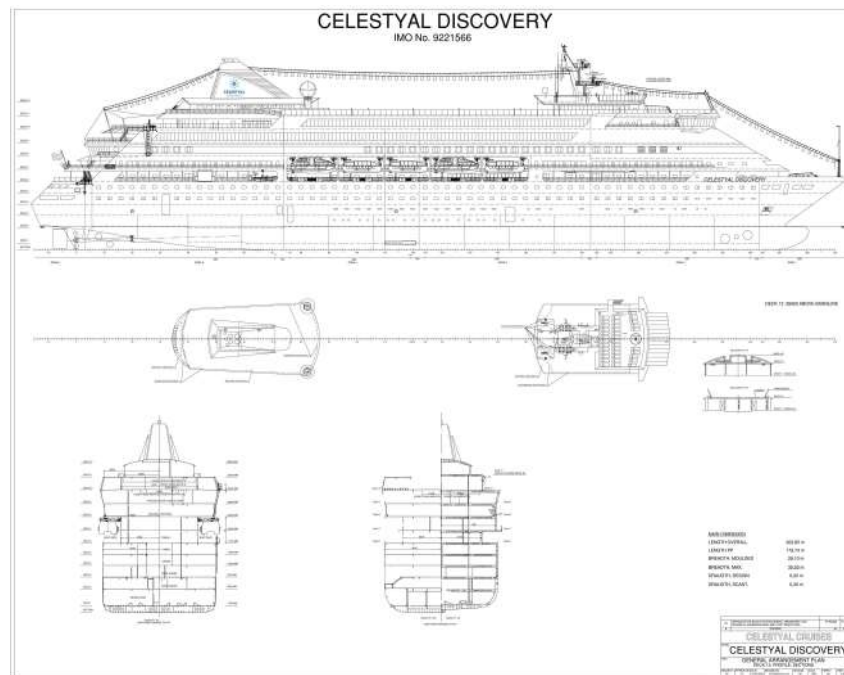


Figure 3 Overview of the Celestyal Discovery cruise ship.

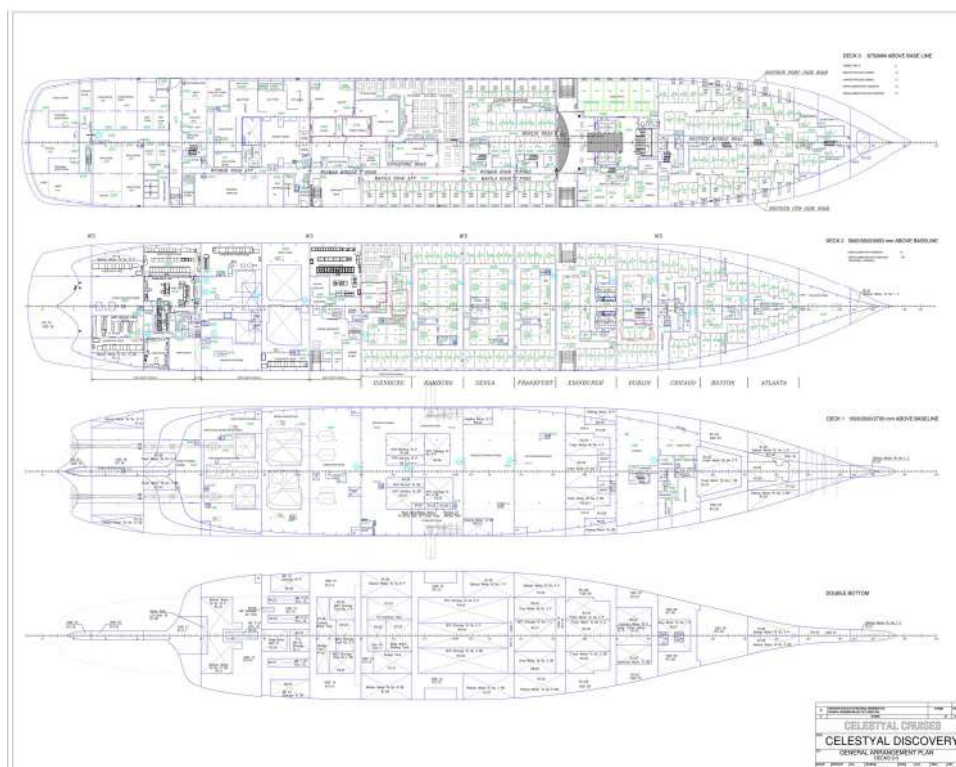


Figure 4 Detailed schematics of Decks 1-3 of Celestyal Discovery cruise ship.

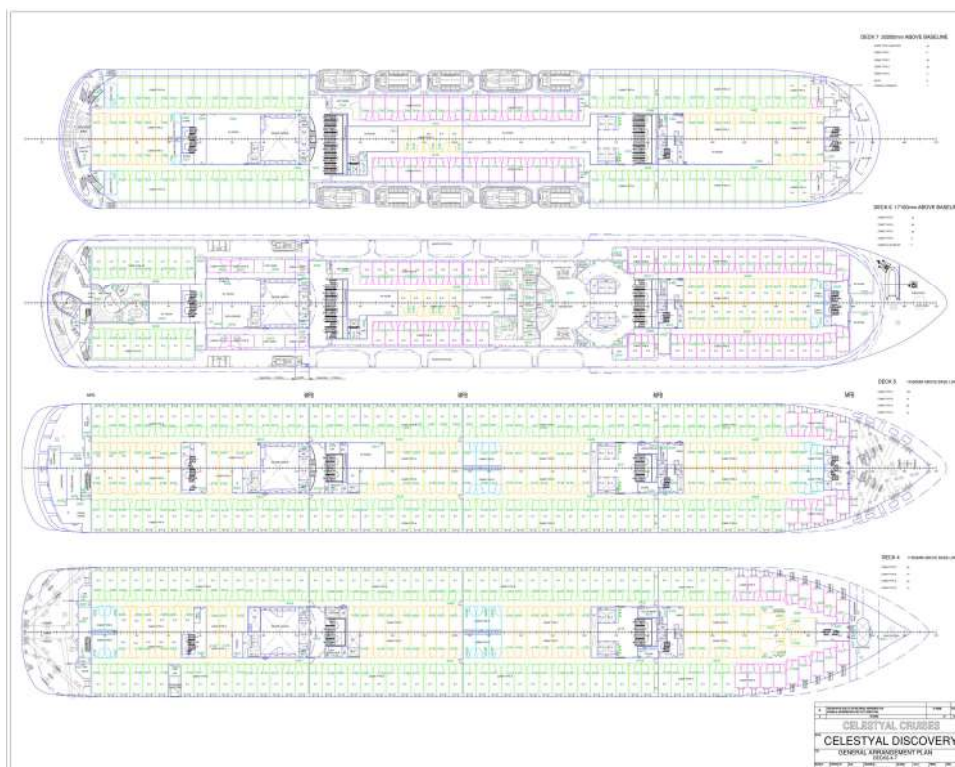


Figure 5 Detailed schematics of Decks 4-7 of Celestyal Discovery cruise ship.

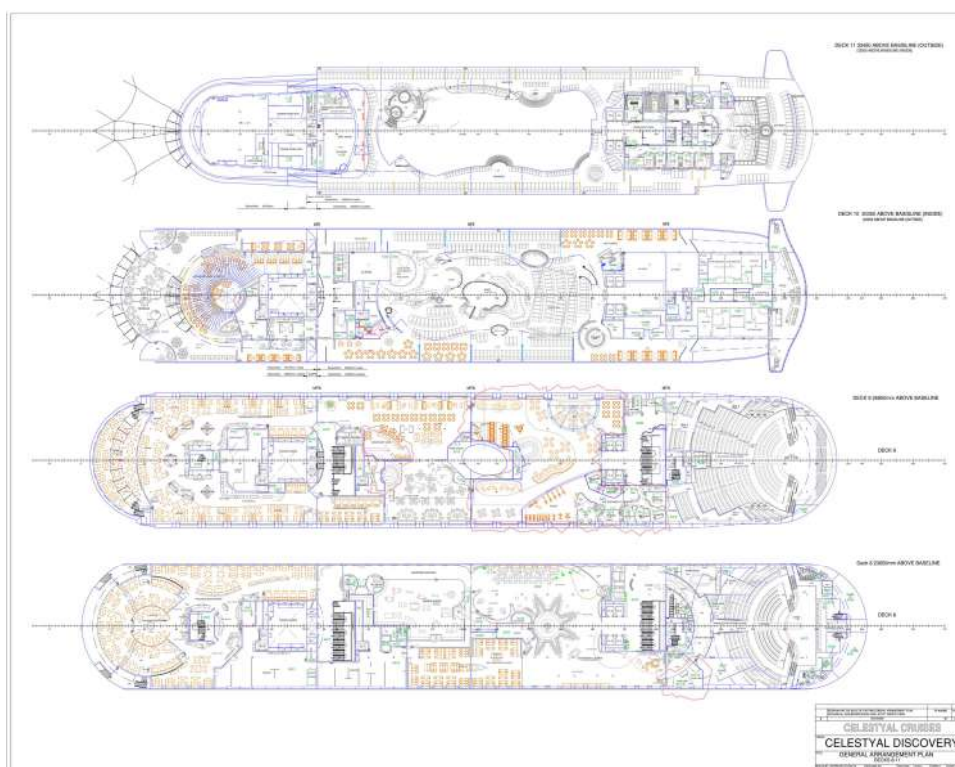


Figure 6 Detailed schematics of Decks 8-11 of Celestyal Discovery cruise ship.

Overall, the schematics were utilized to develop and evaluate the proposed risk assessment methods that will be presented in the following Sections.



2.2 Sensors

A well-defined disease prevention system can provide timely detection, intervention, and control in the context of infectious disease outbreaks. Notably, there is a limited number of dedicated studies on disease monitoring in ships (Fong et al., 2022; Maeda et al., 2021; Mihai & Rusu, 2021; Nolich et al., 2019), compared to that in broader domains such as hospitals and public spaces. The limited research focus, particularly in the context of ships, can be attributed to restricted data access and practical constraints among other factors. More specifically, disease monitoring in crowded indoor spaces can be realized through various methods, including the utilization of surveillance systems (Sága Jr et al., 2022), medical screening (Baig et al., 2017), ventilation control (Hoffman et al., 2022), and contact tracing (Brewster et al., 2022). The likelihood of respiratory transmission is particularly higher in indoor settings, since it encourages prolonged close contact (Morawska et al., 2020). Therefore, to effectively identify and prevent the transmission of infectious diseases in indoor environments, it is preferable to combine different preventive measures, considering the circumstances of the task. For instance, (Vardoulakis et al., 2022) assessed multiple factors for minimizing the risk of bacterial and viral contamination through respiratory inhalation and surface contact in public washrooms. Similarly, enclosed spaces in ships promote frequent contact among individuals onboard, which poses a challenge to disease monitoring and risk management in the event of an outbreak (Brewster et al., 2020). In particular, the recent COVID-19 outbreaks has created the need for mechanisms that promptly identify, isolate, and treat the affected individuals, considering that the main routes of transmission include respiratory droplet inhalation, as well as direct and indirect contact with the virus (W. Zhang et al., 2022).

Several methods incorporate smart technologies to develop effective outbreak response plans with the aim of mitigating such infectious disease epidemics on ships (Aouad et al., 2021), either through Internet of Things (IoT) sensors, drones, thermal cameras, or mobile applications. Ultimately, sensors provide real-time data on environmental conditions, human behavior, and other elements that can affect the spread of infectious diseases. There are various types of smart devices and IoT sensors that could be used in ships for disease monitoring (Aouad et al., 2021; Meraj et al., 2021). These include wearable sensors, air quality sensors, and thermal cameras. Wearable sensors can be utilized by passengers and crew members to track their movement and monitor epidemic indicators such as body temperature, heart rate, and respiration rate. Hence, wearable sensors can enable extensive contact tracing and early symptom identification that allow for rapid isolation and treatment of infected individuals (Guk et al., 2019). However, they may raise data confidentiality and security concerns as they require personal participation and compliance from individuals. In addition, air quality sensors can detect the presence of airborne particles, including viruses and their utilization provides measurements of air temperature, humidity, and ventilation rates, which impact the spread of infectious diseases (Fong et al., 2022). Therefore, the incorporation of air quality sensors enhances the effectiveness of ventilation systems and locates areas with poor air circulation. Nevertheless, most of them lack the capacity to differentiate between various types of airborne contaminants (H. Zhang et al., 2021). Furthermore, thermal cameras can be used to identify elevated body temperatures that could indicate the presence of fever, a symptom of several infectious diseases (Vairavan, 2022). Moreover, thermal cameras are considered non-invasive and can effectively scan crowded places, such as boarding areas. However, they are ineffective at detecting asymptomatic carriers, who may not have fever. There are also approaches that employ other types of sensors to measure environmental parameters, such as infrared-based sensors. For example the approach described in (Salman et al., 2019) investigated the deployment of wireless sensor units to assess indoor air quality. This was accomplished by employing infrared sensors to





measure humidity, CO₂, and temperature, as well as low-power wireless networking and geostatistic methods for the prediction of holistic indoor maps. Another study designed IoT-based smart glasses to identify suspicious cases of COVID-19 among individuals (Mohammed et al., 2020). Testing individuals using laboratory tests might be not available or can delay the detection of infectious diseases; thus, the use of other screening methods, such as biosensors could provide a reliable alternative (Jain, Nehra, et al., 2021). Signal processing and analysis of cough sounds with the use of an AI framework was introduced as an alternate diagnostic method for COVID-19 (Pal & Sankarasubbu, 2021), and more recently, a method that utilized cough, speech, and breath sound processing for diagnosing COVID-19 was proposed (Aly et al., 2022). This innovative way of diagnosing respiratory diseases could be helpful in an epidemic outbreak aboard a ship; thus, such algorithms could be employed for onboard testing, alleviating the need for dedicated medical equipment and even aid with passive surveillance of the ship, i.e., detecting disease-classified sounds in the common areas.

Another alternative direction concerns methodologies that employ IoT-based solutions to acquire data from different sensors and realize disease monitoring. These approaches investigate the implementation of IoT-based indoor air quality (IAQ) monitoring systems, that collect real-time data for effective control of the environmental parameters (Kanál & Tamás, 2020; H. Zhang et al., 2021). More specifically, most methodologies in this context utilize sensors and IoT devices that usually harness cloud computing services to optimize ventilation systems with low energy consumption. Recently, various studies have explored an alternative direction that combines ML techniques and sensor-based systems to detect abnormal patterns in air quality data, whereas provide insights regarding the reason behind the observed irregularities (Ameer et al., 2019; Roskams & Haynes, 2019). ML models have also been utilized to perform disease monitoring, diagnosis, and prediction based on collected health data using sensors, e.g., body temperature and heart rate, while using cloud-based services for real-time data transfer (Awotunde et al., 2021; Yan et al., 2017). In this context, there are various types of Internet-based epidemic intelligence systems that opt for different functionalities, such as social distancing detection, disease identification, and contact tracing (Hossain et al., 2020). Notably, the previously mentioned methodologies showcase the importance of implementing effective disease monitoring strategies that could be incorporated in indoor settings, particularly in the context of infectious disease outbreaks in ships.

However, the utilization of sensors in disease monitoring systems introduces several limitations including maintenance, cost, and data security concerns (Awotunde et al., 2021). In particular, the collection and sharing of personal health information from cameras, wearables, and other sensors for disease monitoring may be subject to regulations related to privacy concerns. For instance, the General Data Protection Regulation (GDPR) establishes rules for the collection of personal data and states that individuals must be appropriately informed regarding their use (Voigt & Bussche, 2017). Therefore, to address these concerns it is essential to implement clear policies and privacy-preserving protocols that ensure the confidentiality of the collected data, as well as to obtain informed consent from individuals prior to sharing their information.

Current studies indicate that processing and analysis of the signals acquired from different sensors can provide useful cues regarding the spread of infectious diseases in closed environments (Jiang et al., 2022; Meraj et al., 2021). Based on the semantics derived from such an analysis, decisions for RA and management can be made by decision support systems designed for this purpose.





To this end, several possible sensors are utilized in the context of the HS4U project aimed at assisting the biomedical RA model. These sensors are part of the smart ship design that is proposed and were identified based on the available information they provide to the RA model (Table 1). Audio sensors can provide crucial information regarding symptomatic passengers, *e.g.*, microphones can be used to detect coughing in the public spaces of the ship. Sensors for detecting pathogens in the air or water, hereinafter air DNA/RNA sensor and water DNA/RNA sensor, could be incorporated in the HVAC and blackwater system (D3.1). The air DNA/RNA sensors could be placed in public spaces of the ship to detect any airborne pathogen, *e.g.*, COVID-19. Similarly, the water DNA/RNA sensors could be placed in key areas of the blackwater system, *e.g.*, cluster of passengers' rooms or public toilets, and can detect pathogens in the wastewater of the ship, *e.g.*, norovirus. The water DNA/RNA sensor could also be placed in swimming pools of the ship and could be combined with the chlorine sensors that measure the chlorine levels in the pools. These two sensors can be beneficial to monitor the risk of a disease outbreak in case of low chlorine levels combined with the presence of a highly infectious disease in the water, such as norovirus. Monitoring public spaces in case of elevated body temperature of passengers can also be useful to assess the risk of disease transmission. Thermal camera sensors that are part of the smart ship design can be used to identify probable symptomatic passengers that develop fever. Personalized Radio Frequency Identification (RFID) sensors can provide additional feedback regarding the risk of disease transmission in case symptoms of a disease are detected in a monitored environment of the ship. These sensors provide information regarding the number of passengers in the room, as well as personalized information that could assist in the RA process, *e.g.*, contact with an infected passenger.

Table 1: Possible sensors (HS4U and beyond)

AUDIO SENSOR	Audio sensor, <i>e.g.</i> , microphones (symptom detection in rooms/public spaces)
DNA/RNA HVAC	Pathogen (DNA or RNA) monitoring system for HVAC (any pathogen/primarily for common areas)
DNA/RNA WATER	Pathogen (DNA or RNA) monitoring system for blackwater (any pathogen detection/full ship)
THERMAL CAMERA SENSOR	Thermal camera (any pathogen/fever detection/entrance & dining areas)
PEOPLE COUNTING SENSOR	RFID or similar sensor that can be used to count the number of persons in a room)
CHLORINE SENSOR	Chlorine level sensor in swimming pool (norovirus, GI diseases)

2.3 Empirical risk levels of compartment

Considering the identified areas based on the available ship schematics and feedback from the partners, a list of empirical risk levels for each compartment of the ship was generated, as illustrated in Figure 7. Related studies (Pluchino et al., 2021; Ventikos et al., 2022) provided additional feedback in regards to these risk levels as it can be observed in Figures 7 & 8, respectively.

Areas	Who	Area traffic	When	Other	risk
Lounge area	adults and kids	medium	all day and evening	sitting down mostly	medium
Bar/ disco	adults	medium	evening	drinking, moving around	high
Public toilet	adults and kids	high	all day	high probability of microbes	high
Terrace with tables & chairs (external space)	adults and kids	medium	all day	sitting down mostly, external space	low
Pantry (food storage)	crew	low	all day	low probability, but severe consequences	high
Galleys (food preparation)	crew	medium	morning/noon/evening	low probability, but severe consequences	high
buffer & Restaurant - passengers	adults and kids	high	morning/noon/evening	sitting down and eating	high
buffer & Restaurant - crew	crew	high	morning/noon/evening	sitting down and eating	high
Reception	adults and kids	high	all day	high volume of people passing by	medium
Cabin (passengers)	adults and kids	low	mostly night		low but good place for symptom tracking
Cabin's toilet (passengers)	adults and kids	low	mostly night		low but good place for symptom tracking

Figure 7: Risk levels of ship compartments provided by partners of the HS4U project.

Classification	Characteristics	Limited ventilation and air exchange	Direct contact with infected surfaces and objects	Possible overcrowding/insufficient capacity	Direct contact between passengers and crew	Difficult cleaning/sanitizing of surfaces/objects	High density of persons (social distancing issues)	Congestions at entrance/exit	No secondary entrance/exit	Direct contact with suspected or positive cases	Example
Low exposure risk	Areas with no direct contacts with persons, or where contacts are limited in time or to the members of a family unit; Areas with no direct contact with a suspect or positive case.	✓	✓	✓	✗	✗	✗	✗	✗	✗	Corridors, Stairs, Cabins
Medium exposure risk	Areas with no direct contact with a suspect or positive case; Areas used as an aggregation point by passengers/crew; Areas where social distancing cannot be kept or PPE cannot be used for limited periods due to proximity; Internal spaces with limited air exchange capability.	✓	✓	✓	✓	✓	✓	✓	✓	✗	Restaurants, Bars, Cinemas, Theatres, Casinos, Elevators,
High exposure risk	Areas with direct contact with a suspect or positive case.	✓	✓	✓	✓	✓	✗	✗	✗	✓	Medical zone, Quarantine areas

Figure 8: Empirical risk levels of ship compartments based on low, medium and high exposure risk.

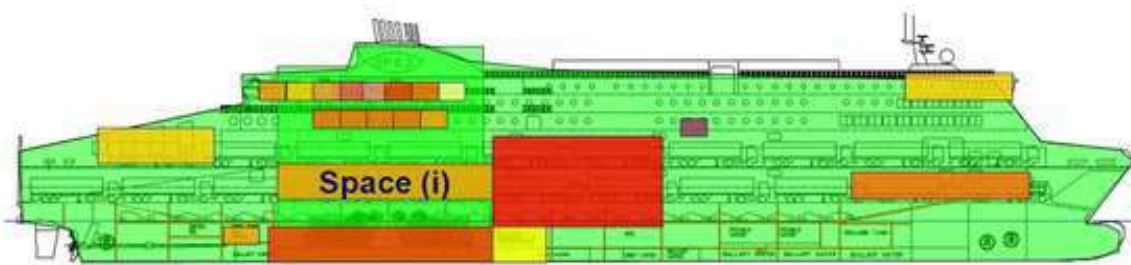


Figure 9: Empirical risk levels of ship compartments based on a spectrum of category levels from low to high (green to red).

2.4 Air-filtration, ventilation and sewage system

Schematics of the air-filtration, ventilation, and sewage system of the Celestyal Discovery cruise ship were acquired in the scope of the HS4U project. The HVAC schematics can be observed in Figures 10-12, where different air-conditioning units and fans of the system are denoted with various colors depending on the type of unit used in each indoor space, e.g., orange, purple and cyan. These schematics were utilized to conduct simulations, allowing us to analyze the potential spread of airborne pathogens within the cruise ship. These simulations played a crucial role in understanding the flow dynamics and potential contamination pathways. In addition, the results of these simulations were utilized to develop the biomedical risk assessment model presented in Section 3. Furthermore, acquired schematics of the blackwater (Figures 13-16) and greywater (Figure 17) sewage system have been obtained. These schematics can provide insights into the probable routes of waterborne pathogens within the ship.



Figure 10 Schematics of the HVAC system for Decks 3-5 of the Celestyal Discovery cruise ship.

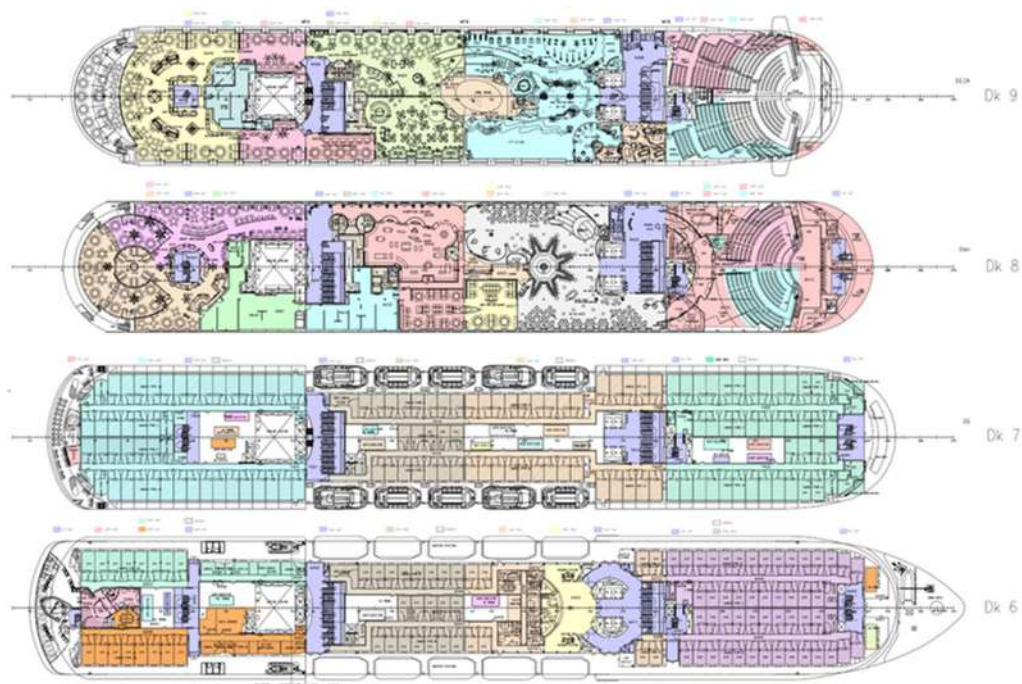


Figure 11 Schematics of the HVAC system for Decks 6-9 of the Celestyal Discovery cruise ship.

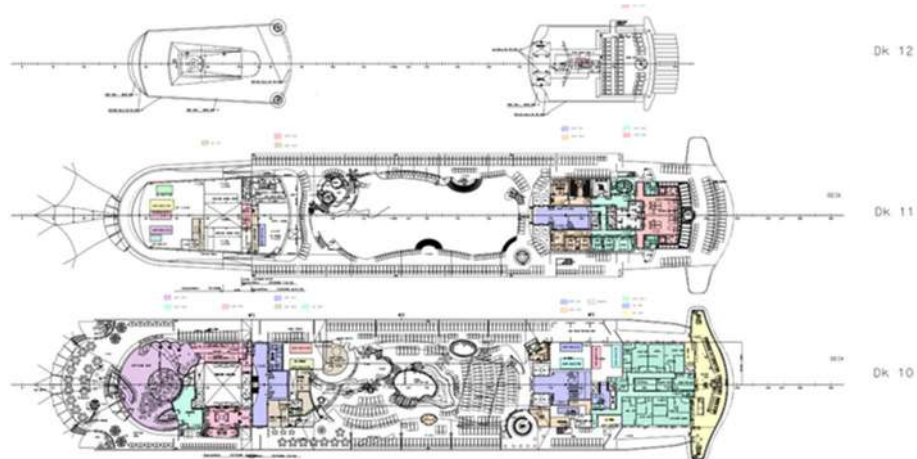


Figure 12 Schematics of the HVAC system for Decks 10-12 of the Celestyal Discovery cruise ship.

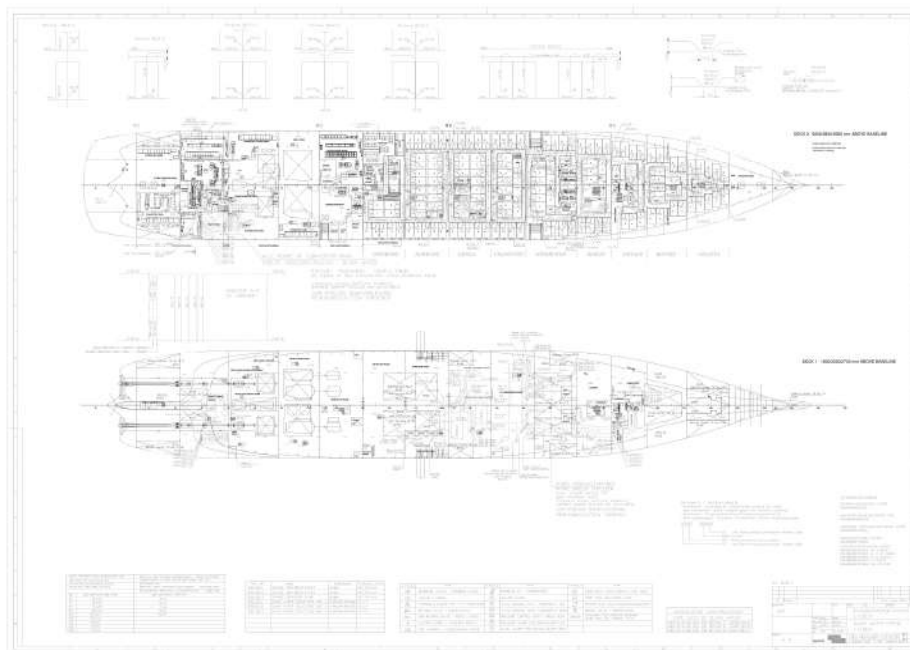


Figure 13 Schematics of the blackwater sewage system for Decks 1-2 of the Celestyal Discovery cruise ship.

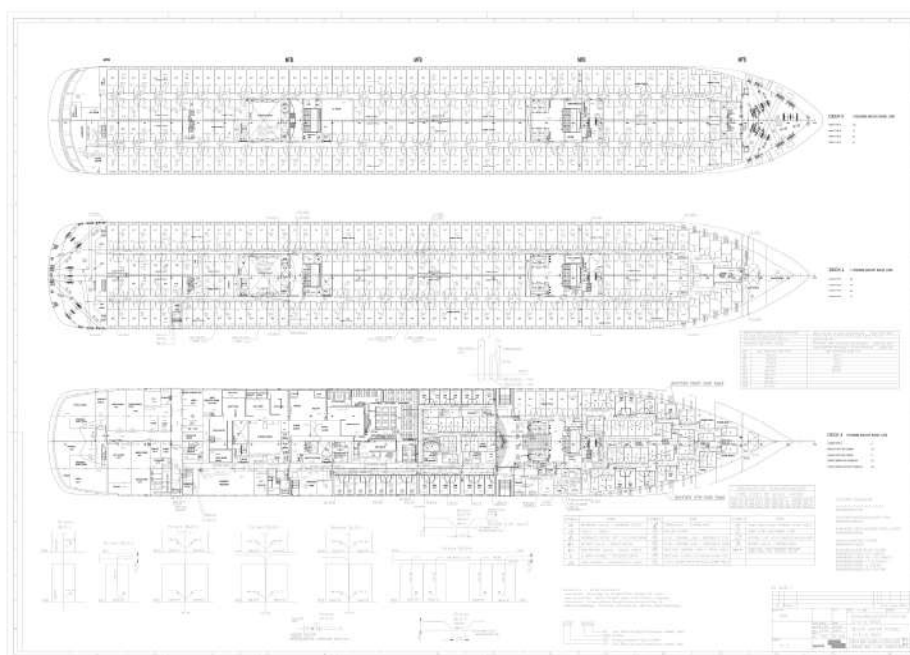


Figure 14 Schematics of the blackwater sewage system for Decks 3-5 of the Celestyal Discovery cruise ship

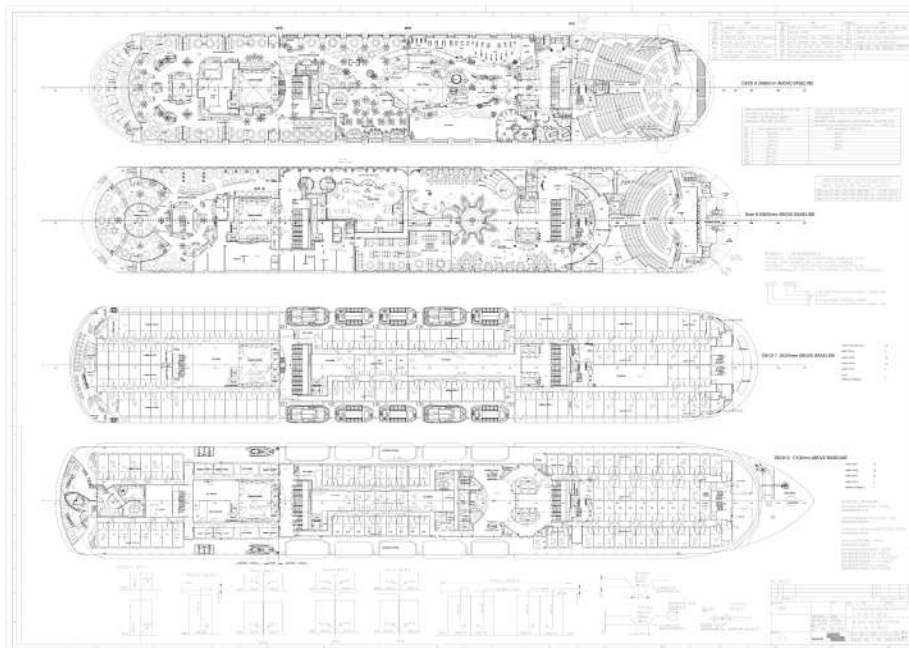


Figure 15 Schematics of the blackwater sewage system for Decks 6-9 of the Celestyal Discovery cruise ship

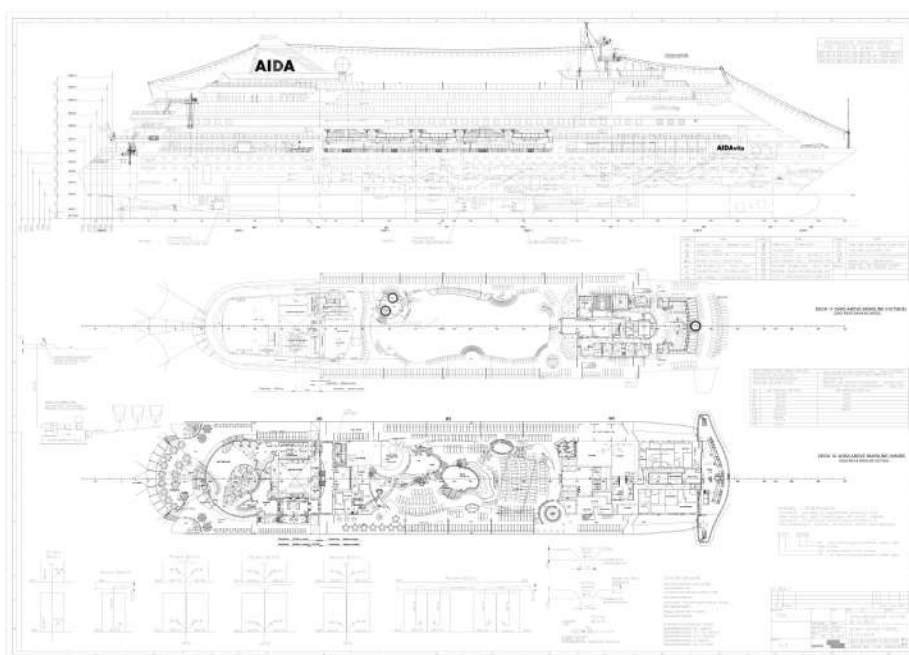


Figure 16 Schematics of the blackwater sewage system for Decks 10-11 of the Celestyal Discovery cruise ship

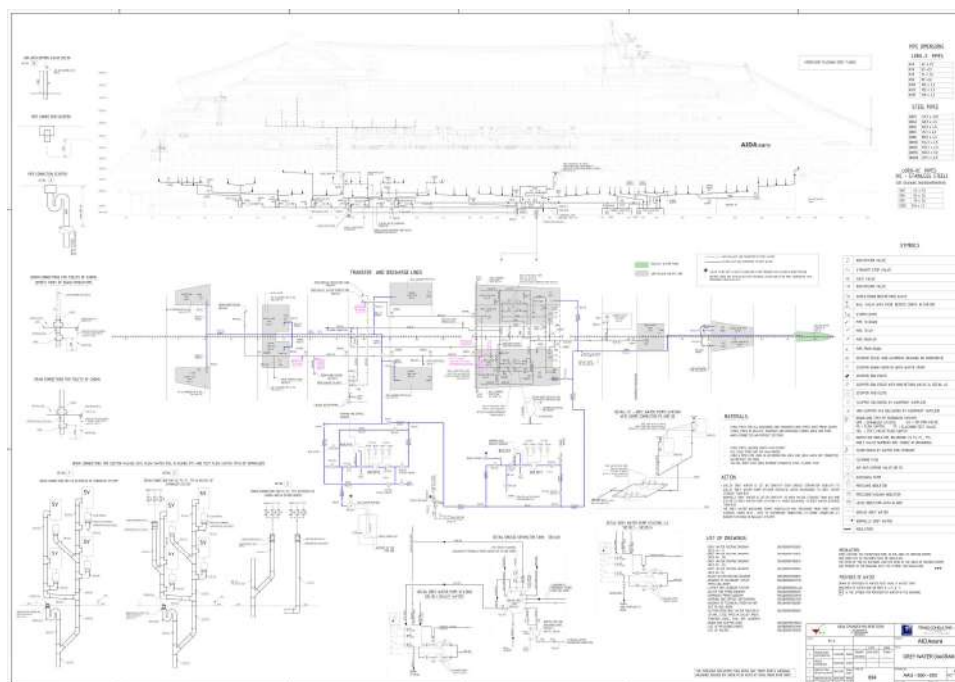


Figure 17 Overview of the greywater pipeline system of the Celestyal Discovery cruise ship.



3. BIOMEDICAL MODELING IN PASSENGER SHIP

In the context of disease spread monitoring various sensors, such as thermal cameras, can be used to derive semantic information about the passengers and the condition of the different areas of the ship after proper analysis of the raw data they acquire, e.g., identify disease symptoms, such as fever, or identify increased passenger concentrations in public areas. The current guidelines and protocols, as well as the experience from multiple disciplines involved, such as experience from medical and naval personnel, can be integrated, e.g., as rules, into knowledge-based decision-making systems, to automatically infer useful information for disease control. Such information may include the infection risk in different areas of the ship over time, and possible actions that need to be taken to limit the spread of the disease. Furthermore, simulation models can be used to predict the evolution of the disease spread considering both microscopic parameters, such as the physical properties of the pathogens and their molecular interactions, and macroscopic parameters, such as the motility of the passengers on board.

A cruise ship may include multiple decks with different spaces accessible by the passengers, e.g., cabin corridors, lounges with sitting areas, shops, and outdoor spaces, such as canteens and swimming pool areas. The risk for the spread of an infectious disease in these spaces may vary, e.g., bathrooms and restrooms are likely to exhibit a higher risk than free spaces; therefore, closer monitoring with special sensors may be required.

Figure 18 provides a schematic representation of the architecture of a generic RA model (GRAM). A fundamental component of this architecture is the RA node (RAN) (Figure 18 (a)). GRAM is fully modular, composed of multiple interconnected RANs, set up for local monitoring and decision making in different areas within a cruise ship, as illustrated in Figure 18(b). A RAN p considers an environment e in a ship area of interest, monitored by a set of sensors. The raw data from the sensors, along with relevant data that may be available from the information system of the ship, are processed and analyzed to recognize and extract semantic information about the status of the environment and possible events taking place in that environment, e.g., using a machine learning (ML)-based classification system. This higher-level information is provided as input into a decision-making algorithm designed to infer the risk r_p of the environment being contaminated with a pathogen, such as SARS-CoV-2, and possible actions a_p to mitigate this risk. Implementing the inferred actions depends on the confidence of inferred decisions. If the confidence is low, implying high uncertainty based on the available data, a simulation module is activated. The simulation module will provide RAN with additional data that could enhance the confidence of the decision making. Running simulations will enable testing various alternative scenarios in silico, e.g., using different passenger populations and activities, or predicting the outcome of different mitigation measures. Thus, based on the predicted data, the decision-making module should be able to infer decisions of higher confidence about the risk of disease spreading over time. It is important to consider the risk as a function of time, $\bar{r}_p(t)$, for future values of t , because the spread of a disease depends on the evolution of pathogens both in space and time. Also, the decision-making module will also be able to infer the actions for risk mitigation with higher confidence. These actions will result in changes in the monitored environment e , and the whole monitoring and disease control process will follow a closed-loop approach (where the decision-making module plays the role of the controller), like the one typically followed in automatic control systems and robotics (Niku, 2020).



The actions needed to effectively mitigate the risk of the spread of an infectious disease, should consider social aspects, since a cruise ship is usually a diverse human community that includes people with different personalities, ages, cultural background, and habits. Also, passengers are customers investing in their cruise vacation, and despite the critical situation that must be managed by strictly following relevant health protocols, they should feel comfortable and convenient within a safe, caring environment. To this end this chapter introduces the concept of the Crew-in-the-Loop (CiL). Instead of having a fully autonomous actuation system for disease spread control, the CiL approach considers that the crew is continuously being informed by the decision-making system



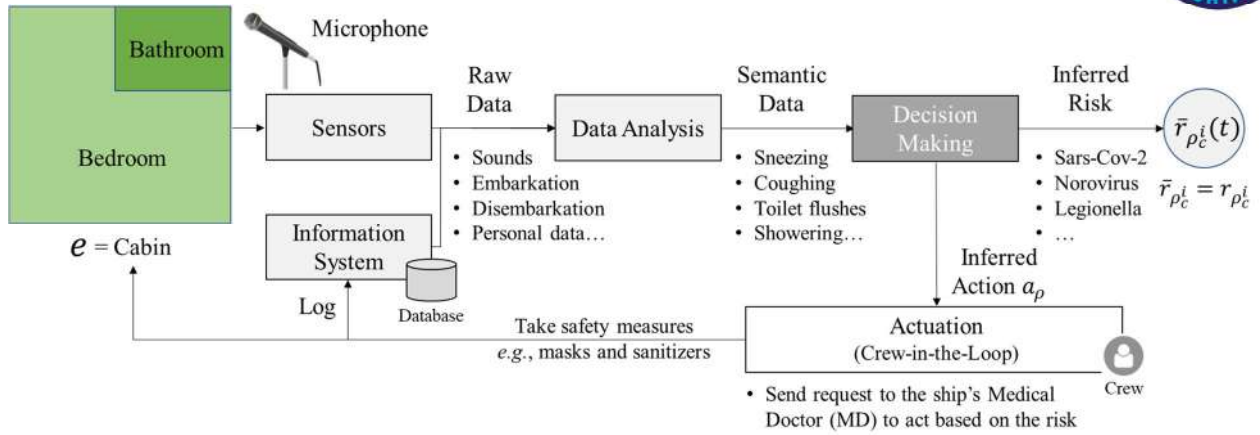
about the risk in different spaces of the ship and a set of possible mitigation actions that can be taken. Thus, the crew will be able to select socially appropriate ways to implement the actions suggested by the system. Such actions may or may not involve personal contact with the passengers, depending on the situation and the passengers' profile, e.g., different approaches would be required for kids or elderly adults.

An advantage of using automatic systems for decision making is that they can incorporate knowledge from multiple domain experts and other sources; thus, being able to infer a less subjective decision. However, it is almost inevitable to infer decisions without an error likelihood, mainly due to the uncertainty introduced in the input data, the acquisition of knowledge (e.g., from training data, or directly from experts) and its representation, and in the reasoning, process used for the inference. Such uncertainty often affects users' trust in the system's decisions, resulting in limited compliance of the users to the actions the system may recommend. Enhancing the users' trust in automatic decision-making requires that the system is able to explain the inferred decisions, e.g., by providing the basis and/or the reasoning steps for these decisions.

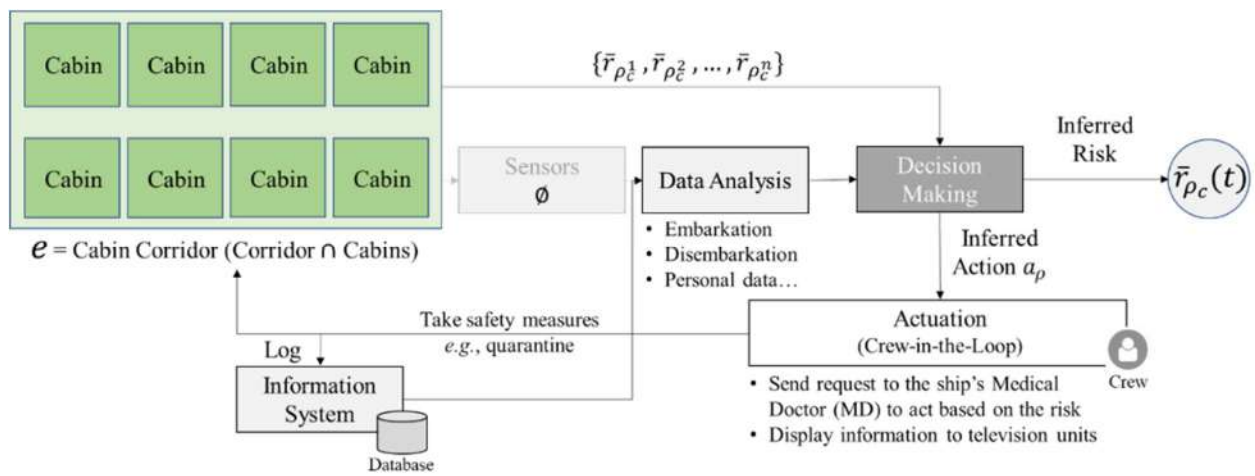
Considering that the passengers can move between the different spaces of a cruise ship, the decision-making module of a RAN should also consider the risks inferred from other RANs within the vessel, e.g., by following a decision-fusion approach, such as a weighted aggregation of these risks (Torra & Narukawa, 2007). Therefore, as illustrated in Figure 18(a), the decision-making module receives as an additional input a set of risks $\{\bar{r}_{\rho'}\}$ originating from RANs $\rho' \neq \rho$ set up in other spaces. For example, the abstract scheme of Figure 18(b), shows that a RAN may receive input from other RAN setups in different spaces of the different decks; therefore, this way, RANs may address wider areas, even the whole ship (ρ_{ship}).

To make this concept more concrete, an example multi-node GRAM instantiated for the cabin spaces, a cabin corridor, and a lounge, is illustrated in Figure 19. Let us consider a scenario where cabins have a privacy-preserving microphone sensor to monitor sounds relevant to the symptoms of an infectious disease, e.g., sneezing, coughing etc., or relevant to passengers' activities that may result in a contamination, e.g., visiting the toilet. As illustrated in Figure 19 (a) the data analysis module of the cabin's RAN receives as input the sounds captured by the microphone but also relevant data about the passenger from the information system of the ship. The semantic data resulting from the data analysis are subsequently inputted into the decision-making module. Assuming that the inferred decision about the risk of space being infected by a pathogen, e.g., SARS-CoV-2, Norovirus etc., has a sufficiently high confidence level, the system informs the crew to take safety measures, e.g., the ship's medical doctor (MD) to examine the situation and to provide masks and sanitizers to the passengers in the cabin if necessary.

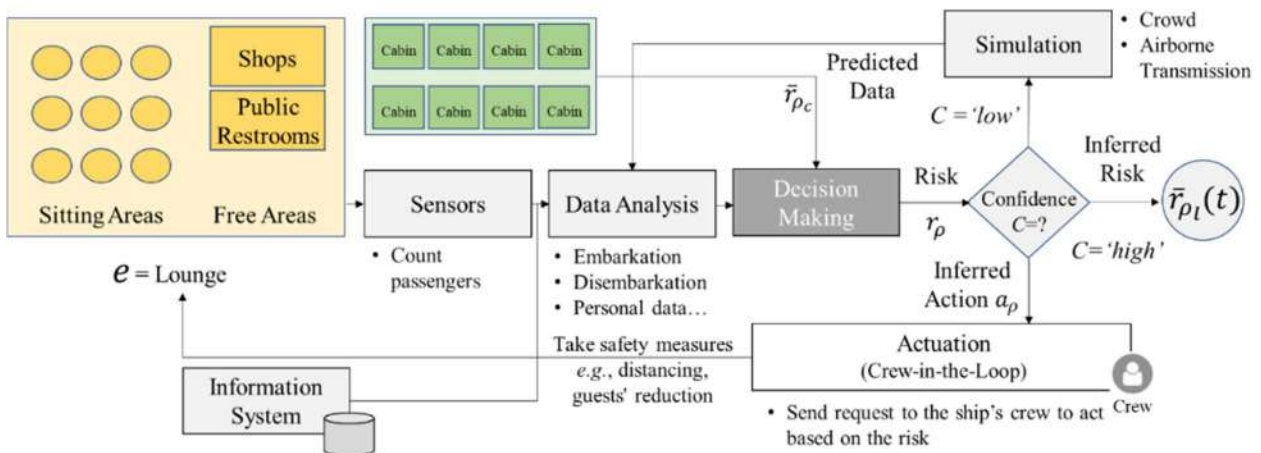
Considering that all cabins in the corridor of the ship are equipped with the same RANs, a RAN dedicated to the corridor area can be set up. Figure 19 (b) illustrates such a RAN, in a corridor area without any sensors. The data analysis module of this RAN processes relevant data from the ship's information system, e.g., if the cruise ship has stopped in a destination or not, embarkation and disembarkation data, and the processed data are entered into the decision-making module, which co-evaluates the risks inferred from the RANs of all other cabins in the corridor. Similarly, the risk of a lounge area is inferred by considering the risk inferred from the cabin corridor that resides on the same deck. Figure 19 (c) illustrates such an example, where the lounge has a sensor to count the passengers entering and/or leaving the area. Also, in this case, it is assumed that the confidence of the output risk is initially low; therefore, a simulation should be run to produce additional (predicted) data to increase the confidence. Considering the structure of the lounge space, the passengers'



(a)



(b)



(c)

Figure 19: Example implementations of the closed-loop model for different ship spaces. (a) Cabin. (b) Cabin corridor. (c) Lounge

crowd, and the probability of them being infected (e.g., based on the RAN of the cabin corridor), a hybrid CFD and agent-based simulation of the crowd, could provide predictions enabling a more accurate estimation of the risk in the lounge $\bar{r}_{\rho_l}(t)$. Given that risk, actions may include the



presentation of messages in the lounge television sets to preserve distances, and crew in the lounge entrances prohibiting the entrance if the space is too crowded.

Considering the multi-module nature of the proposed closed-loop model, several modules needed to be implemented. To achieve that, a literature review was conducted to identify state-of-the-art methods for monitoring, risk assessment and simulation of disease outbreaks. Methodologies for risk assessment were examined, and several datasets were selected to assist the development of the decision-making module. In addition, simulation methods for disease spread were considered as part of the simulation module and several simulation scenarios were conceptualized based on the available sensors. Software related to decision-making, simulation and visualization was also explored to assist with the development of the proposed closed-loop model.

3.1 DECISION MAKING FOR RISK ASSESSMENT

RA is defined as the process of gathering, processing, and storing information in order to assign a level of risk to specific scenarios, such as an epidemic outbreak (Organization & others, 2012). The RA cycle can be divided into three stages, i.e., risk identification, risk analysis, and risk evaluation (Han, 2020). RA is usually coupled with control measures and continuous evaluation of the risk (Organization & others, 2012). RA tools have been employed in healthcare to assess and manage various scenarios, such as disease transmission, assessment of the potential risk for a patient to develop different diseases, or even management of hospital operations. From toxicology to epidemic outbreaks, RA tools have been proposed to mitigate potential hazardous situations, such as exposure to toxic chemicals (Faustman & Omenn, 2012), transmitted diseases (Ross et al., 2022), or predict the risk of developing high-morbidity diseases, e.g., cancer (Ewing et al., 2016). COVID-19 has greatly affected the healthcare sector (Moynihan et al., 2021; H. Xiao et al., 2021) and this is also apparent based on the influx of scientific research papers related to the disease.

The RA field has also been in the center of this trend as it is paramount for managing epidemic outbreaks (Calò et al., 2020; Recchia et al., 2022). Epidemic outbreaks on cruise and cargo ships have been extensively analyzed in the relevant literature (Bertagna et al., 2021; Guagliardo et al., 2022; L.-S. Huang et al., 2021; Kordsmeyer et al., 2021; Rooney et al., 2004; Willebrand et al., 2022); nonetheless, there is a limited number of suggested RA tools applied in such scenarios (Braidotti et al., 2022; Ventikos et al., 2022; Z. Wang et al., 2020). Regarding the broader spectrum of disease spread RA, the most common tools are based on three principal types of methods, i.e., knowledge-based, ML, and hybrid methods.

Knowledge-based methods are methods that contain information in the form of rules or relations that guide the system to decide the appropriate action. Experts' knowledge or experimental data can be analyzed to generate these rules. Statistical analysis and mathematical modeling of patient data combined with golden-standards are also employed to generate such rules and establish the knowledge base that the health practitioners should utilize to make informed decisions (Pirneskoski et al., 2019).

Regarding the broader spectrum of disease-spread-related RA methods, conventional knowledge-based methods, such as case-based-reasoning (CBR) or expert methods that are employed in emergencies (Duan & Jiao, 2021; Han, 2020). Emergency protocols are usually created with the help of experts in the healthcare sector, often based on Delphi studies, to assess the risk during epidemic outbreaks (Ling et al., 2021; Organization & others, 2012; Wen-yan, 2012). The World Health Organization (WHO) has also established a RA tool based on disease characteristics and experts' opinions focused on influenza pandemic outbreaks (Organization & others, 2016). CBR



methods are derived by extracting information from previous scenarios, i.e., previous pandemic outbreaks (Duan & Jiao, 2021). Despite the importance of utilizing information from past events to create informed RA tools, these methods lack flexibility in terms of adjustability to new pathogens and different conditions (Duan et al., 2022). Apart from the use of experts and previously acquired information, epidemic RA methods should also take into consideration the nature of the pathogens, e.g., virus or bacteria, that causes the disease, since it is essential for estimating the risk of a potential pandemic outbreak (Schröder, 2020).

During the early days of the COVID-19 pandemic, transmission-specific information was not clear even amongst experts. Therefore, certain studies attempted to estimate transmission and fatality factors by statistically analyzing epidemic data, such as those from the Diamond Princess cruise ship (Mizumoto & Chowell, 2020; Mizumoto et al., 2020a; Russell et al., 2020; S. Zhang et al., 2020). These methods could be helpful if incorporated in RA tools to predict epidemic outbreaks of recently discovered communicable diseases, especially in maritime scenarios. To the best of our knowledge, RA tools related to epidemic outbreaks in ships have been based only on knowledge-based methods (Braidotti et al., 2022; Ventikos et al., 2022; Z. Wang et al., 2020). An early study identified risk factors related to waterborne diseases associated with ships by analyzing data from previous epidemic outbreaks; however, these data were not incorporated in an RA tool (Rooney et al., 2004). In (Z. Wang et al., 2020), an RA framework was proposed to assess the risk of epidemic outbreaks in ships based on the ports that they have visited. The risk of an epidemic outbreak was estimated based on a rule-based system that was employed to assign a level of risk to each ship, i.e., low, medium, and high risk. The system utilized a proposed cumulative exposure index (CEI) for each ship to assign a level of risk, by comparing the CDI to a reference index inferred from the Wuhan outbreak data (e.g., high risk when CEI is higher than the reference index). This index for each ship was provided by a mathematical model that calculated the infection exposure during the last 14 days based on the population density and the growth factor of the visited countries. The growth factor was a proposed mathematical equation that accounted for the infection risk in each country based on the daily change of confirmed cases. Casual networks are another knowledge-based approach that has been used for assessing the risk of infection in cruise ships (Oliveira et al., 2021).

Uncertainty is inherent in medical decision making (Begoli et al., 2019; Helou et al., 2020), which also applies in the RA of epidemic outbreaks (Rasmussen & Sahay, 2021). Fuzzy logic has been proven helpful to combat this problem, since it exploits the ambiguity found in real life (Arji et al., 2019). This is further highlighted in (Jiang et al., 2022), where the fusion of fuzzy systems with edge computing is considered a promising methodology for RA of epidemic outbreaks. In addition, uncertainty may arise in the early stages of an epidemic outbreak, thus fuzzy logic was employed to account for that. Fuzzy cognitive maps (FCM) have been used to assess the risk of an epidemic outbreak on a national level and combine a knowledge-based approach with fuzzy logic (P. P. Groumpos & Apostolopoulos, 2021). FCMs have been also utilized to predict the risk of positivity to infectious diseases (P. P. Groumpos, 2021; P. Groumpos, 2021). In (P. P. Groumpos, 2021), an FCM with 10 symptoms-concepts that is considering the causality factors of COVID-19 infections is proposed. Similarly, an FCM with 16 symptoms-concepts was proposed to infer the probability of COVID-19 infection in (P. Groumpos, 2021). Other fuzzy logic-based methods have utilized rule-based systems to assess the risk of infection and disease spread on a national level (Cihan, 2020; X. Guo et al., 2022; Kalampakas et al., 2024; Padmanabhan et al., 2021; Painuli et al., 2020). These types of methods can be especially useful in domains with insufficient data that hinder the implementation of a data-driven approach.



3.1.1 Available data

Knowledge-based RA methods for decision-making do not rely on large datasets, as they utilize experts' knowledge to assess the risk of a situation. Nevertheless, prior knowledge of incidents in the form of even small datasets can benefit the inference process by providing additional information that experts might not consider in their decision-making process. This can be done by utilizing the provided data to statistically analyze each incident and extract essential information that can be utilized in the decision-making module.

The proposed RA method utilizes sensors to detect the presence of an infectious disease and utilizes the analyzed information provided by the sensors and information system of the ship to infer a risk level. Therefore, a knowledge-based method would benefit from datasets that contain information entailing the causality between symptoms and infection risk, information about epidemic outbreaks in ships and datasets that can be utilized to detect disease-related symptoms, e.g., cough detected from an audio sensor. Nevertheless, there is limited data available for disease transmission in enclosed areas of cruise ships. Most studies are aimed at examining the long-term disease transmission in cruise ships. In addition, the datasets resulting from these studies are often inconsistent with each other. The rest of this Subsection presents a summarization of the available data related to assessing risk of infection based on symptoms of the individual, long-term disease transmission in cruise ships based on the number of infected passengers and symptom classification, *i.e.*, whether a symptom is classified as disease related.

Risk of infection

A crucial aspect of assessing the risk of disease transmission in enclosed areas of the cruise ship is the efficient identification of symptoms. These symptoms can be utilized as risk factors in the biomedical RA model. The two most prominent viruses that were examined in the context of this project are COVID-19 and norovirus. The COVID-19 virus is considered an airborne transmitted disease, whereas norovirus is considered a waterborne transmitted disease. Both of these viruses can also be transmitted through surfaces. Thus, they were selected due to their potential to rapidly spread in a closed environment such as a cruise ship and their capability to spread through different means of transmission. Since these viruses are highly transmissible, they have been extensively studied. These studies can further assist in creating an accurate biomedical RA model. Based on the available literature and input from the partner of the project **HPI**, several symptoms related to COVID-19 (Table 2 and Table 3) and norovirus (Table 4 and Table 5) have been identified, aiming to assess the probability of a passenger being infected. The results are shown in logic terms (Low, Medium, High), together with the numerical probability, which was retrieved from the literature (Alimohamadi et al., 2020; Grant et al., 2020; Rosa Mesquita et al., 2021).

According to the findings of Table 2, the ranking of COVID-19 symptoms sorted from the highest to the lowest probability of being infected when displaying the relevant symptom was: **fever, dry cough, fatigue, dyspnea, diarrhea and vomiting**. Furthermore, according to (Antonelli et al., 2021), the following symptoms combinations increase the likelihood of a person having COVID-19:

1. Fever, fatigue, headache, cough, dyspnea (92% sensitivity)
2. Fever, cough, dyspnea, anosmia / ageusia (69% sensitivity)
3. Fever, cough, dyspnea (60% sensitivity)



4. Cough, dyspnea (46% sensitivity).

Table 2 Probability of a passenger being infected with COVID-19, should one of the following symptoms be detected.

If one of the following symptoms is detected via a sensor, how probable is it for a passenger to have the condition?	Probability			Numerical value
	Low	Medium	High	
1. Fever (Thermal camera, smart wearable)			✓	81.20%(Alimohamadi et al., 2020), 78% (Grant et al., 2020), 58.66%(Rosa Mesquita et al., 2021)
2. Coughing (Audio sensor)			✓	58.50%(Alimohamadi et al., 2020), 58%(Grant et al., 2020), 54.52% (Rosa Mesquita et al., 2021)
3. Sneezing (Audio sensor)	✓			NA
4. Vomiting (Audio sensor)	✓			4%(Grant et al., 2020), 7.33% (Rosa Mesquita et al., 2021)
5. Decreased Oxygen level (Smart wearable, P.O.)		✓		26.50%(Alimohamadi et al., 2020), 23%(Grant et al., 2020), 30.82% (Rosa Mesquita et al., 2021)
6. Fatigue (Smart wearable, H.R. meter)			✓	38.50%(Alimohamadi et al., 2020), 31%(Grant et al., 2020), 28.16% (Rosa Mesquita et al., 2021)
7. Diarrhea (body waste sensor?)		✓		7.60%(Alimohamadi et al., 2020), 10%(Grant et al., 2020), 9.59%(Rosa Mesquita et al., 2021)
8. Dehydration (Smart wearable)	✓			NA

In addition, the effect of other factors on the total probability of a person being infected with COVID-19 was examined when one of the symptoms above was present. Specifically, the factors



under examination were age, gender, contact with a confirmed case and travel to country with epidemic load. These factors were provided to the project partner HPI by UTH and are expected to be available through the ship's reception department.

Table 3 Probability of a passenger being infected with COVID-19 if one of the following factors is present.

Does any of the below factors increase the probability of infection when a symptom from the above list is present?		Numerical value		Comment
		Yes	No	
Age	Children – teens (3-16)		✓	
	Young (17-34)		✓	
	Middle age (35-64)		✓	
	Elderly people (65+)		✓	
Gender	Male		✓	
	Female		✓	
Contact with confirmed case		✓		
Travel to country with epidemic load		✓		When the country of departure is experiencing a more intense transmission of SARS-CoV-2 virus than the country of arrival, the risk of adversely affecting the epidemiological situation in the country of arrival is higher.

As seen in Table 3, there is no association between age and gender classification with increased probability of being infected with COVID-19, in the cases when a passenger displays a symptom (Biswas et al., 2020). On the other hand, contact with confirmed cases (*Are you higher risk Severe illness COVID-19? - Ada — ada.com*, n.d.) or travel to countries with epidemic load (Organization & others, 2020b; *WHO advice international traffic Relation SARS-CoV-2 Omicron variant (B.1.1.529) — who.int*, n.d.) increase the risk of infection.

Additional factors such as smoking, comorbidities and vaccination were also investigated. The evidence for the relationship between tobacco smoking and COVID-19 incidence remains uncertain and impaired by a number of case series. There is only a certain relationship between smoking and risk of progression of COVID-19 (Gallus et al., 2023; Simons et al., 2021). Regarding comorbidities, COVID-19 may be more severe and prolonged in individuals with medical comorbidities such as hypertension, diabetes, chronic kidney disease, coronary heart disease, chronic obstructive pulmonary disease (COPD), cerebrovascular disease, chronic liver disease, arrhythmia, ischemic heart disease, heart failure, cancer, and obesity. However, there is no direct evidence that the presence of comorbidities increases the risk of infection (Vardavas et al., 2022; J. Yang et al., 2021; Yekedüz et al., 2020). People who received a full course of vaccination may still



experience flu-like symptoms but are less likely to suffer from severe disease and require hospitalization. Nevertheless, the risk of infection remains the same as in the general public (Williams et al., 2022).

Table 4 Probability of a passenger being infected with Norovirus, should one of the following symptoms be detected.

If one of the following symptoms is detected via a sensor, how probable is it for a passenger to have the condition?	Probability			Numerical value
	Low	Medium	High	
1. Fever (Thermal camera, smart wearable)			✓	31.20%(Arias et al., 2010), 16.70%(Y. Wang et al., 2018)
2. Coughing (Audio sensor)	✓			NA
3. Sneezing (Audio sensor)	✓			NA
4. Vomiting (Audio sensor)			✓	64.90%(Arias et al., 2010), 95.30%(Y. Wang et al., 2018)
5. Decreased Oxygen level (Smart wearable, P.O.)	✓			NA
6. Fatigue (Smart wearable, H.R. meter)			✓	7.60%%(Arias et al., 2010)
7. Diarrhea (body waste sensor?)			✓	78.80%(Arias et al., 2010), 10.40%(Y. Wang et al., 2018)
8. Dehydration (Smart wearable)		✓		NA

Based on Table 4, ranking of norovirus symptoms varies for different age groups (Arias et al., 2010), (Y. Wang et al., 2018). The most common symptom in children is vomiting, whereas in adults is diarrhea. Fever is the third most common symptom and fatigue is also reported in the literature. The impact of other factors on the total probability of a person being infected with Norovirus, when one of the aforementioned symptoms was present, was also explored. The factors



reviewed were age, gender, contact with a confirmed case and travel to a country with epidemic load. As presented in Table 5, there is an association with age classification and norovirus infection as higher incidence rates occur in two different age groups (children and elderly) (Arias et al., 2010). Moreover, females are more probable to develop acute symptoms than males (Verstraeten et al., 2017).

Table 5 Probability of a passenger being infected with Norovirus if one of the following factors is present.

Does any of the below factors increase the probability of infection when a symptom from the above list is present?		Numerical value		Comment
		Yes	No	
Age	Children – teens (3-16)	✓		The higher incidence rates occur in the age groups 5-14 (children and teens) and >65 (elderly people)
	Young (17-34)			
	Middle age (35-64)			
	Elderly people (65+)	✓		
Gender	Male			Infectious gastro-enteritis due to Norovirus, occurs more frequently to females than males.
	Female	✓		
Contact with confirmed case		✓		
Travel to a country with epidemic load		✓		When there is a norovirus outbreak in a country, incidence rates are increasing.

It is important to acknowledge that the symptoms associated with norovirus infection are indistinguishable from those of food poisoning. The main difference is that food poisoning symptoms have an earlier onset than those of norovirus (30min – 8hours vs 12hours-48hours). However,



norovirus symptoms last longer (more than a week vs 48 hours) (Mutchler, n.d.). As in COVID-19, contact with confirmed cases greatly increases the risk of infection (Marsh et al., 2018). Additional factors such as smoking, comorbidities and vaccination are un-associated with an increase in the risk of infection with Norovirus.

Based on the results, vomiting was found to be the primary driver of norovirus transmission. Results presented in three relevant studies (Adams et al., 2020; Y. Chen et al., 2023; Kirby et al., 2016) suggest that individuals who vomit are more infectious, whereas diarrhea also plays a role in norovirus transmission, but to a lesser extent than vomiting. It is also reported that a single vomiting event can contaminate a large area, hence the viral concentration tends to increase with each additional vomiting episode (Kirby et al., 2016). This results in a consequent increase in the risk of transmission.

Available datasets of COVID-19 symptoms were also considered when assessing the potential use of each symptom as a risk factor for the biomedical RA model. The “COVID-19 Symptoms Checker” dataset provides information to identify whether any person is having a coronavirus disease or not based on some pre-defined standard symptoms. These symptoms are based on guidelines given by the World Health Organization ([WHO](#)) and the Ministry of Health and Family Welfare, India (The results or analysis of these data should not be taken as medical advice). The dataset contains seven major variables that will be having an impact on whether someone has coronavirus disease or not, the description of each variable are as follows, Country: List of countries person visited. Input features:

- Age: Classification of the age group for each person, based on WHO Age Group Standard Symptoms: According to WHO, 5 are major symptoms of COVID-19, Fever, Tiredness, Difficulty in breathing, Dry cough, and sore throat.
- Experience any other symptoms: Pains, Nasal Congestion, Runny Nose, Diarrhea and Other. Severity: The level of severity, Mild, Moderate, Severe
- Contact: Has the person contacted some other COVID-19 Patient.

With all these categorical variables, a combination for each label in the variable will be generated and therefore, in total 316800 combinations are created ([link](#)). It should be noted that this dataset is not validated.

The purpose of the “Symptoms and COVID Presence (May 2020 data)” dataset is to provide symptoms as input and it should be able to predict if COVID is possibly present or not (It cannot be used for serious medical purposes) ([link](#)). This dataset contains more categories than the “COVID-19 Symptoms Checker” dataset, including travel abroad, some comorbidities, but not severity level (only yes or no if infected). It should be noted that this dataset is not validated.

Another dataset that is also evidence-based is the “Flatten” dataset. This dataset is the Canada’s first publicly available pre-clinical COVID-19 dataset, based on survey responses collected from 294,106 Canadians from March 23rd until July 30th 2020, using a platform developed by Flatten, a Canadian non-profit organization (Jain, Charpignon, et al., 2021). This data is provided for academic and industry research ([link](#)), through the PhysioNet research data resource (Goldberger et al., 2000). The Flatten dataset consists of three versions of the survey referred to as Schema 1, Schema 2, and Schema 3. As compared to Schema 1, subsequent versions either include additional



questions or refine existing questions and answer options. Each survey response is stored as an individual record (row) in the dataset.

Across all survey versions, each record in the Flatten dataset consists of temporal, spatial, and survey response attributes. Temporal data include the weekly number or month during which the survey response was recorded. Survey response data primarily consists of a binary variable indicating whether the respondent is aged 60 or over, and their symptoms related to COVID-19 at the time of response (*i.e.*, fever, cough, and shortness of breath). The survey also asks whether the survey participant has travelled outside of Canada in the past 14 days, or if they suspect they have been in contact with someone infected with COVID-19 in the past 14 days.

Survey responses associated with Schema 1 are the most numerous, consisting of 263,640 individual level records submitted in the early weeks of the pandemic (March 23rd to April 8th of 2020). These responses also correspond with the peak of Flatten's presence in the media. Survey responses associated with Schema 2 consist of 14,932 records (April 8th to April 28th of 2020), and Schema 3 consists of 15,534 records (April 28th to July 30th of 2020). Although Schema 2 and Schema 3 contain far fewer records than Schema 1, they contain valuable information about the demographic profile of the survey participant that Schema 1 does not have, such as their race, ethnicity, sex, age, and pandemic-induced most pressing needs (*i.e.*, food, medical, financial, emotional, other).

The raw Flatten dataset consists of 498,211 survey submissions (90.81% responses from unique participants) with granular temporal, spatial, and survey participant socio-demographic and health factors data. Only a de-identified subset of survey responses is made available in this version's release, due to ethical as well as privacy and identity protection reasons. Furthermore, only the subset of survey responses where the participant indicates living in Ontario are made available, given the prevalence of the province in the collected data records (60.3% of the responses).

The dataset contains four variables related to the health status of a survey respondent, labelled as follow: "probable", "vulnerable", "is_most_recent", and "any_medical_conditions". The definition of these variables was elaborated based on guidance from public health professors of the University of Toronto Dalla Lana School of Public Health at the time of which data was collected.

A survey respondent was considered to be a "probable" COVID-19 case if they fit into one of the three following combinations: have come in contact with illness; have travelled outside of Canada and have the symptoms (fever, cough, shortness of breath); have travelled outside of Canada and have the symptoms (cough, shortness of breath). The decision tree of this definition can be found in the following script: <https://github.com/flatten-official/flatten-scripts/blob/staging/dags/sanitisation/sanitisation.py>.

A survey respondent was considered to be "vulnerable" to COVID-19 disease if they were aged 65 or more or if they had at least one of the following comorbidities: diabetes, cancer, diabetes, high blood pressure, heart disease, asthma or other breathing-related illness, immunocompromising condition, kidney disease, history of stroke. The code can also be found in the script linked above.

A survey response is considered the most recent if it is the most recent submission from the respondent based on their unique user identifier. This variable is used in the event a respondent makes multiple survey submissions across the survey data collection time period.

Considering this analysis, the most prominent symptoms for COVID-19 and norovirus were examined to determine which symptoms could also be used as risk factors for transmission of these





diseases. In case of COVID-19, fever, coughing and fatigue are considered symptoms with higher correlation to a positive case of the virus (Table 2). In this study, fever and coughing were selected as risk factors in the Decision-Making Module for COVID-19 transmission (see Subsection 5.1), since these are symptoms that can contribute to pathogen transmission (see Section 4 and Subsection 5.1.1). Regarding norovirus, diarrhea, vomiting, and fatigue were considered the most correlated symptoms to the infection (Table 4). In addition, norovirus incidences have been identified to be more common for children in the 4-15 age group (Table 5). In the case of norovirus, diarrhea and age were considered as risk factors in the Decision-Making Module, since these were also identified as the most correlated factors of norovirus transmission (see Subsection 5.1.5).

Risk of long-term disease transmission

An outbreak of coronavirus disease 2019 (COVID-19) unfolded on board a Princess Cruises' ship called the Diamond Princess. Shortly after arriving in Yokohama, Japan, this ship had been placed under quarantine orders from 5 February 2020, after a former passenger had tested positive for the virus responsible for the disease (*i.e.*, severe acute respiratory syndrome coronavirus 2; SARS-CoV-2), subsequent to disembarking in Hong Kong. By 21 February 2020, 2 days after the scheduled 2-week quarantine came to an end, a total of 634 people including one quarantine officer, one nurse and one administrative officer tested positive for SARS-CoV-2. These individuals were among a total of 3,711 passengers and crew members on board the vessel. Laboratory testing by PCR had been conducted, prioritizing symptomatic or high-risk groups. Daily time series of laboratory test results for SARS-CoV-2 (both positive and negative), including information on presence or absence of symptoms from 5 February 2020 to 20 February 2020 were extracted from secondary sources [1]. The reporting date, number of tests, number of people tested positive by PCR (*i.e.*, cases), and number of symptomatic and asymptomatic cases at the time of sample collection are provided, while the time of infection and true asymptomatic proportion are not available.

A total of 634 people tested positive among 3,063 tests as of 20 February 2020. Of 634 cases, a total of 313 cases were female and six were aged 0–19 years, 152 were aged 20–59 years and 476 were 60 years and older. Cases were from a total of 28 countries, with most being nationals of six countries, namely Japan ($n = 270$ cases), the United States ($n = 88$ cases), China ($n = 58$ cases; including 30 from Hong Kong), the Philippines ($n = 54$ cases), Canada ($n = 51$ cases) and Australia ($n = 49$ cases). Several variations of the outbreak have been identified in the literature (Emery et al., 2020; Mizumoto et al., 2020b; Nishiura, 2020; J. Zhang et al., 2020).

In (Codreanu et al., 2021), the successful use of the ship as a quarantine facility during the response to the outbreak on the MS Artania, which docked in Western Australia, Australia. The health-led 14-day quarantine regime was based on established principles of outbreak management and experiences of coronavirus disease outbreaks on cruise ships elsewhere. The attack rate in the crew was 3.3% (28/832) before quarantine commencement and 4.8% (21/441) during quarantine on board. No crew members became symptomatic after completion of quarantine. Infection surveillance involved telephone correspondence, face-to-face visits, and testing for severe acute respiratory syndrome coronavirus 2. No serious health issues were reported, no response staff became infected, and only 1 quarantine breach occurred among crew. Onboard quarantine could offer financial and operational advantages in outbreak response and provide reassurance to the shore-based wider community regarding risk for infection. The data are provided in an unstructured format (image) with symptomatic/asymptomatic cases, number of disembarked individuals, age, categories (passengers, crew) in total.





On March 19, 2020, when the Ruby Princess docked in Sydney Harbor, nearly 2,700 tourists disembarked without being quarantined (Zhou et al., 2020). Subsequently, more than 600 people were infected with COVID-19 and 21 died. On April 22, 2020, another 115 crew members were allowed to disembark, 21 of whom tested positive for the new coronavirus. Of the 2,700 passengers who were allowed to disembark before the test results came out, almost 1700 were Australians, which further exacerbated the outbreak of COVID-19 in Australia, as well as in other countries. In the case of the Ruby Princess, passengers disembarked in Sydney without being quarantined, which suggests inadequate core capacity and insufficient supervision of the points of entry in Australia. The number of cases only counted the total number of confirmed cases of passengers and crews from the Ruby Princess. The data of March 31, April 3 to April 6, April 10 to April 12 were missing, the vacancies with missing data between two points were directly connected with lines. The number of cases only counted the number of confirmed cases of crews from the Ruby Princess. The data from March 21 to March 31, April 3 to April 6 were missing, the vacancies with missing data between two points are directly connected with lines. The data are provided in an unstructured format (image and text) with symptomatic/asymptomatic cases, number of disembarked individuals, age of infected, categories (crew, passengers), nationality and port embarked.

On March 7, 2020, a passenger ship (2,500-passenger and 1,606-bed capacity) with 33 crew members sailed from Piraeus, Greece, to Cesme, Turkey, where an additional 350 crew members embarked on March 8, 2020 (Hatzianastasiou et al., 2021). For 21 days, the ship sailed without any disembarkations or embarkations until the first suspected coronavirus disease (COVID-19) case was reported to the health authority of the Piraeus port on March 28, 2020. We describe results of the outbreak investigation, including risk factors for transmission of severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2). We collected data by completing standardized forms through interviews and medical examinations of all travelers onboard and by reviewing ship records and logs. We used descriptive statistics to analyze the study variables and performed univariate and multivariate analyses. In conducting clinical management of cases, the guidelines from the Hellenic National Public Health Organization (NPHO) for health measures on travelers and repatriation were followed, which were based on the European Union Healthy Gateways Joint Action advice for management of COVID-19 cases onboard ships. NPHO and the Piraeus Port Health Authority provided passengers with information about using medical facemasks at all times when outside of their cabins, as well as handwashing, physical distancing, and cleaning and disinfecting of cabins; ship officers supervised. Food preparation and laundry and cleaning services were halted; travelers were instructed to clean their own cabins and store used linens in plastic bags. Cleaning and disinfection of the terminal was done by a private company under supervision of the Piraeus Port Health Authority, after all travelers disembarked the ship at the port of Piraeus. A catering company provided packaged meals; personal hygiene supplies were also provided (including facemasks and hand sanitizer). Methods and results of the environmental sampling have been published elsewhere. Oropharyngeal specimens were collected from all travelers onboard. Molecular tests for SARS-CoV-2 detection were performed by using the Cobas SARS-CoV-2 test qualitative assay and the Cobas 6800/8800 System (La Roche, <https://www.roche.com>). Serologic tests were performed on blood specimens collected from 116 cases. Serum samples were initially tested with the Xiamen Boson Biotech (<https://www.bosonbio.com>) Rapid 2019-nCoV IgG/IgM Combo Test Card, a rapid lateral flow (immunochromatographic) test, and subsequently with the MAGLUMI800 chemiluminescence immunoassay (Snibe Diagnostic, <https://www.snibe.com>). This study was a public health response as part of activities of the Hellenic NPHO and local authorities (i.e., Piraeus Port Health Authority and Port Administration). Participants provided verbally informed consent for recording and processing of information during interviews, and written consent was obtained from participants for





blood specimen analysis. All required ethics considerations were applied according to rules of the Hellenic NPHO and the Ministry of Health. The first 3 symptomatic cases occurred on March 20 among travelers (passengers and crew) of different nationalities and working departments (hotel, dining room service, and housekeeping [cabin steward]). The peak of the outbreak occurred during March 30–April 1. We conducted laboratory tests for SARS-CoV-2 and for antibodies during 3 follow-up examinations. Travelers who tested positive were isolated onboard (except the first case-patients, who were hospitalized, and 2 travelers who were isolated in hotels designated by the government of Greece for that purpose). All travelers onboard who tested negative were considered contacts and quarantined individually in quarantine facilities ashore (hotels designated by the government of Greece), except 36 crew members who tested negative but quarantined in separate decks and facilities onboard to ensure safe ship operation. No deaths occurred; 7 patients were hospitalized, including the first patient, who was intubated. The data were provided in an unstructured format (image and text) with symptomatic/asymptomatic cases, number of disembarked individuals, age of infected, categories (crew, passengers), nationality and port embarked.

A large outbreak of SARS-CoV-2 infections among passengers and crew members (60 cases in 132 persons) on a cruise ship sailing for 7 days on rivers in the Netherlands was investigated in (Veenstra et al., 2023). Whole-genome analyses suggested a single or limited number of viral introductions consistent with the epidemiologic course of infections. Although some precautionary measures were taken, no social distancing was exercised, and air circulation and ventilation were suboptimal. The most plausible explanation for the introduction of the virus is by people (crew members and 2 passengers) infected during a previous cruise, in which a case of COVID-19 occurred. The crew was insufficiently prepared on how to handle the situation, and efforts to contact public health authorities were inadequate. The data are provided in an unstructured format (image and text) with symptomatic cases. Cases were identified based on symptoms and confirmed through tests after disembarkation.

Classification of detected symptoms

VocalSound (Gong et al., 2022) is a free dataset consisting of 21,024 crowdsourced recordings of laughter, sighs, coughs, throat clearing, sneezes, and sniffs from 3,365 unique subjects. The VocalSound dataset also contains meta information such as speaker age, gender, native language, country, and health condition. This repository contains the official code of the data preparation and baseline experiment in the ICASSP paper VocalSound: A Dataset for Improving Human Vocal Sounds Recognition (Yuan Gong, Jin Yu, and James Glass; MIT & Signify). Specifically, we provide an extremely simple one-click Google Colab script ([link](#)) for the baseline experiment, no GPU / local data downloading is needed. The dataset is ideal for:

- Build vocal sound recognizer.
- Research on removing model bias on various speaker groups.
- Evaluate pretrained on vocal sound classification to check their generalization ability.
- Combine with existing large-scale general audio datasets to improve vocal sound recognition performance.

Another dataset is the Dataset of sounds of symptoms associated with respiratory sickness. It has been created for the [Pfizer Digital Medicine Challenge](#). Early detection of respiratory tract infections can lead to timely diagnosis and treatment, which can result in better outcomes and reduce the likelihood of severe complications. Respiratory sounds carry rich information that can be mined to develop automated approaches for detection of sickness behaviors like coughing and sneezing. In



this challenge, we invite you to build machine learning models for automatic detection of sickness sounds by using audio recordings from open datasets. The dataset was created using audio files from [ESC-50](#) and [AudioSet](#). We used the open source [BMAT Annotation Tool](#) to annotate this dataset. ([link](#))

3.1.2 General Framework of the Biomedical Risk Assessment Model

Real-life scenarios of epidemic incidents in ships can be simulated to assist the development of RA tools. In this project several scenarios have been selected based on the available sensors (Table 1), identified use cases and partners' feedback. A general framework for RA of disease transmission in cruise ships is presented in the following Subsection (Figures 20 & 21) based on the literature review conducted in the scope of this project, the selected scenarios, and the available sensors. The selected scenarios including details related to a possible incidence of a disease transmission event are also presented in this Section.

Monitoring: Sensors detect/identify a pathogen in the ship.

Data Analysis: System analyses information provided by the sensors, the ship's information system (retrospective data), and relevant external datasets (literature, web, etc.).

Decision Making: System assesses risk based on the analyzed information. If confidence interval is sufficient, then inform crew members; otherwise run simulations until confidence reaches a sufficient level for decision making.

Simulations: Run simulations based on physical/stochastic and/or epidemiological models.

Reassess risk level: Updated and more informed decision-making based on provided data from simulations.

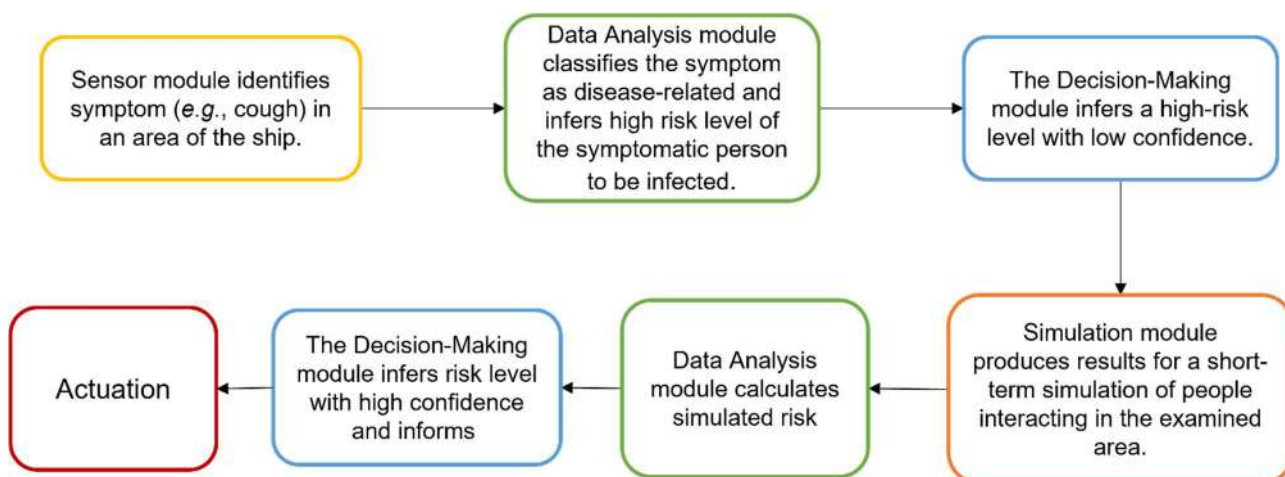


Figure 20 Example of the RA node's workflow for a cabin scenario.

An example of the proposed framework can be observed in Figure 20. The Sensor Module identifies coughing, and the Data Analysis module classifies it as disease caused. Then the Decision-Making Module infers risk level with low confidence, which leads to the Simulation Module approximating a short-term simulation of the two people interacting in the cabin. This approximation is utilized by the Data Analysis module to infer a simulated risk that is then employed by the Decision-Making module to make an informed decision with high confidence.

As highlighted in Subsection 3.1.1, there are only a few studies that focus on disease outbreaks in cruise ships. These studies are aimed at the long-term transmission of infectious diseases, such as COVID-19, and provide inconsistent information regarding the exact progress of the disease transmission, e.g., missing values or different estimated values for the number of infected passengers. Since there is no available dataset aimed at short-term RA in enclosed spaces of cruise ships, a knowledge-based fuzzy logic approach was examined in the Decision-Making module of the RA model. An example of such a fuzzy knowledge-based system that utilizes a Mamdani inference model can be observed in Figure 21.

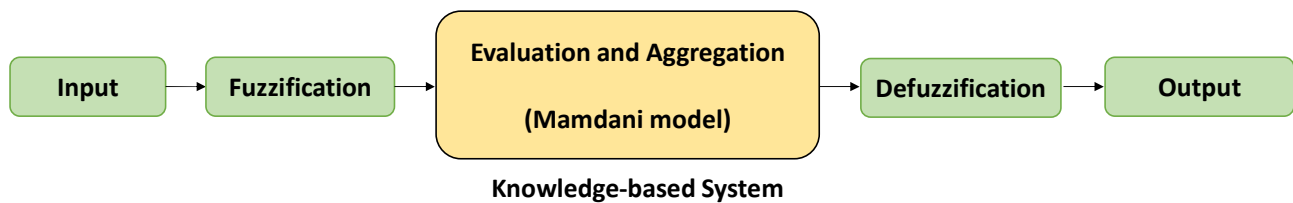


Figure 21 Example of a fuzzy knowledge-based system

3.1.3 Decision-Making Module

A fuzzy rule-based system was employed in the decision-making module to infer the risk of disease transmission within these areas. To perform short-term transmission risk (TR) assessment on-board a knowledge-based method implemented through fuzzy rules was proposed by UTH in (Sovatzidi et al., 2024; Triantafyllou, Sovatzidi, et al., 2024). An overview of the proposed method is illustrated in Figure 22.

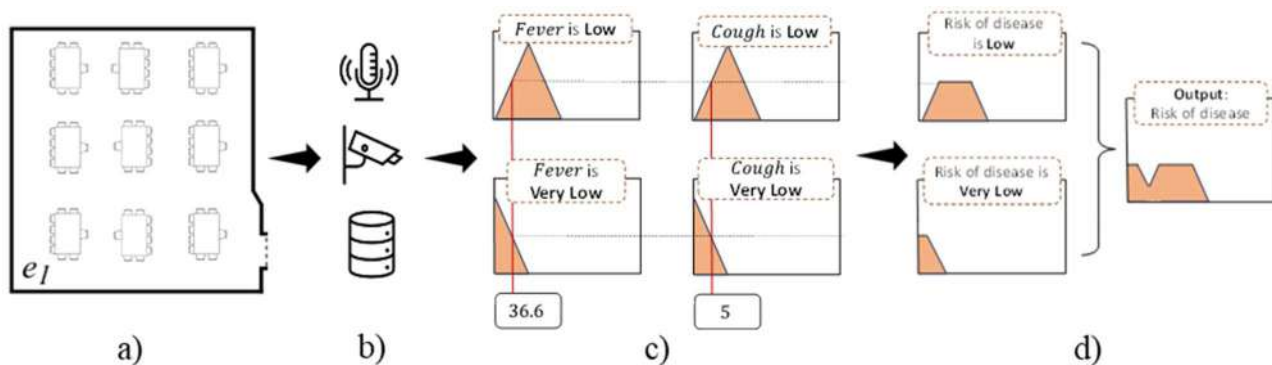


Figure 22 Overview of the Decision-Making module process.

The risk assessment process begins when one or more sensors identify disease-related symptoms inside a monitored environment (e). The characteristics of e, i.e., surface area, height, and maximum capacity are provided through the SIS. Then, the risk assessment process utilizes the data derived from the sensors and the SIS to assess the COVID-19 TR. Finally, the RA procedure incorporates a knowledge-based approach implementing several fuzzy rules defined by domain experts and information that has been retrieved from the literature.

To perform the RA of COVID-19 and norovirus transmission, the construction of a Mamdani fuzzy inference system is performed (Ahmad Shukri & Isa, 2021; Mamdani & Assilian, 1975): (a) the input entries are fuzzified based on the defined membership functions. The fuzzy sets are defined in such a way to overlap covering the range of values of each risk factor. (b) The determination of the relations among the risk factors and the output risk is then inferred based on 'IF-THEN' rules. As the number of rules increases, the result is better approximated and estimated. For the TR assessment



problem, the fuzzy rules are elicited and empirically selected by domain experts. (c) The activation of the fuzzy rules is performed, depending on the input entries and the logic operators; (d) the resulting output membership functions (R_j) are aggregated and defuzzified, based on Eq. (1), resulting in a final crisp output.

$$R_j(x, y, z, w, q, p) = \bigvee_{i=1}^n (A_i(x) \wedge B_i(y) \wedge C_i(z) \wedge D_i(w) \wedge E_i(q) \wedge F_i(p)) \quad (1)$$

where “ $\vee$ ” represents the fuzzy union and “ $\wedge$ ” the fuzzy intersection operation. In addition, $j = 1, \dots, R$, where R is the total number of activated fuzzy rules; the variables x, y, z, w, q are the considered input risk factors, *i.e.*, HVAC airflow, body temperature, number of coughs, number of passengers, time of exposure, respectively, whereas p is the estimated TR. Each variable is defined by a corresponding fuzzy set $A_i, B_i, C_i, D_i, E_i, F_i$, respectively, with $i = 1, \dots, n$. Regarding the TR, the confidence value is defined as the degree of membership to the respective fuzzy set.

The total risk of disease transmission is defined as the aggregated risk of all monitored environments. The calculation of the total risk (ρ_τ) for the pathogen transmission is performed based on the following equation (Xia et al., 2023):

$$R_\tau = \odot_{i=1}^P R_i \quad (2)$$

where P corresponds to the total number of monitored environments, R_i is the estimated risk for e_i , where $\odot$ is an aggregation operator. The calculated R_τ is fuzzified using the corresponding defined fuzzy sets.

Table 6 Literature-based risk mitigation measures (suggested actuations).

Risk levels	Literature-based Actuations
Low	• Immediate disinfection of affected areas. • Track and quarantine infectious individual.
Medium	• Immediate disinfection of area. • Decrease maximum allowed passengers by at least 50% until area is disinfected. • Track and quarantine infectious individual. • Track and monitor close conducts of the infectious individual and test them every 2 days. • Suggest the use of masks. • Implement social distance policy of 2 m. • Crew should conduct an information campaign for hygienic guidelines.
High	• Isolate the high-risk affected areas. • Increase airflow rate of isolated areas (>15 ACH) for at least 12 minutes. • Immediate disinfection of high-risk areas. • Increase disinfection frequency in the monitored environments. • Decrease maximum allowed passengers by at least 50% in areas of the affected subdeck. • Implement social distance policy of 2 m. • Track and quarantine infectious individual. • Monitor passengers exposed in the high-risk areas and test them every 2 days. • Mandatory use of masks for all passengers. • Disembark infectious passengers in the nearest port when feasible.

Once the risk assessment system defines a risk level related to the possibility of an epidemic outbreak, control measures are implemented based on the severity of the risk. These measures, in line with outbreak management guidelines and relevant studies, such as the research in (Triantafyllou, Kalozoumis, et al., 2024) and the SHIPSAN manual (SHIPSAN, 2016), include isolation and disinfection of affected areas, increased disinfection throughout the ship, and limiting the number of passengers in public areas. The recommended measures vary depending on the identified level of risk. The correspondence between the risk level and the risk mitigation measures, hereinafter suggested actuations is presented in Table 6, where actuations are suggested to limit the transmission of the disease.



3.1.4 Simulation Module

For the simulation module, several Agent-Based Models (ABMs) were utilized to assist the Decision-Making Module in the RA process. Specifically for airborne disease transmission the ABM framework Vadere was utilized to perform airborne disease transmission simulation (Rahn et al., 2022). Due to limited available data on short-term airborne disease transmission, this ABM framework was also utilized to validate the generated fuzzy rule set described in the Decision-Making Module. Regarding waterborne disease transmission, a validated ABM tailored for assessing the risk of exposure for passengers inside a swimming pool was used (Pintar et al., 2010). This ABM was coupled with the Wells-Riley model to provide additional feedback related to the risk of disease transmission. Similarly, for surface-based disease transmission a validated ABM was used to assess the risk of disease transmission coupled with a the Wells-Riley model (Arav et al., 2021).

3.2 SIMULATION OF DISEASE SPREAD

3.2.1 Airborne Transmission Modeling

Airborne disease transmission refers to the spread of infectious agents, such as viruses, through the air, and is considered the primary transmission mode for several infectious diseases (Zhao et al., 2022). For example, the relative contribution rate of aerosol particles on the Diamond Princess cruise ship was assessed as the most dominant infection route for COVID-19 transmission (Azimi et al., 2021). More specifically, airborne transmission primarily occurs in confined spaces when exhaled respiratory droplets remain suspended in the air and can be potentially inhaled by other individuals (Burridge et al., 2021). Therefore, the risk for infectious disease outbreaks in indoor spaces is generally higher, since the concentration of contaminants is more likely to increase, considering the factors of insufficient ventilation and confined prolonged human contact (Miller et al., 2021; Rowe et al., 2021).

Notably, the quality of the HVAC system in an indoor setting is crucial for the spread of infectious diseases, since it regulates the movement and advection of any aerosols, pollutants, and carbon dioxide (CO₂) (Wiryasaputra et al., 2022). Furthermore, (Baboli et al., 2021) reported that low humidity, low temperature, and a lack of air filtration constitute contributing factors to disease spread. Hence, measuring IAQ is crucial for determining whether the airflow of the HVAC system can mitigate the risk of airborne transmission (Kurabuchi et al., 2021). This can be achieved by implementing different strategies such as air filtration, ventilation control, humidity and temperature regulation, as well as monitoring of environmental parameters (Megahed & Ghoneim, 2021; Qian & Zheng, 2018).

Although technical interventions can be employed to limit airborne transmission, modelling the dynamics of disease spread is essential for the development of effective prevention strategies (Hussain et al., 2022; Liu et al., 2021). Modelling the evaporation and dispersion of droplets is a challenging and complex task when considering the multiphase interactions and variability of airflow conditions in an indoor setting. In this regard, CFD models incorporate these elements of variation to simulate respiratory actions, such as coughing and sneezing, to assess their effect on disease spread. There have been several studies that utilize CFD modelling to provide detailed information of the spatial distribution of infectious aerosol particles indoors (Mohamadi & Fazeli, 2022; Motamedi et al., 2022; Tsang et al., 2022).

For instance, a recent study investigated the transport, dispersion, and evaporation of saliva particles arising from a human cough (Dbouk & Drikakis, 2020a). More specifically, the proposed



methodology incorporated a three-dimensional model based on fully coupled Eulerian–Lagrangian techniques, that takes into account the relative humidity, turbulent dispersion forces, droplet phase-change, evaporation, and breakup parameters. The study showed that when someone coughs, the wind speed in an open space environment significantly affects the distance airborne droplets travel. Other studies focus on assessing the effect of ventilation and face masks under various airflow settings, to further enhance our understanding of droplet dynamics in these conditions. These studies, for instance, utilize CFD models to simulate aerosol plume dynamics (Ho, 2021) or examine the fluid dynamics phenomena that affect face mask efficiency under a coughing incident (Dbouk & Drikakis, 2020b). Furthermore, there are recent studies in the literature that focus on simulating long-range transport of infectious aerosols in ventilated indoor environments. One such example is explored by the authors in (Dbouk & Drikakis, 2021), where they investigated the impact of air ventilation systems and aerosols in an elevator under different airflow settings and found that the placement and design of the air purifier and ventilation systems significantly affect droplet dispersion. Additionally, other studies assess the possibility of airborne transmission in realistic indoor environments, for example, by measuring the ventilation rate in a restaurant using the tracer gas concentration decay method (Y. Li et al., 2021), or by investigating aerosol transport and surface deposition in a realistic classroom environment using computational fluid-particle dynamics simulations (Abuhegazy et al., 2020). In a similar regard, there are studies that aim to identify the transmission mechanisms of respiratory aerosols and assess strategies for risk mitigation aboard an enclosed bus environment (X. Yang et al., 2020; Z. Zhang, Han, et al., 2021). These studies combine experimental, numerical analysis and CDFs to simulate particle evaporation and transport. However, despite the potential usefulness of CFD models, one major challenge is their high computational cost and their limited capacity to capture the full complexity of a given system. Another simulation method is Lagrangian Particle Tracking (LPT), which has been used to track aerosol hazards in operating rooms (D’Alicandro et al., 2021). LPT methods can calculate particle trajectories and forces applied on them, such as gravity, buoyancy, drag, and inertia, that can alter their velocity and direction in the flow. LPT can adequately simulate the motion of a discrete number of particles, but it is considered computationally expensive.

An alternative direction to monitor disease transmission through the airborne route is to employ ABMs to simulate the movement and behavior of individuals within a pre-defined computational environment (Reveil & Chen, 2022). Several studies have employed ABMs to investigate disease transmission and exposure risk in various indoor settings, such as airplane cabins (Löhner et al., 2021), fever clinics (J. Wang et al., 2022), subway stations (Löhner et al., 2021), and restaurants (Löhner et al., 2022). Moreover, certain studies have specifically focused on developing ABMs for aerosol-based airborne transmission (Altamimi et al., 2021; Farthing & Lanzas, 2021), while others address disease forecasting (Petropoulos et al., 2022). Notably, ABMs are considered computationally intensive and challenging to calibrate as they rely heavily on prior assumptions.

CFD models can accurately approximate real-life scenarios of airborne transmission using equations related to airflow based on experimental studies (Zhao et al., 2022). Nevertheless, simulations of airborne diseases that can be transmitted through human-to-human interaction need to consider the human factor in order to assess the risk of epidemic outbreaks in social scenarios (Tsang et al., 2022). This results in scenarios where the CFD models are required to recalculate the airflow field to account for exposed or infected individuals and the spatial changes of the simulated space through time, which are affected by people movement. The need for recalculations leads to computationally expensive simulations that are impractical (Y. Guo et al., 2021). Therefore, in order



to mitigate this effect, researchers have proposed hybrid methods which incorporate probabilistic models and ABMs.

Probabilistic-CFD approaches are usually employed to find the probability of infection of individuals based on dose-exposure models (La et al., 2021; Motamedi et al., 2022; Wan et al., 2009), the Wells-Riley model (Y. Guo et al., 2021; Gupta et al., 2012; Qian et al., 2009; Yin et al., 2012; Z. Zhang, Capecelatro, et al., 2021), and other probabilistic models such as the Markov Chain Model (MCM) (C. Chen et al., 2014) or probability distribution functions (PDFs) (Tan et al., 2022). The effectiveness of such models has been presented in studies that compare CFD-based and probabilistic-CFD methods (J. Huang et al., 2021; Z. Zhang, Capecelatro, et al., 2021). Probabilistic-CFD models consist of two parts, *i.e.*, the exposure equation that calculates the exposure dose of individuals based on the concentration of pathogens provided by CFD simulations and the infection probability equation, usually an exponential model, that estimates the probability of infection based on the calculated dose exposure and other infection-related parameters (Aliabadi et al., 2011). These infection-related parameters can either be determined based on previous research, *e.g.*, experimental or CFD studies (Gupta et al., 2012), or by statistical analysis, *e.g.*, maximum likelihood estimation or MCM (Cheng et al., 2022; La et al., 2021; Yin et al., 2012). Probabilistic models such as the Wells-Riley model assume that the pathogen concentration is uniformly distributed, which is less accurate in realistic scenarios (Mukherjee & Wadhwa, 2022). In (Tan et al., 2022), the use of a PDF was proposed as a solution to this problem. More specifically, the parameters of the PDF, *e.g.*, mean and standard deviation of pathogen concentration, were determined by statistically analyzing 174 high-resolution CFD simulations. Such probabilistic methodologies mostly focus on predicting infected individuals without considering social factors and spatial changes of the environment. A solution to this problem has been proposed in (Y. Guo et al., 2021), where a spatial flow impact factor was incorporated in the Wells-Riley model to account for spatial changes. Furthermore, this approach could be used for minimizing the overall infection rate at a specific location by optimizing the location distribution of population and facilities.

ABM-CFD approaches introduce motion mechanisms, thus providing more realistic simulations of airborne disease transmission scenarios (Harweg et al., 2023; Mukherjee & Wadhwa, 2022). These methods utilize CFD simulations to predict the airflow field, such as droplet distribution and then incorporate the inferred pathogen concentration to the ABM that predicts infected and exposed human agents based on deterministic, probabilistic, or epidemiologic dynamics (Harweg et al., 2023; Lazebnik & Alexi, 2023; Mukherjee & Wadhwa, 2022; Schinko et al., 2022; J. Wang et al., 2022). Approaches considering a deterministic disease transmission model consider an infection occurrence based on thresholds determined by experimental studies or relevant literature (Löhner et al., 2022; Mukherjee & Wadhwa, 2022). Non-deterministic approaches either utilize probabilistic infection models, such as the dose-exposure model (J. Wang et al., 2022), or epidemiological models, such as the Susceptible-Infected-Removed and Susceptible-Exposed-Infected models (Ghoroghi et al., 2022; Lazebnik & Alexi, 2023). Based on the newly infected population, the ABM model updates the infection status and location of the population, which are then used as boundary conditions for the next time step of the CFD simulation (Ghoroghi et al., 2022; Mukherjee & Wadhwa, 2022; Schinko et al., 2022; J. Wang et al., 2022). ABM methods that incorporate social features that occur in real-life scenarios, such as contact avoidance of agents, employ the Social Force Model (SFM) (Harweg et al., 2023) which has been reported to provide high-fidelity simulation results (Marlow et al., 2021). Similar methods utilize computational crowd dynamics (CCD) models (Löhner et al., 2022), discrete event simulation (DES) models (Ghoroghi et al., 2022), and clustering methods (Schinko et al., 2022) to simulate spatio-temporal changes in the system. Moreover, some



methodologies incorporate more sophisticated mechanisms in the ABM simulation, such as coughing, use of protective equipment, hand hygiene, vaccination, and different ventilation techniques (Ghoroghi et al., 2022). In addition, several studies combine airflow parameters, e.g., airflow velocity, and agent related variables, e.g., height, face orientation, and inhalation/exhalation cycle (Lazebnik & Alexi, 2023; Mukherjee & Wadhwa, 2022). In (Lazebnik & Alexi, 2023), the impact of agent movement in the airflow field of the simulation is considered by incorporating a wake model, namely the Actuator Line Model (ALM), in the simulation.

ABMs can be simulated on 2D or 3D mesh grids. ABMs based on a 3D grid system can provide more fine-grained simulations that can result in more realistic results (Lazebnik & Alexi, 2023; Marlow et al., 2021); nevertheless, they can become computationally expensive (Mukherjee & Wadhwa, 2022). In contrast, an ABM simulation based on a 2D grid mesh could be more computationally efficient but may compromise the fidelity of the simulation due to interpolation of data from a 3D to 2D mesh grid system. In (Löhner et al., 2022), a hybrid method was adopted which utilized a CCD model based on a 2D-background mesh grid and a CFD model based on a 3D mesh grid to simulate pedestrian motion. The translation from 3D to 2D and vice versa was achieved by utilizing interpolation coefficients that were computed at the start of the coupled simulation.

Hybrid methods often utilize an Eulerian-based CFD or a Lattice-Boltzmann (LB)-based model to calculate the airflow and other analytical methods to find the trajectory and dispersion of droplets (Tsang et al., 2022). More recently, an LB-based method using a Large Eddy Simulation (LES) model was combined with an SFM-based ABM to simulate pathogen dispersion in evacuation scenarios (Marlow et al., 2021). In (Mukherjee & Wadhwa, 2022), a semi-analytical approach utilized a set of coupled ordinary differential equations (ODEs) to simulate the dynamics of droplets as a function of the airflow. In addition, mechanics involving exposure to pathogens take into consideration short- and long-range airborne routes (Cheng et al., 2022), as well as direct inhalation of coarse droplets and direct deposition of medium droplets on facial membranes (J. Wang et al., 2022). Another parameter that is considered in hybrid methods is the size range of droplets, since it affects the possibility of infection. Studies often define an interval-based size range (La et al., 2021; Motamedi et al., 2022; Schinko et al., 2022) or a discrete set of size ranges (Cheng et al., 2022; Wan et al., 2009; Yin et al., 2012), while others focus on one type of droplet size (Qian et al., 2009). In addition, methods that study droplet deposition on surfaces could incorporate surface disease transmission mechanics to provide a more realistic disease transmission model (Cheng et al., 2022). A hybrid method could also incorporate variations of coupled long-range, close-contact and surface dose exposure mechanisms in a dose-response model to predict risk of infection and disease transmission. Long-range airborne transmission could be calculated based on CFD simulations or the multi-zone infiltration and exfiltration model (MIX) and fomite transmission based on discrete-time non-homogeneous MCM. Furthermore, dose exposure related to close-contact interaction depends on short-range airborne transmission, direct deposition of large droplets on mucous membranes and inhalation of droplets based on the normal distribution model (S. Xiao et al., 2017).

In summary, the methods used to model airborne disease transmission comprise numerical physical models, mechanistic models, ABMs, or any combination of them. The novelty regarding the methods mostly focuses on the case study (e.g., COVID-19 transmission in buildings) and the parameters regarded in the models (e.g., ventilation incorporated, specific droplet size, use of motion mechanics in ABM, different SFM parameters considered).



3.2.2 Waterborne Transmission Modelling

Waterborne transmission refers to the acquisition of disease by exposure to pathogens through contaminated drinking water, recreational water (e.g., pools), bathing, washing, or eating food exposed to contaminated water, and overall lack of clean water supply, sanitation, and hygiene. Water can become contaminated at the source, during transport to the storage facility, in storage containers, or via improper handling. Several studies have attempted to model waterborne transmission, and it has been shown that, apart from the direct introduction of pathogens into the body, *i.e.*, drinking water and eating contaminated food, waterborne transmission takes place through aerosols containing contaminated water particles of different sizes (Ali et al., 2021; Hamilton & Haas, 2016; Y. Li et al., 2020; Mari et al., 2019; Pintar et al., 2010; L. Zhang et al., 2016).

It has been reported that stack aerosols are generated within vertical building drainage stacks during the discharge of wastewater containing fecal matter and exhaled mucus from toilets and washbasins. Experimental measurements regarding the stack air pressure and temperature distributions indicated that stack aerosols can spread to indoors through pipe leaks, providing direct evidence for the long-range aerosol transmission of COVID-19 through drainage pipes via the chimney effect (Q. Wang et al., 2022). Another study reviewed the transmission of COVID-19 through aerosolized wastewater and aerosols generated by toilet flushing (Ali et al., 2021). In (Y. Li et al., 2020), the VOF method was employed to simulate different flushing processes and the VOF–DPM method was used to model the trajectories of aerosol particles during flushing. The simulation results indicated the massive upward transport of virus particles, with 40%–60% of particles being transported above the toilet seat, leading to large-scale virus spread. The VOF–DPM was also employed in to investigate the transmission of infectious diseases in restrooms during male urination. The results revealed that male urination can induce strong turbulent flow with an average urine impinging velocity of 2.3 m/s, which can agitate virus particles and raise them (Cao et al., 2022). A similar study was conducted regarding virus transmission from urinals. It was reported that the trajectory of the particles generated by urinal flushing exhibited an outward spreading mode, reaching a height of 0.84 m within 5.5 s (J.-X. Wang et al., 2020). In (J.-X. Wang et al., 2022), CFD and DPM were used to quantitatively and visually demonstrate the effects of ventilation airflow speed, fan locations, and fan size on virus aerosol distribution due to toilet flushing in a typical family bathroom. They reported that the traditional ceiling fan was barely functional since aerosol particles were not adequately removed, while the side-wall fan functioned more efficiently, and its ventilation capability and performance were significantly better, removing nearly 80.9% of the lifted aerosol particles. Putting the toilet lid down before flushing is an effective method to prevent virus transmission. Nonetheless, male urinals do not have a lid or other barriers and people do not always have the habit of putting the toilet lid down before flushing to prevent aerosol cloud generation. In (L. Zhang et al., 2016), both direct and indirect transmission pathways were incorporated into a reaction–diffusion waterborne pathogen model, considering the spatial heterogeneity and the mobility of host population and flowing water on a spatial continuous and bounded domain.

Mathematical modelling has also been utilized to estimate the risk of infection based on simulations of water-mediated pathogen transportation in water distribution systems. Waterborne disease transmission scenarios have been explored, calculating the probability of infection based on dose-response models or deterministic infection mechanisms (Hamilton & Haas, 2016; Heida et al., 2022). In (Mari et al., 2019), a spatially explicit network model was utilized to simulate short-term pathogen transport throughout communities. The network model contains nodes that represent human communities that are arranged in a spatial setting and are connected through hydraulic



pathways. The evolution of pathogen transportation is monitored by an ODE epidemiological system that is affected by the population size (susceptible and infected individuals), pathogen concentration in the water supply, and human mobility. In (Chaysiri et al., 2021), the impact of water and sanitation services on waterborne disease transmission was investigated. A variation of the SIR model was introduced to simulate a cholera outbreak in Haiti. The so-called susceptible–infected–water–dumpsite–recovered (*SIWDR*) model incorporated the impact of open dumpsites as pathogen concentration sites and deficits of water sanitation services in the SIR ODE system. The affected water systems included were the drinking water supply system and the wastewater and sewage system. For the dumpsite-related parameter, deficits in municipal solid waste management and other non-water-related pathogen concentration sites were also considered in the model. In this model, the infectious population affected the number of concentrated pathogens in the dumpsite-related ODE, as well as in the water-related ODE. The dumpsite-related ODE also affected the water-related one, and both subsequently affected the number of newly infected population.

3.2.3 Surface Transmission Modelling

Surface transmission, also known as fomite-mediated transmission, occurs when susceptible individuals come into contact with surfaces that have been contaminated by infected individuals through direct touching, direct deposition of respiratory droplets, and/or deposition of respiratory aerosols under different conditions (Azimi et al., 2021). Numerical simulations have been conducted regarding the virus deposition on surfaces via aerosol/droplet transport due to inhalation or coughing under different scenarios (Sen, 2021; Vuorinen et al., 2020). However, the transmission modelling from contaminated surfaces to humans has been mainly focused on mechanistic or stochastic models. In (Canales et al., 2019), the contribution of fomite-mediated exposure to infection and illness risks during outbreaks was estimated. In particular, a stochastic simulation model in discrete time was developed to predict 17 h of simulated human behavior, taking into consideration hand-to-porous surfaces, hand-to-nonporous surfaces, hand-to-mouth, -eyes, -nose, as well as hand washing events. In another study (Pitol & Julian, 2021), two mechanistic models of indirect transmission within the quantitative microbial RA (QMRA) framework were adopted to estimate the infection risk for COVID-19 in community settings and provide guidance on potential intervention strategies. More specifically, the first model was used to estimate the infection risk for single contacts with contaminated surfaces; the SARS-CoV-2 RNA concentration on surfaces was obtained from the literature and concerned surface contamination in public spaces, e.g., bus stations, gas stations, stores, and playgrounds. The second model was used to estimate risks from surface-mediated community transmission as a function of the prevalence of COVID-19 cases in the community and assess the efficacy of feasible intervention strategies of hand and surface disinfection. In (Wilson et al., 2020), the transmission of pathogens from surfaces to fingertips was examined as an alternative way to simulate fomite-mediated transmission. The potential magnitude of exposure from surfaces to fingertips was calculated based on a mechanistic model. More specifically, the model calculated the pathogen concentration on the fingertips after contact with a contaminated surface based on the pathogen concentration of the surface before the contact, the pathogen concentration of the fingertips after the contact, and the transfer efficiency of the pathogen. The concentration-related parameters were calculated based on experimental data and statistically adjusted to account for the swabbing efficiency in the experimental study. In (Lei et al., 2018), comparative analyses on the routes of transmission of influenza A (H1N1), SARS CoV, and norovirus in an air cabin were conducted. A review on the mathematical modelling of fomite-mediated transmission, factors that affect transmission of microbes between fomites and humans, and the implications for human health can be found in (Stephens et al., 2019).



Fomite-mediated transmission has also been simulated using mathematical models such as the Environmental Infection Transmission System (EITS) framework. The EITS is a compartmental model that incorporates live pathogens of the environment as a parameter in the SIR model. It was proposed in (S. Li et al., 2009), where the epidemiological dynamics of the EITS are described by an ODE system that is affected from the traditional transition rates of infection and recovery, as well as environmental related probabilities such as fraction of pathogens picked by a susceptible person, probability of infection based on pathogens picked, number of pathogens deposited to environment per unit of time and rate at which pathogens are eliminated from the environment. The dynamics of the model can be simulated in a deterministic or a stochastic way, where events (e.g., a susceptible becomes infected) happen simultaneously and continuously or a single event randomly occurs in each case respectively. An extension of the EITS was proposed in (Kraay et al., 2018), where a model combined hand contamination due to fomite touching and infection based on self-inoculation, i.e., infection due to contaminated hands touching the mouth or other membranes.

3.3 SIMULATION-BASED ANALYSIS OF INFECTION TRANSMISSION

3.3.1 Analysis and Modelling of Accessible Areas

The implementation of the proposed system was divided into several modules. The closed-loop system was represented by an object-oriented ship structure that encompassed the RA node that comprised Sensors, Data Analysis, Decision-Making, and Simulation Modules. These can be observed in Figure 23, where a Unified Modelling Language (UML) diagram of the ship is presented. Each compartment of the ship contains information that can be used by the RA node, such as a passenger and furniture list, and are implemented as classes in Python.

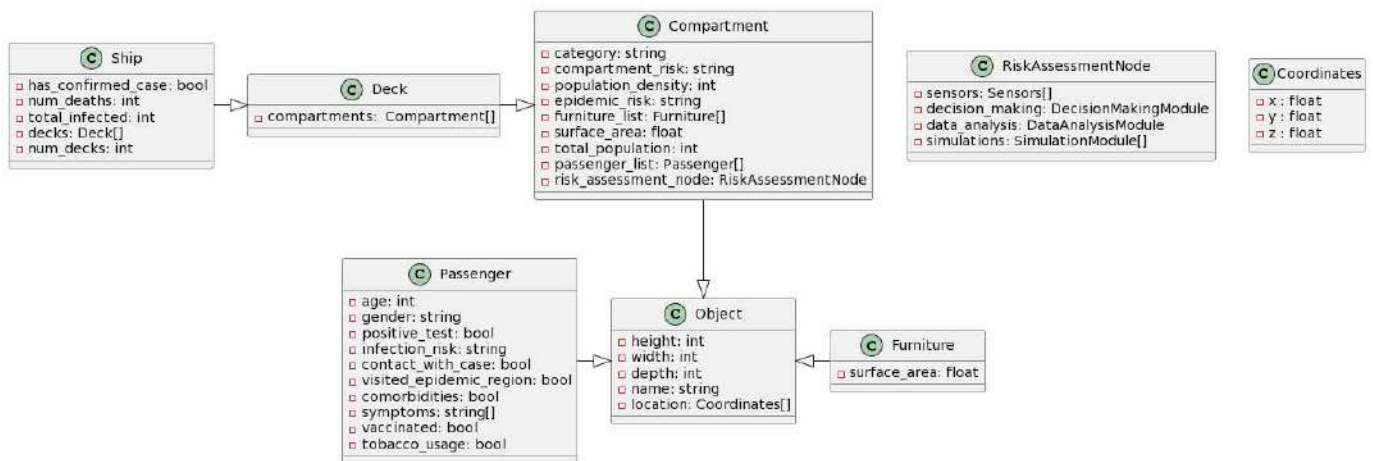


Figure 23: The implemented object-oriented ship structure scheme.

3.3.2 Simulation Platforms

There are several simulation platforms that can be used for modelling the transmission mechanics of infectious diseases in indoor and outdoor spaces that also incorporate human interactions. The identified simulation methods would require the use of CFD-related and agent-based modelling. The simulation software utilized in such a multi-simulation module should also be configurable to encompass mechanistic or probabilistic models. Several such tools have been examined and presented in this subsection, namely PyNetLogo, MESA and Vadere. PyNetLogo and MESA were



selected based on the review provided in (Antelmi et al., 2022) and Vadere due to the related study on airborne transmission provided in (Rahn et al., 2022).

PyNetLogo is interface to use and access [NetLogo](#) (Wilensky 1999) from Python. One can interact with NetLogo in either headless (no GUI) or interactive GUI mode. The library provides functions to load models, execute commands, and get values from reporters. It is compatible with NetLogo 6.1 and newer. It is largely similar to the [NetLogo Mathematica Link](#) and [RNetLogo \(deprecated\)](#). NetLogo is a multi-agent programmable modelling environment. It is used by many hundreds of thousands of students, teachers, and researchers worldwide. It also powers [HubNet](#) participatory simulations. It is authored by [Uri Wilensky](#) and developed at the [CCL](#). You can download it free of charge. You can also try it online through [NetLogo Web](#). NetLogo allows modelers to develop their models through a simple-to-use dedicated modelling language while offering a VPL to create and edit components to realize any simulation. However, its accessibility leads to significant limitations regarding model complexity. ([link](#)) (Antelmi et al., 2022)

Features

- Tools for analysis with extension
- Random number generator with extension
- Batch-runner with extension
- Visualization in 2D and 3D
- Parallel and distributed simulation with extension
- Grid, continuous, network, Geographic Information Systems (GIS) with extension
- Model exploration and optimization with BehaviourSpace. BehaviorSpace is a software tool integrated with NetLogo that allows you to perform experiments with models. BehaviorSpace runs a model many times, systematically varying the model's settings and recording the results of each model run. This process is sometimes called "parameter sweeping". It lets you explore the model's "space" of possible behaviors and determine which combinations of settings cause the behaviors of interest. If your computer has multiple processor cores, then by default, model runs will happen in parallel, one per core. ([link](#))

[MESA](#) is an Apache2 licensed agent-based modelling (or ABM) framework in Python (Kazil et al., 2020). Mesa allows users to quickly create agent-based models using built-in core components (such as spatial grids and agent schedulers) or customized implementations; visualize them using a browser-based interface; and analyze their results using Python's data analysis tools. Its goal is to be the Python 3-based counterpart to NetLogo, Repast, or MASON. One of the main advantages of Mesa is its extensibility, allowing users to develop and share their components through an open-source ecosystem. This approach created a rich community providing extensions for any need, including the possibility to exploit a multi-processor system, support for GIS data, and advanced analysis (Antelmi et al., 2022).

Features





- Modular components
- Browser-based visualization
- Built-in tools for analysis
- Random number generator
- Batch-runner
- Visualization in 2D and 3D
- Parallel and distributed simulation
- Grid, continuous, network, Geographic Information Systems (GIS) with Mesa-Geo
- Model exploration and optimization

Vadere is an open-source simulation framework to promote interdisciplinary understanding (Kleinmeier et al., 2019). Pedestrian dynamics is an interdisciplinary field of research. Psychologists, sociologists, traffic engineers, physicists, mathematicians, and computer scientists all strive to understand the dynamics of a moving crowd. In principle, computer simulations offer means to further this understanding. Yet, unlike for many classic dynamical systems in physics, there is no universally accepted locomotion model for crowd dynamics. On the contrary, a multitude of approaches, with very different characteristics, compete. Often only the experts in one special model type are able to assess the consequences these characteristics have on a simulation study. Therefore, scientists from all disciplines who wish to use simulations to analyze pedestrian dynamics need a tool to compare competing approaches. Developers, too, would profit from an easy way to get insight into an alternative modelling ansatz. Vadere meets this interdisciplinary demand by offering an open-source simulation framework implemented in Java, that is lightweight in its approach and in its user interface while offering pre-implemented versions of the most widely spread models.

Features

- Modular components
- Implemented various useful features such as behavioral, airborne transmission, dose exposure models and topographic elements
- Graphical User Interface
- Visualization in 2D
- Relies on target-based movements of agents for simulations
- Needs implementation for custom simulation settings

Agent-based modelling can be employed as a preliminary simulation method for the Simulation Module. The Snapshots of example simulation cases generated from Vadere are illustrated in Figure 24. In detail, one or two infectious passengers (infectious agents) in red are placed in a room with healthy passengers (healthy agents) in blue. They move with a set breathing and coughing cycle. While the infectious agents move, they release an aerosol cloud of fixed radius and pathogen load. The healthy agents are being exposed to the pathogen load when they move in the areas that the aerosol clouds were released. These healthy agents accumulate pathogen



exposure that can be then used to calculate the risk of infection. Then, the number of the newly infected agents can be used to assess the risk of disease spread. Agent-based modelling software can also be used to visualize the simulated scenarios by importing the information provided in the ship classes of Figure 23.

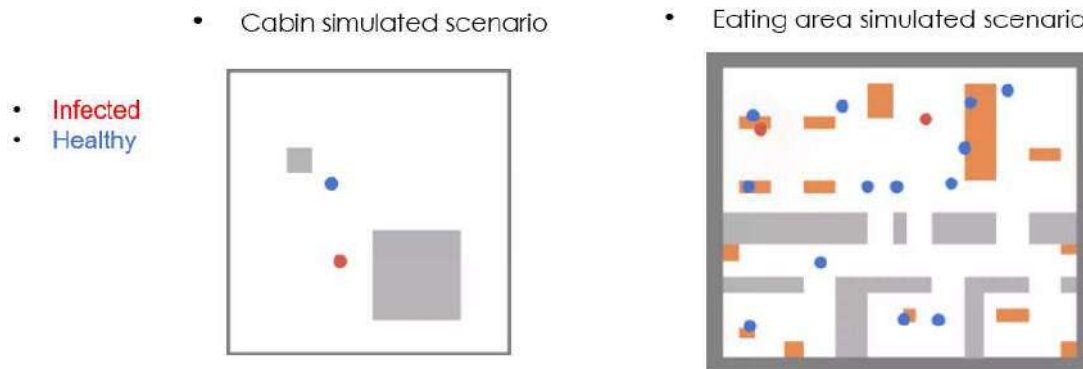


Figure 24: Two simulated scenarios of disease spread in a cabin and eating room. Infected agents with red, health with blue.

3.4 SIMULATED SCENARIOS

As part of the experiments conducted in this study, several scenarios of disease transmission were simulated considering the ship schematics of ships (Figures 1-6), identified sensors and information that can be obtained from these sensors (Table 1), schematics of the air-filtration and ventilation system, (10-12), as well as schematics of the sewage system (Figures 13-17). To assess disease transmission dynamics for viruses such as COVID-19 and norovirus and to evaluate our method, we simulated scenarios in specific areas of the ship that were selected based on empirical data from the literature (Figures 8 & 9) and insights from partners of the project (Figure 7). These included indoor areas, such as eating areas, bars and cabins, as well as outdoor areas such as swimming pools. The impact of the sanitation systems on waterborne disease spread were not examined since these systems provide adequate safeguards to prevent waterborne disease spread.

3.4.1 Eating Area

Monitoring: An **audio sensor** in an eating area receives/does not receive symptom sounds, such as coughing. A **thermal camera sensor** senses the elevated temperature of one or more individuals. A **DNA/RNA sensor** located in the HVAC system in the same area detects and identifies a pathogen. The number of passengers in the area is also tracked by an **RFID sensor**. The **ship's information system** sends data about the vaccination status in the eating area, based on the passenger's key card detected by the **RFID sensor** upon entrance. The information obtained from each of these sensors can be processed independently or combined.

Data Analysis: The data analysis block receives information from the sensors and translates it into relevant semantics.

Decision Making: Infer infection risk level based on the results of the data analysis and the domain knowledge encoded into the decision making (DM) module.

If enough information is available for DM to infer and the confidence interval is sufficient, then inform crew members of the risk level.



If the confidence interval is insufficient, then the system does not have enough information. In this case, run simulations to gather more information about possible spreading scenarios of the disease in the ship compartment.

Simulations: Run simulations based on physical and/or epidemiological models

Computational Fluid Dynamics/Particle Tracking simulations provide information about the aerosol suspension time in the air and the droplet deposition on surfaces. Preventive measures, such as the effect of masks, can also be considered.

ABM models are utilized to simulate airborne and/or surface-mediated disease transmission.

Probabilistic/Deterministic models (e.g., Dose-response model) are then utilized to assess the risk of infection for individuals in the room.

All acquired information is fed back to the decision-making module to reassess the risk level with a sufficient confidence interval.

3.4.2 Vessel's other high-risk public spaces

Monitoring: An *audio sensor* in a high-risk public space, e.g., bar (Figure 7), receives/does not receive symptom sounds, such as coughing. A *thermal camera sensor* senses the elevated temperature of one or more individuals. A *DNA/RNA sensor* located in the HVAC system in the same area detects and identifies a pathogen. The number of passengers in the area is also tracked by an *RFID sensor*. The *ship's information system* sends data about the vaccination status of passengers, based on the passenger's key card detected by the *RFID sensor* upon entrance. The information obtained from each of these sensors can be processed independently or combined.

Data Analysis: The data analysis block receives information from the sensors and translates it into relevant semantics.

Decision Making: Infer infection risk level based on the results of the data analysis and the domain knowledge encoded into the decision making (DM) module.

If enough information is available for DM to infer and the confidence interval is sufficient, then inform crew members of the risk level.

If the confidence interval is insufficient, then the system does not have enough information. In this case, run simulations to gather more information about possible spreading scenarios of the disease in the ship compartment.

Simulations: Run simulations based on physical and/or epidemiological models. For example,

Computational Fluid Dynamics/Particle Tracking simulations provide information about the aerosol suspension time in the air and/or the droplet deposition on surfaces. Preventive measures, such as the effect of masks, can also be considered.

ABM models are utilized to simulate airborne and/or surface-mediated disease transmission.

Probabilistic/Deterministic models (e.g., Dose-response model) are then utilized to assess the risk of infection for individuals in the room.

All acquired information is fed back to the decision-making module to reassess the risk level with a sufficient confidence interval.



3.4.3 Vessel's low-risk public spaces

Monitoring: An **audio sensor** in a low-risk public space, e.g., lounge area (Figures 7 & 8), receives/does not receive symptom sounds, such as coughing. A **thermal camera sensor** senses the elevated temperature of one or more individuals. A **DNA/RNA sensor** located in the HVAC system in the same area detects and identifies a pathogen. The number of passengers in the area is also tracked by an **RFID sensor**. The **ship's information system** sends data about the vaccination status of passengers, based on the passenger's key card detected by the **RFID sensor** upon entrance. The information obtained from each of these sensors can be processed independently or combined.

Data Analysis: The data analysis block receives information from the sensors and translates it into relevant semantics.

Decision Making: Infer infection risk level based on the results of the data analysis and the domain knowledge encoded into the decision making (DM) module.

If enough information is available for DM to infer and the confidence interval is sufficient, then inform crew members of the risk level.

If the confidence interval is insufficient, then the system does not have enough information. In this case, run simulations to gather more information about possible spreading scenarios of the disease in the ship compartment.

Simulations: Run simulations based on physical and/or epidemiological models. For example,

Computational Fluid Dynamics/Particle Tracking simulations provide information about the aerosol suspension time in the air and/or the droplet deposition on surfaces. Preventive measures, such as the effect of masks, can also be considered.

ABM models are utilized to simulate airborne and/or surface-mediated disease transmission.

Probabilistic/Deterministic models (e.g., Dose-response model) are then utilized to assess the risk of infection for individuals in the room.

All acquired information is fed back to the decision-making module to reassess the risk level with a sufficient confidence interval.

3.4.4 Public Swimming Pool

Monitoring: An **audio sensor** in the public swimming pool area receives symptom sounds, such as coughing or sneezing of symptomatic cases. A **thermal camera sensor** senses the elevated temperature of one or more individuals. A **DNA/RNA sensor** located in the swimming pool detects and identifies a pathogen. A **chlorine sensor** evaluates whether the chlorine levels in the swimming pool are sufficient to mitigate the risk of infection and the spread of the disease. The number of passengers may also be tracked by a sensor (an **RFID sensor** calculating how many passengers enter the swimming pool area using their key cards). The **ship's information system** sends information about the population demographics in the swimming pool area, based on the passenger's key card detected by the **RFID sensor** upon entrance. The information obtained from each of these sensors can be processed independently or combined.



Data Analysis: The data analysis block receives information from the sensors and translates it into relevant semantics.

Decision Making: Infer infection risk level based on the results of the data analysis and the domain knowledge encoded into the decision-making (DM) module.

If enough information is available for DM to infer and the confidence interval is high, then inform crew members of the risk level.

If the confidence interval is low, then the system does not have enough information. In this case, run simulations to gather more information about possible spreading scenarios of the disease in the ship compartment.

Simulations: Run simulations based on stochastic models. For example,

Probabilistic models for pathogen transmission in water are utilized to estimate the number of infected individuals in the swimming pool.

All acquired information is fed back to the decision-making module to reassess the risk level with a sufficient confidence interval.

3.4.5 Public toilet

Monitoring: An audio sensor in a public toilet area receives/does not receive symptom sounds, such as coughing or sneezing of symptomatic cases. A thermal camera sensor senses the elevated temperature of one or more individuals. A **DNA/RNA sensor** located in the HVAC system in the same area detects and identifies a pathogen. A **DNA/RNA sensor** located in the blackwater pipeline system of the ship within the same area detects and identifies a pathogen. The number of passengers may also be tracked by a sensor (an RFID sensor if the toilet door opens only by the passenger key card). The **ship's information system** sends data about the vaccination status of passengers, based on the passenger's key card detected by the **RFID sensor** upon entrance. The information obtained from each of these sensors can be processed independently or combined.

Data Analysis: The data analysis block receives information from the sensors and translates it into relevant semantics.

Decision Making: Infer infection risk level based on the results of the data analysis and the domain knowledge encoded into the decision-making (DM) module.

If enough information is available for DM to infer and the confidence interval is high, then inform crew members of the risk level.

If the confidence interval is low, then the system does not have enough information. Then run simulations to gather more information about possible spreading scenarios of the disease in the ship compartment.

Simulations: Run simulations based on physical and/or epidemiological models. For example, Computational Fluid Dynamics/Particle Tracking simulations are utilized to provide information about droplet deposition on the surfaces of the area. Preventive measures, such as the effect of masks, may also be considered.

ABM models are utilized to simulate airborne and/or surface-mediated disease transmission.





Probabilistic/Deterministic models (e.g., Dose-response model) are then utilized to assess the risk of infection for individuals in the room.

All acquired information is fed back to the decision-making module to reassess risk level with a sufficient confidence interval.

3.4.6 Ship Cabin

Monitoring: An **audio sensor** in a ship cabin receives/does not receive symptom sounds, such as coughing or sneezing of symptomatic cases. A **thermal camera sensor** senses the elevated temperature of one or more individuals. A **DNA/RNA sensor** located in the HVAC system in the same area detects and identifies a pathogen. A **DNA /RNA sensor** located in the blackwater pipeline system of the ship within the same area detects and identifies a pathogen. The number of passengers in the area is also tracked by an **RFID sensor**. The **ship's information system** sends data about the vaccination status of passengers, based on the passenger's key card detected by the **RFID sensor** upon entrance. The information obtained from each of these sensors can be processed independently or combined.

Data Analysis: The data analysis block receives information from the sensors and translates it into relevant semantics.

Decision Making: Infer infection risk level based on the results of the data analysis and the domain knowledge encoded into the decision making (DM) module.

If enough information is available for DM to infer and the confidence interval is high, then inform crew members of the risk level.

If the confidence interval is low, then the system does not have enough information. Then run simulations to gather more information about possible spreading scenarios of the disease in the ship compartment.

Simulations: Run simulations based on physical and/or epidemiological models. For example,

Computational Fluid Dynamics/Particle Tracking simulations provide information about the aerosol suspension time in the air and the droplet deposition on surfaces. Preventive measures, such as the effect of masks, may also be considered.

ABM models are utilized to simulate airborne and/or surface-mediated disease transmission.

Probabilistic/Deterministic models (e.g., Dose-response model) are then utilized to assess the risk of infection for individuals in the room.

All acquired information is fed back to the decision-making module to reassess the risk level with a sufficient confidence interval.

4. Computational modelling, simulation, analysis, and assessment

The biomedical RA model proposed in Section 3 can benefit from computational modelling and simulations. These simulations can approximate real-life scenarios of pathogen transmission based on *in-vivo* experiments. The effect of the HVAC system on disease transmission has been

extensively studied as it is considered an important countermeasure against airborne disease transmission, e.g., COVID-19. For this project, several CFD simulation experiments were conducted by the partner of the project **UNIC** aimed at assessing the risk of airborne disease transmission based on droplet dispersion expelled through coughing (Ritos et al., 2023, 2024). These experiments examined the effect of the HVAC system's airflow rate on the dispersion of droplets in enclosed areas of the cruise ship. CFD simulations can often become computationally expensive as the complexity of the problem increases. Therefore, machine learning approaches can accelerate the simulation process by acting as surrogate models of CFD simulations. Subsequently, an unsupervised machine learning algorithm was developed and experiments were conducted by the partner of the project **UNIC** to predict droplet dispersion in enclosed spaces of a cruise ship (Christakis & Drikakis, 2023a, 2023b; Christakis et al., 2024).

4.1 Computational Fluid Dynamics for airborne pathogen transmission

Virus outbreaks on cruise ships present significant challenges due to their enclosed environment and high passenger density. Managing these outbreaks has become even more critical as cruise ships have increased in size and passenger capacity. In (Ritos et al., 2023), effects of ventilation rates and positions of the coughing person in a typical passenger cabin room onboard a cruise ship were investigated.

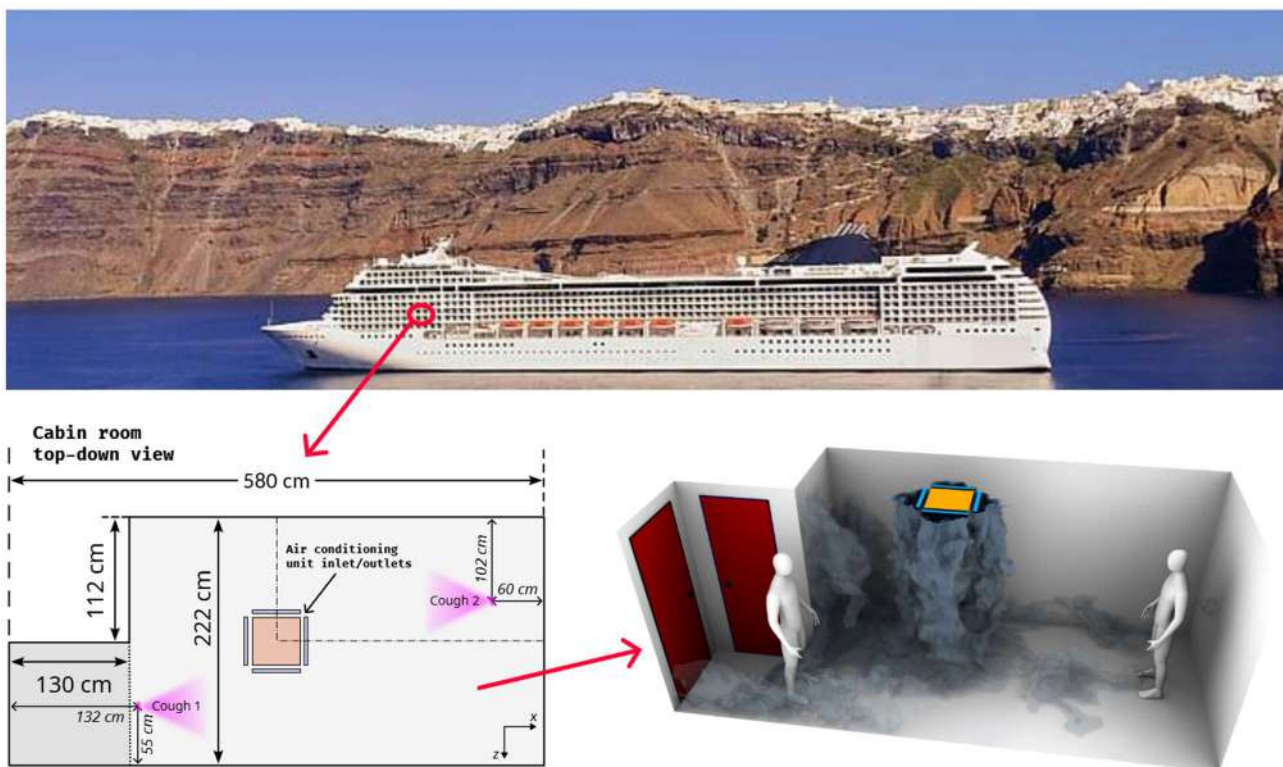


Figure 25: Illustration of a typical passenger cabin room onboard a cruise ship, illustrating the scenario and test case configuration considered.

The study also emphasized the importance of including evaporation models to simulate the process accurately. A higher ventilation rate is not always the best strategy to avoid the spread of airborne diseases, as saliva droplets can spread further at high ventilation rates. Regardless of the ventilation strategy, they evaporate faster than the room's air renewal. One should aim for minimum droplet

spreading inside the cabin and different ventilation strategies for occupied cabins. The authors propose using ventilation systems at medium flow rates of around 3 air changes per hour (ACH) when a cabin is occupied. This value is also close to the recommended value of 108 m³/h from the latest standard by the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE). The suggested value minimizes droplet spreading while maintaining good ventilation, comfort, and energy consumption.

In (Ritos et al., 2024), the effects of ventilation strategies on mitigating airborne virus transmission in a generic indoor space representative of a lobby area or information desk found in a hotel, company, or cruise ship were examined. Multiphase CFD simulations were employed in conjunction with evaporation modelling. Similar to the cabin experiments, four different ventilation flow rates were examined based on the most updated post-COVID-19 pandemic standards from health organizations and recent findings from research studies. Three air changes per hour provided the best option for minimizing droplet spreading at reasonable energy efficiency. Given the results presented in this study, excessively high flow rates, over 5 ACH, can have the opposite effect, leading to higher droplet spreading and high energy costs and adding probable discomfort to the occupants. Ventilation strategies like those proposed by WHO lead to results close to those observed with the best flow rate of 3 ACH tested in this study. Higher flow rate strategies, like those proposed by the recent ASHRAE Standard (ASHRAE, 2023) and Centers for Disease Control and Prevention (CDC) (Disease Controls (CDC), 2023), do not offer any advantage in this case and also create higher droplet scattering. Thus, a higher ventilation rate is not the best solution to avoid spreading airborne diseases. Simultaneous coughing of all occupants revealed that contagious droplets could be trapped in regions of low airflow and on furniture, significantly prolonging their evaporation time. Moreover, multiphase flow simulations can help define ventilation standards to reduce droplet spreading and mitigate virus transmission while maintaining adequate ventilation with lower energy consumption.

Recently, a CFD study was carried out to investigate the dispersion of airborne respiratory droplets and aerosols within a cruise ship passenger cabin, focusing on the influence of mechanical ventilation jet flow angles, as the figure below shows:

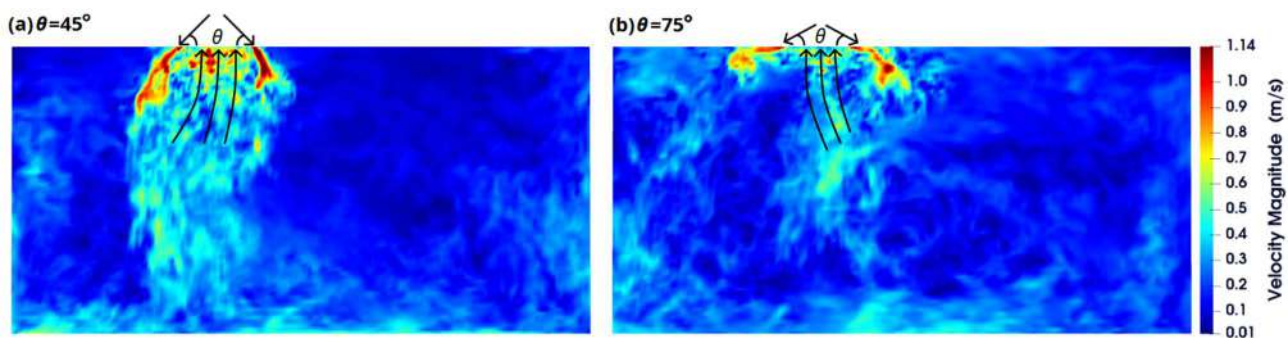


Figure 26: Sketch illustrating the inflow angle of the cooled air from the a/c unit considered in the present study: (a) 45- and (b) 75-degree angle. Contour surface plot of the air velocity magnitude. Red color indicates the maximum velocity of the air expelled by the a/c unit (1.14 m/s or 11 ACH).

While previous research primarily concentrated on larger respiratory droplets, which rapidly settle, this study emphasizes aerosols under 10 μm that can remain airborne for extended periods. The findings demonstrate that slight variations in airflow can significantly impact aerosol dispersion. The research suggests that lower ventilation rates might be beneficial in minimizing the spread of microdroplets and aerosols. Additionally, a 75-degree inlet angle of the ventilation system effectively

restricts the travel distance of larger droplets. However, a 45-degree angle may offer better outcomes when a cough occurs near the ventilation unit. These insights underline the importance of tailored air circulation strategies to reduce transmission risks in confined spaces, such as cruise ship cabins, highlighting the need for optimized ventilation design to manage infectious disease outbreaks.

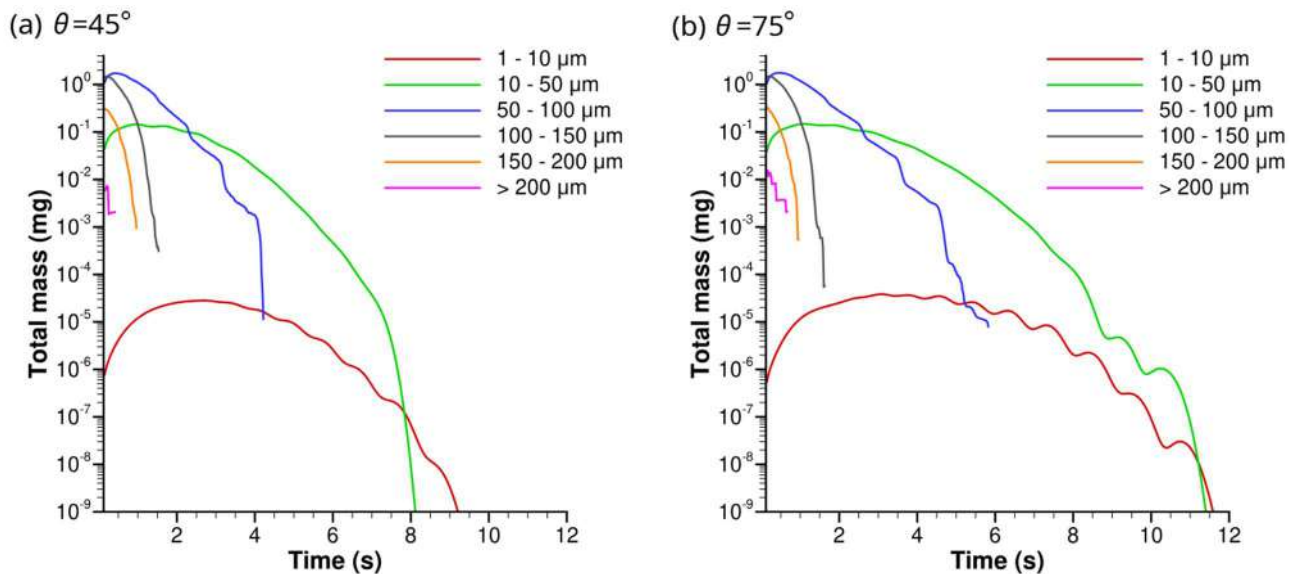


Figure 27: Time plot of the total saliva mass of the airborne respiratory droplets located 1.4 m above the floor, grouped into separate size ranges depending on the diameter of the droplets, for (a) 45- and (b) 75-degree a/c inlets angle.

The effect of natural ventilation on the distribution of airborne pathogens in narrow, typical corridor onboard cruise ships has also been investigated. Two scenarios are examined: a milder cough at 6 m/s and a stronger cough at 12 m/s. A reference baseline case with no airflow is compared to cases featuring an incoming airflow velocity of 1 m/s (3.6 km/h), examining differences in the dispersal of respiratory droplets from two individuals coughing spaced 5 m apart, as per the figure below:

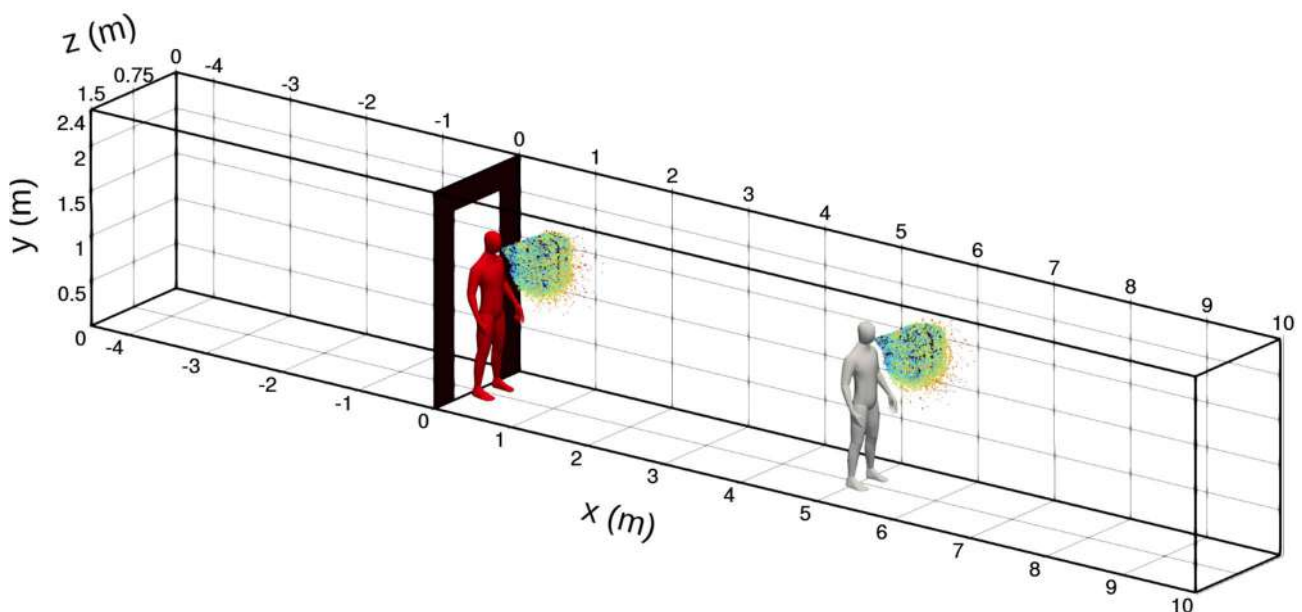


Figure 28: Sketch illustrating a typical corridor on a cruise ship outside passenger cabin rooms, showcasing the dimensions of the computational domain and the position of the two coughs.



Both individuals cough in the direction of the airflow, assuming one-way traffic to minimize airborne pathogen transmission. Findings indicate that airflow accelerates past the door, exceeding 3 m/s, with gusts reaching 4 m/s due to interaction with recirculation zones. This acceleration affects droplet dispersal. Larger droplets ($>150\ \mu\text{m}$) maintain a ballistic trajectory, traveling 2-4 m, potentially increasing transmission risk but suggesting that a 5-metre distancing policy could suffice for protection. Smaller droplets ($<150\ \mu\text{m}$), especially those $<100\ \mu\text{m}$, spread extensively regardless of cough strength while containing the most viral mass overall, as is illustrated in the following two figures:

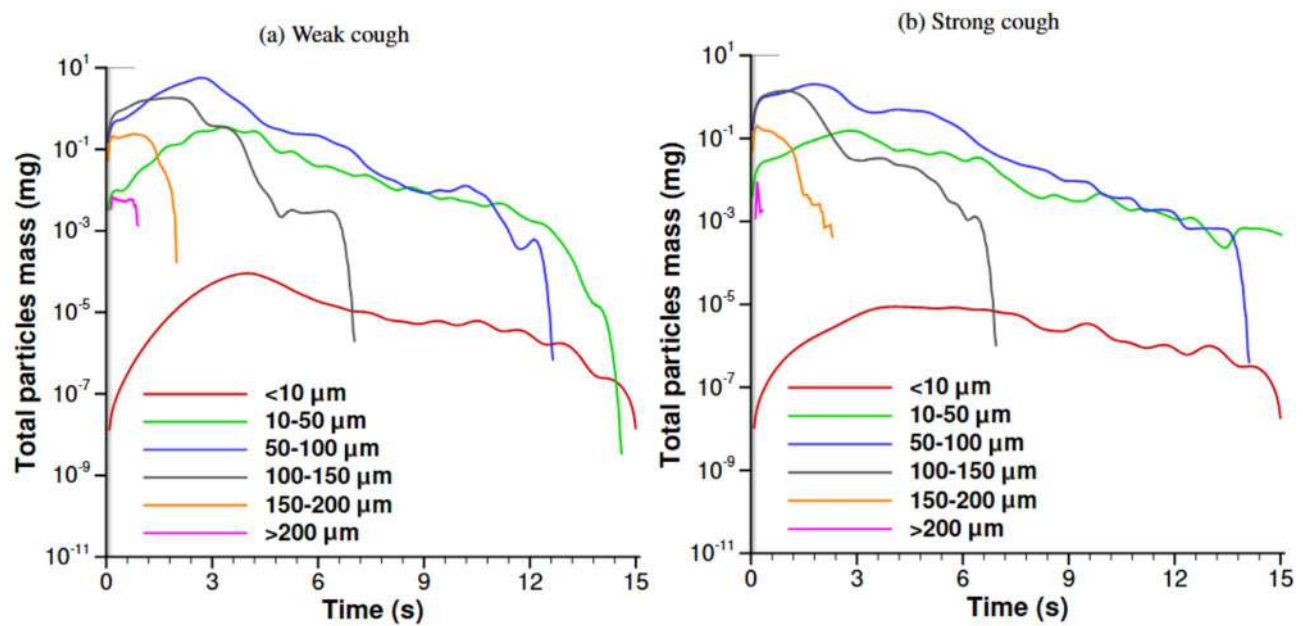


Figure 29: Total mass of airborne droplets situated 1.5 m above ground in the corridor, plotted in groups of particle sizes by diameter for (a) a weak cough, and (b) a strong cough.

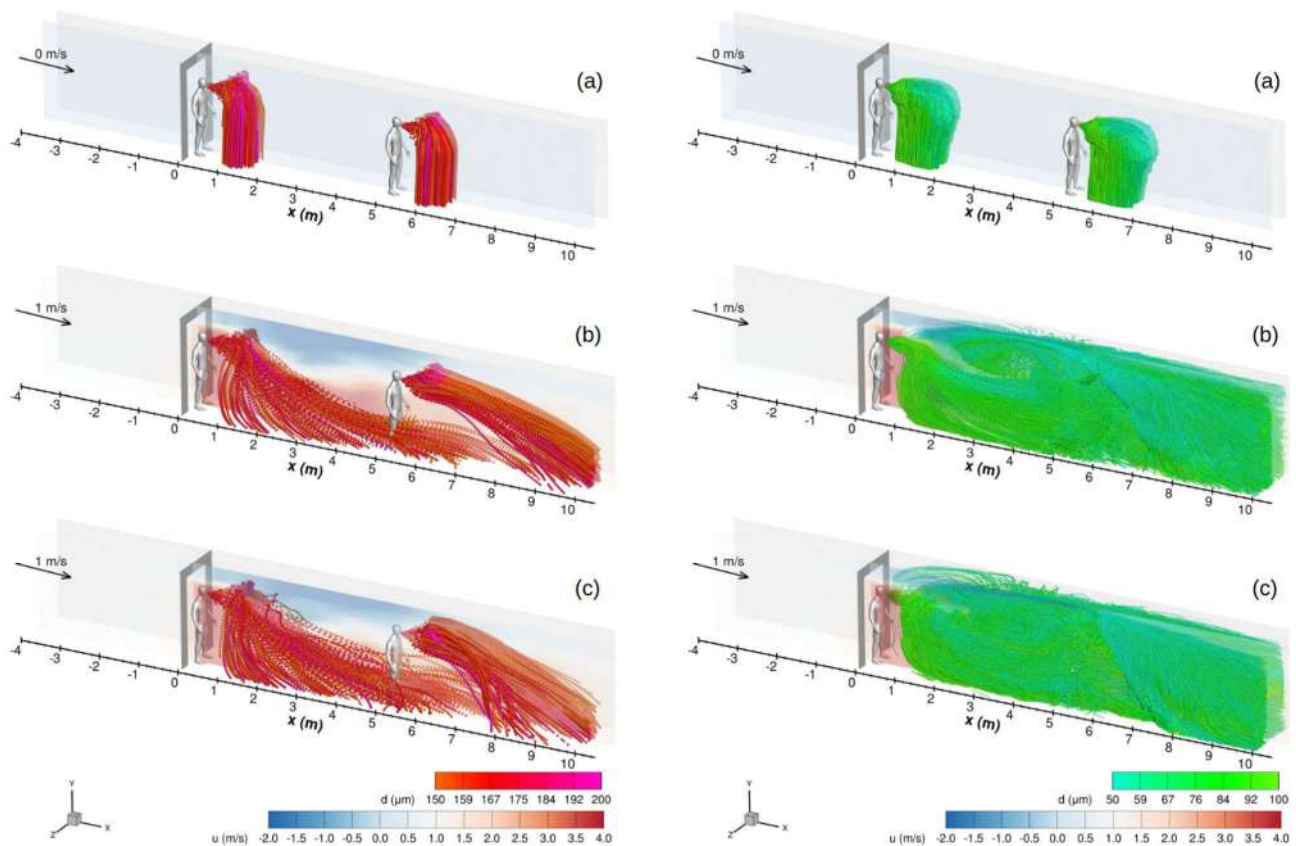


Figure 30: Trajectories for particles during 15 s after coughing for (a) a strong cough with no draft, and also with an incoming draft of 1 m/s for (b) a weak cough, 6 m/s, and (c) a strong cough 12 m/s. Left column (red particles) for airborne respiratory droplets with a diameter between 50–100 μm , Right column (green droplets) for particles with a diameter between 150–200 μm .

Thus, distancing alone is insufficient. The study recommends that additional safety measures be enforced, such as wearing masks, stricter usage protocols for corridors by limiting corridor use to one person every 20–30 seconds or eliminating natural ventilation when feasible to effectively mitigate transmission risks in such environments.

4.2 Unsupervised machine learning for predicting airborne pathogen droplet dispersion

In (Christakis & Drikakis, 2023a) the development of a novel algorithm for unsupervised learning called RUN-ICON (Reduce UNcertainty and Increase CONfidence) was presented. The primary objective of the algorithm is to enhance the reliability and confidence of unsupervised clustering. RUN-ICON leverages the K-means++ method to identify the most frequently occurring dominant centers through multiple repetitions. It distinguishes itself from existing K-means variants by introducing novel metrics, such as the Clustering Dominance Index and Uncertainty, instead of relying solely on the Sum of Squared Errors, for identifying the most dominant clusters. The algorithm exhibits notable characteristics such as robustness, high-quality clustering, automation, and flexibility. Extensive testing on diverse data sets with varying characteristics demonstrated its capability to determine the optimal number of clusters under different scenarios.



In (Christakis & Drikakis, 2023b), the RUN-ICON algorithm was applied on a numerical experiment to evaluate the RUN-ICON algorithm's ability to represent the collective behavior of a group of 1000 non-interacting particles originating from a common point. These particles were left to propagate on a 2D plane, following a set of ordinary differential equations, allowing multiple particles to follow the same trajectory. The parameters of these differential equations were randomly selected from a uniform distribution. The primary objective was to assess the algorithm's capacity to capture the complex dynamics exhibited by the particle group and its potential applications in simulating particle-based systems without the need for computationally expensive inter-particle force calculations. The particle trajectories and final positions were recorded after 10 dimensionless time units in the dimensionless x-y plane. The particles were clustered using the RUN-ICON algorithm based on their final positions. The algorithm separated the particles into either four clusters (for the smallest range of parameters c and d) or three clusters (for the higher ranges of parameters c and d , when particle separation was evident) with high confidence and low uncertainty. In contrast, the repeat and Bayesian K-means and DBSCAN algorithms did not manage to separate the particles confidently. Moreover, when noise was added to the system, RUN-ICON predicted with increased confidence (almost 100%) the separation of the particles in five clusters. The performance of the other methods was unsatisfactory. These findings provide evidence about the accuracy and efficiency of the RUN-ICON algorithm, which performs extremely well in data sets where noise is present.

The RUN-ICON algorithm was also used to analyze virus droplet dynamics resulting from coughing events within a confined environment using, as an example, a typical cruiser's cabin (Christakis et al., 2024). It is of paramount importance to be able to comprehend and predict droplet dispersion patterns within enclosed spaces under varying conditions. Data from multi-phase computational fluid dynamics simulations of coughing events at different flow rates were utilized with the RUN-ICON unsupervised learning algorithm to identify prevailing trends based on the distance travelled by the droplets and their sizes. The analysis in this study revealed the existence of three distinct stages for droplet dispersion during a coughing event, irrespective of the underlying flow rates. An initial stage where all droplets disperse homogeneously, an intermediate stage where larger droplets overtake the smaller ones, and a final stage where the smaller droplets overtake the larger ones. This is the first time CFD is coupled with unsupervised learning to study particles' dispersion and understand their dynamic behavior.

Understanding the dispersion of particles in enclosed spaces is crucial for controlling the spread of infectious diseases. In (Christakis & Drikakis, 2024), an innovative approach that combines an unsupervised learning algorithm with a Gaussian mixture model to analyze the behavior of saliva droplets emitted from a coughing individual. The algorithm effectively clusters data, while the Gaussian mixture model captures the distribution of these clusters, revealing underlying sub-populations and variations in particle dispersion. Using CFD data, this integrated method offers a robust, data-driven perspective on particle dynamics, unveiling intricate patterns and probabilistic distributions previously unattainable. The combined approach significantly enhanced the accuracy and interpretability of predictions, providing valuable insights for public health strategies to prevent virus transmission in indoor environments. The practical implications of this study were profound, as it demonstrated the potential of advanced unsupervised learning techniques in addressing complex biomedical and engineering challenges. Moreover, it underscored the importance of coupling sophisticated algorithms with statistical models for comprehensive data analysis. The potential impact of these findings on public health strategies is significant, highlighting the relevance of this research to real-world applications.

The RUN-ICON algorithm was also used to optimize sensor placement in indoor air-conditioned environments (Christakis et al., 2025) by integrating computational fluid dynamics simulations with artificial intelligence techniques in an unsupervised learning framework. Spatially distinct thermal and velocity clusters based on temperature and velocity magnitude distributions were identified. Optimization of sensor positions within these clusters, guided by sequential least squares programming, resulted in an effective strategy to minimize probe redundancy while maximizing spatial coverage. The investigation highlighted the interplay between temperature, relative humidity, velocity, and turbulence intensity, revealing critical insights into airflow behavior and its implications for occupant comfort. In addition, the findings also underscored the potential for targeted sensor placement to provide a robust framework for advanced indoor climate control.

5. EXPERIMENTS & RESULTS

5.1 DECISION-MAKING MODULE

5.1.1 Eating Area

For experiments regarding eating areas of the ship two representative areas were selected from the ship schematics of the World Dream cruise ship, presented in Section 2 (Figure 2). Two adjacent eating areas of varying surface area and passenger capacity were selected. These eating areas are presented in Figure 31. The two examined restaurant areas, *i.e.*, e_1 and e_2 had a surface area equal to 276 m² and a maximum capacity of 42 people, and Restaurant 2 has a surface area of 379 m² and a maximum capacity of 82 people, respectively; both restaurants have a height of 3 m.

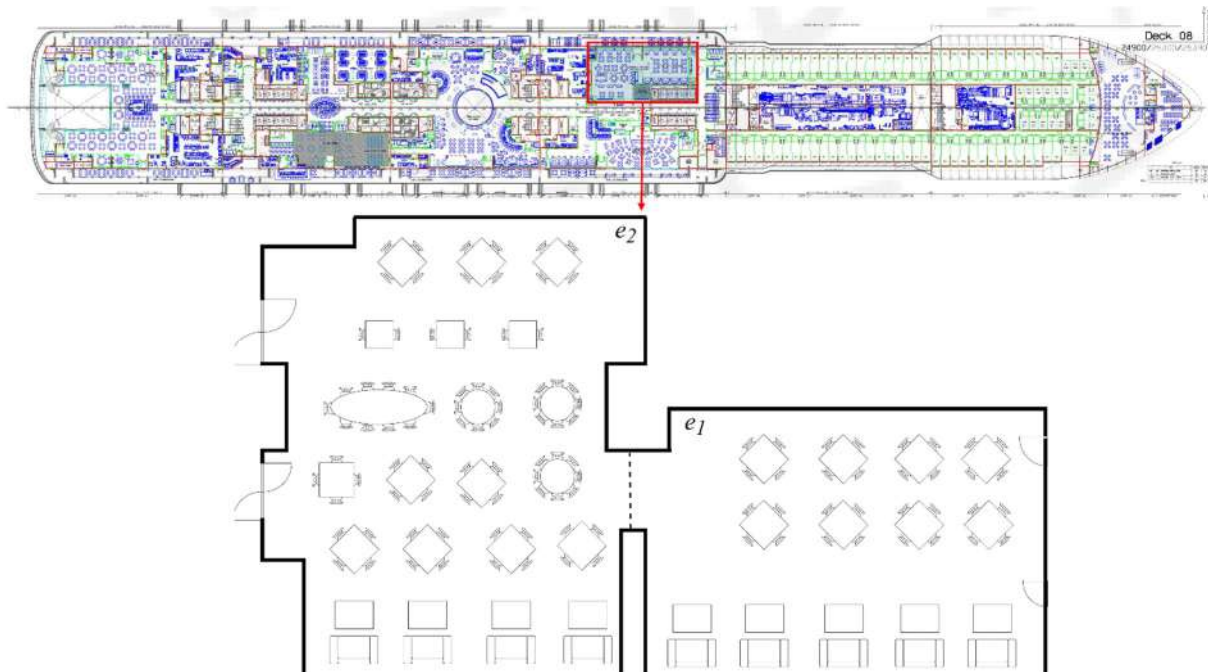


Figure 31 Topography of the two examined restaurant areas e_1 and e_2 residing in Deck 08, highlighted with red.

In addition, the following five risk factors were considered based on the sensors included in the smart ship design proposed in (Triantafyllou, Kalozoumis, et al., 2024) and the most probable symptoms



of COVID-19 that were identified by the partner **HPI** in Subsection 3.1.1 (Table 2). A mapping of the available sensors and the corresponding risk factor for COVID-19 can be observed in Table 7.

Table 7 Information provided by each available sensor.

Sensors	Information
1. RNA sensor (in HVAC)	Detected pathogen
2. Audio sensor	Number of coughs
3. Thermal camera sensor	Fever
4. RFID sensor	Number of passengers, exposure time

Analysis of Risk Factors related to airborne disease transmission

Body Temperature: Elevated body temperature levels, above 39°C, assist in reducing the pathogen concentration within the infected host while impeding its replication rate (Singh et al., 2022; Wrotek et al., 2021). The proposed method considers the maximum body temperature detected over a period of time for the assessment of COVID-19 TR.

Room Ventilation: An important countermeasure against airborne infectious diseases in indoor environments is the HVAC system, which is responsible for circulating air from the outdoor environment inside the room. This circulation is defined as the airflow rate Q (m³/h) calculated as follows:

$$Q = ACH \cdot V \quad (3)$$

where ACH is the number of air changes per hour and V the volume of the examined area (m³).

Several studies have examined the importance of different ventilation systems, as well as the optimal airflow rate and position of the HVAC system to mitigate the transmission of infectious diseases (Christakis et al., 2024; Motamedi et al., 2022; Ritos et al., 2023, 2024). The Centers for Disease Control and Prevention has proposed a minimum of 5 ACH as the optimal airflow rate (CDC, 2023). In (Ritos et al., 2023, 2024), the effect of ACH was examined through CFD simulations. The optimal balance between HVAC effectiveness and passenger comfort for both private rooms and public indoor areas was identified as 3 ACH by the partner of the project **UNIC**, while an upper boundary of 6 ACH was suggested in (Ritos et al., 2024) and a minimum of 1.5 ACH was suggested in (Ritos et al., 2023). These boundaries resulted from CFD simulations that were conducted by the partner of the project **UNIC**. According to the identified limits and based on Eq. (3), the maximum, minimum, and optimal airflow rates for the HVAC system are set as $Q = 6 \cdot V$, $Q = 1.5 \cdot V$, and $Q = 3 \cdot V$, respectively.

Cough: The proposed method considers the number of coughs captured by audio sensors in a ship compartment over a certain period of time to assess the TR. To determine the severity of the risk

with respect to the number of coughs per hour, the pathogen concentration in a room is estimated based on the Wells-Riley probabilistic model (Sze To & Chao, 2010). Since the total pathogen concentration in the room cannot be easily quantified at a given moment, it is estimated based on the number of coughs as:

$$c_v(t) = n_c(t) \cdot c_l \quad (4)$$





where $n_c(t)$ is the number of coughs detected over a period of time t and c_l is the average number of virus particles per mL emitted in one cough.

The Wells-Riley model assumes a well-mixed air distribution in indoor environments and defines the risk of one individual contracting the infection based on the exposure time in the room as:

$$P = 1 - e^{-\frac{q n_b t}{Q}} \quad (5)$$

where P is the probability that an individual will get infected, q is the quanta emission rate (quanta/h). The quanta describe the number of virus particles per mL emitted in the room (Sze To & Chao, 2010). The variable n_b is the breathing rate (m^3/h), t is the exposure time (h), and Q is the airflow rate (m^3/h) in the room. The quanta emission rate (q) is calculated as:

$$q = \frac{c_v(t)}{ID_{50}} \quad (6)$$

where ID_{50} corresponds to the minimum infectious dose that can cause infection in 50% of the population (Sze To & Chao, 2010).

To find the maximum number of coughs ($n_c(t)$) the following variables were used in Eq. (5) : $P \cong 1$, $n_b = 0.5 \text{ m}^3/\text{h}$ (Zheng et al., 2016), $t = 1 \text{ h}$, $ID_{50} = 1 \cdot 10^3$ virus particles per mL (Karimzadeh et al., 2021), $c_l = 1 \cdot 10^5$ virus particles per mL (Y. Wang et al., 2020) and $Q = 3 \cdot V$ (Ritos et al., 2024). For example, regarding Restaurant 1 (e_1) with a surface area of 276 m^2 and a height of 3 m, the maximum number of coughs is 200/h.

Exposure Time: In an indoor area, the exposure time increases the risk of infection for each individual in the room. Here, the RA is performed assuming that a passenger can stay indoors for a period of 15-120 min.

Occupancy: The population density in an indoor space affects the transmission of infectious diseases (Braidotti et al., 2022; Moon & Ryu, 2021). Droplets emitted through coughing can travel up to 0.92 m from the source (infectious individual) until they are no longer contributing to the transmission of the disease, *i.e.*, they have either evaporated or settled on the floor (Ritos et al., 2023). Therefore, it is essential to reconsider the way that the occupancy of a room is calculated and incorporate the distance between each person in the room in the occupancy calculation process. This distance is defined as the minimum distance between two individuals, assuming that they are uniformly distributed within the room. Thus, the area occupied by each person can be defined as:

$$D = \frac{N \cdot \pi \cdot r^2}{A} \quad (7)$$

where N is the number of people inside the room, r is the contact radius for each person in the room (m), and A is the surface area of the room (m^2). Since the surface area of the room is constant r depends on the number of people inside the room. Therefore, considering that each person occupies a surface area of $D = 1 \text{ m}^2$, the maximum radius r_{max} for a room can be calculated as:

$$r_{max} = \sqrt{\frac{A}{N \cdot \pi}} \quad (8)$$

Assuming that each person resides in the center of a circle characterized by a specific radius r_{max} , then the distance between two individuals is estimated as $2 \cdot r_{max}$. As reported in (Ritos et al., 2023), the maximum cough range, under suboptimal HVAC settings, is denoted by the distance $d_c = 0.92 \text{ m}$. Therefore, based on Eq. (8), the risk increases as the distance between two individuals calculated as $2 \cdot r_{max}$ is less than d_c . The relation between r_{max} and d_c can be classified into three



possible cases corresponding to $2 \cdot r_{max} < d_c$, $2 \cdot r_{max} = d_c$, and $2 \cdot r_{max} > d_c$. The resulting fuzzy sets for the eating areas e_1/e_2 can be observed in Table 8 and in Figure 32.

Table 8 Fuzzy set for each identified risk factor.

Fuzzy Set		Room Ventilation	Body Temperature	Total Number of Coughs	Total Number of Passengers	Exposure Time	Risk
Low	e_2	[0,3369]	[35,38]	[0,61]	[2,20]	[15,45]	[0,0.3]
	e_1	[0,2400]		[0,44]	[2,10]		
Med.	e_2	[1685,6738]	[36,39]	[25,97]	[10,40]	[30,60]	[0.1,0.5]
	e_1	[1200,4800]		[17,71]	[5,20]		
High	e_2	[3369,6738]	[38,42]	[61,250]	[20, 81]	[45,120]	[0.3,1]
	e_1	[2511,5022]		[50,200]	[10,42]		

Additionally, the correlation between each factor and the risk of disease transmission is summarized in Table 9.

Table 9 Correlation of each factor with risk of COVID-19 transmission.

Risk factors	Impact on Transmission Risk	
1. HVAC (Air Flow Rate)	Lower, Higher ↑	Moderate ↓
2. Coughing	Lower ↓	Higher ↑
3. Fever	Lower ↑	Higher ↓
4. Number of Passengers	Lower ↓	Higher ↑
5. Surface Area	Lower ↑	Higher ↓
6. Passenger Exposure Time	Lower ↓	Higher ↑

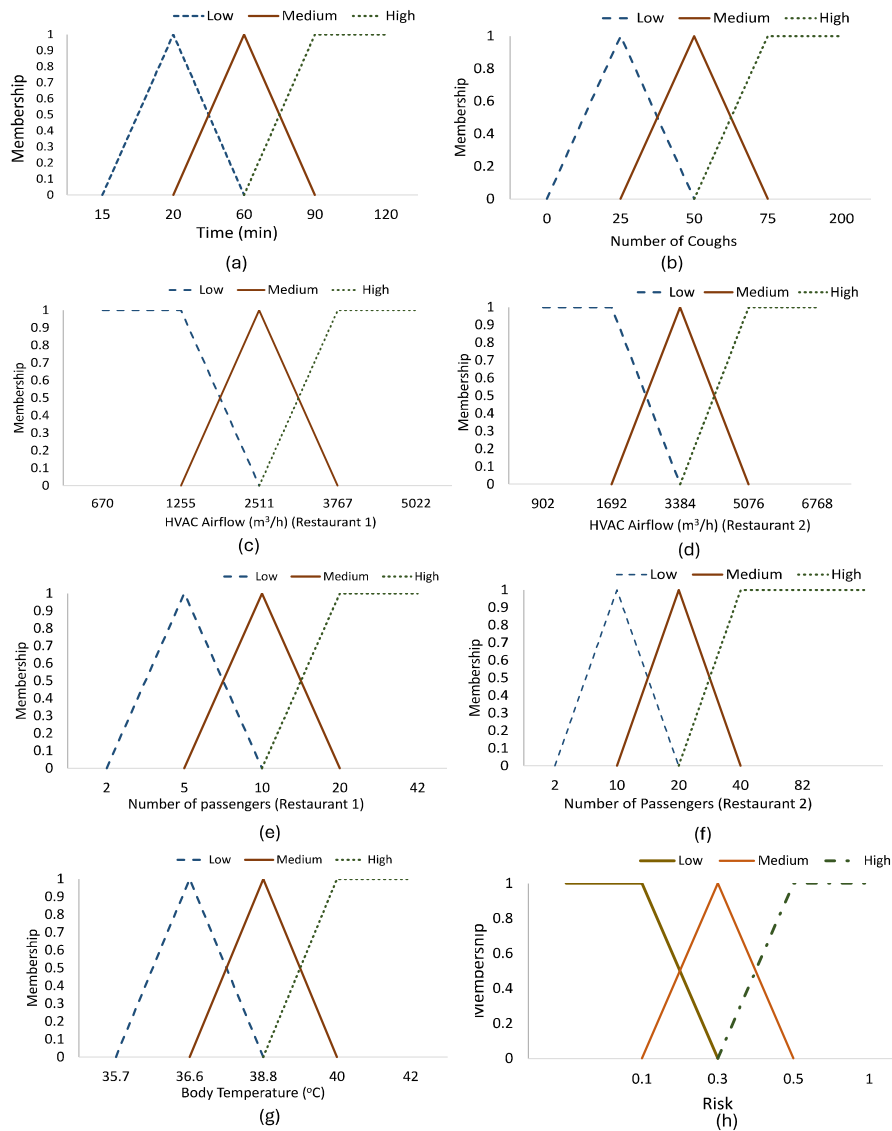


Figure 32 Fuzzy sets for the input factors: (a) time; (b) number of coughs; (c)-(d) HVAC airflow; (e)-(f) number of passengers; (g) body temperature; (h) risk of COVID-19 transmission.

Fuzzy Rules

An overview of the 57 generated fuzzy rules can be observed in Figure 33. In detail, the fuzzy rules defined for the examined problem under investigation are the following:

1. **IF** HVAC airflow is Low **AND** Body Temperature is Low **AND** Number of Coughs is Low **AND** Number of Passengers in Restaurant is Low **AND** Time of Exposure is Low **THEN** Transmission Risk is Low
2. **IF** HVAC airflow is Low **AND** Body Temperature is Medium **AND** Number of Coughs is Low **AND** Number of Passengers in Restaurant is Low **AND** Time of Exposure is Low **THEN** Transmission Risk is Low



3. **IF** HVAC airflow is Low **AND** Body Temperature is Low **AND** Number of Coughs is Medium **AND** Number of Passengers in Restaurant is Low **AND** Time of Exposure is Low **THEN** Transmission Risk is Low
4. **IF** HVAC airflow is Low **AND** Body Temperature is Low **AND** Number of Coughs is Low **AND** Number of Passengers in Restaurant is Medium **AND** Time of Exposure is Low **THEN** Transmission Risk is Low
5. **IF** HVAC airflow is Low **AND** Body Temperature is Low **AND** Number of Coughs is Low **AND** Number of Passengers in Restaurant is Low **AND** Time of Exposure is Medium **THEN** Transmission Risk is Low
6. **IF** HVAC airflow is Low **AND** Body Temperature is Medium **AND** Number of Coughs is Medium **AND** Number of Passengers in Restaurant is Low **AND** Time of Exposure is Low **THEN** Transmission Risk is Low
7. **IF** HVAC airflow is Low **AND** Body Temperature is Medium **AND** Number of Coughs is Medium **AND** Number of Passengers in Restaurant is Medium **AND** Time of Exposure is Medium **THEN** Transmission Risk is Medium
8. **IF** HVAC airflow is Low **AND** Body Temperature is High **AND** Number of Coughs is Medium **AND** Number of Passengers in Restaurant is Medium **AND** Time of Exposure is Medium **THEN** Transmission Risk is Medium
9. **IF** HVAC airflow is Low **AND** Body Temperature is High **AND** Number of Coughs is High **AND** Number of Passengers in Restaurant is Medium **AND** Time of Exposure is Medium **THEN** Transmission Risk is Medium
10. **IF** HVAC airflow is Low **AND** Body Temperature is High **AND** Number of Coughs is High **AND** Number of Passengers in Restaurant is High **AND** Time of Exposure is Medium **THEN** Transmission Risk is High
11. **IF** HVAC airflow is Low **AND** Body Temperature is High **AND** Number of Coughs is High **AND** Number of Passengers in Restaurant is High **AND** Time of Exposure is High **THEN** Transmission Risk is High
12. **IF** HVAC airflow is Low **AND** Body Temperature is Medium **AND** Number of Coughs is High **AND** Number of Passengers in Restaurant is Medium **AND** Time of Exposure is Medium **THEN** Transmission Risk is High
13. **IF** HVAC airflow is Low **AND** Body Temperature is Medium **AND** Number of Coughs is Medium **AND** Number of Passengers in Restaurant is High **AND** Time of Exposure is Medium **THEN** Transmission Risk is High
14. **IF** HVAC airflow is Low **AND** Body Temperature is Medium **AND** Number of Coughs is Medium **AND** Number of Passengers in Restaurant is Medium **AND** Time of Exposure is High **THEN** Transmission Risk is High



15. **IF** HVAC airflow is Low **AND** Body Temperature is Medium **AND** Number of Coughs is High **AND** Number of Passengers in Restaurant is High **AND** Time of Exposure is Medium **THEN** Transmission Risk is High
16. **IF** HVAC airflow is Low **AND** Body Temperature is Medium **AND** Number of Coughs is Medium **AND** Number of Passengers in Restaurant is High **AND** Time of Exposure is High **THEN** Transmission Risk is High
17. **IF** HVAC airflow is Low **AND** Body Temperature is Medium **AND** Number of Coughs is High **AND** Number of Passengers in Restaurant is High **AND** Time of Exposure is High **THEN** Transmission Risk is High
18. **IF** HVAC airflow is Medium **AND** Body Temperature is Medium **AND** Number of Coughs is Medium **AND** Number of Passengers in Restaurant is Medium **AND** Time of Exposure is Medium **THEN** Transmission Risk is Medium
19. **IF** HVAC airflow is Medium **AND** Body Temperature is Low **AND** Number of Coughs is Low **AND** Number of Passengers in Restaurant is Low **AND** Time of Exposure is Low **THEN** Transmission Risk is Low
20. **IF** HVAC airflow is Medium **AND** Body Temperature is Medium **AND** Number of Coughs is Low **AND** Number of Passengers in Restaurant is Low **AND** Time of Exposure is Low **THEN** Transmission Risk is Low
21. **IF** HVAC airflow is High **AND** Body Temperature is High **AND** Number of Coughs is Low **AND** Number of Passengers in Restaurant is Low **AND** Time of Exposure is Low **THEN** Transmission Risk is Low
22. **IF** HVAC airflow is Medium **AND** Body Temperature is High **AND** Number of Coughs is Low **AND** Number of Passengers in Restaurant is Low **AND** Time of Exposure is Low **THEN** Transmission Risk is Low
23. **IF** HVAC airflow is Medium **AND** Body Temperature is Low **AND** Number of Coughs is Medium **AND** Number of Passengers in Restaurant is Low **AND** Time of Exposure is Low **THEN** Transmission Risk is Low
24. **IF** HVAC airflow is Medium **AND** Body Temperature is Low **AND** Number of Coughs is Low **AND** Number of Passengers in Restaurant is Medium **AND** Time of Exposure is Low **THEN** Transmission Risk is Low
25. **IF** HVAC airflow is Medium **AND** Body Temperature is Low **AND** Number of Coughs is Low **AND** Number of Passengers in Restaurant is Low **AND** Time of Exposure is Medium **THEN** Transmission Risk is Low
26. **IF** HVAC airflow is Medium **AND** Body Temperature is Medium **AND** Number of Coughs is Low **AND** Number of Passengers in Restaurant is Low **AND** Time of Exposure is Low **THEN** Transmission Risk is Low



27. **IF** HVAC airflow is Medium **AND** Body Temperature is Medium **AND** Number of Coughs is Medium **AND** Number of Passengers in Restaurant is Low **AND** Time of Exposure is Low **THEN** Transmission Risk is Low
28. **IF** HVAC airflow is Medium **AND** Body Temperature is Medium **AND** Number of Coughs is Medium **AND** Number of Passengers in Restaurant is Medium **AND** Time of Exposure is Medium **THEN** Transmission Risk is Medium
29. **IF** HVAC airflow is Medium **AND** Body Temperature is High **AND** Number of Coughs is Medium **AND** Number of Passengers in Restaurant is Medium **AND** Time of Exposure is Medium **THEN** Transmission Risk is Medium
30. **IF** HVAC airflow is Medium **AND** Body Temperature is High **AND** Number of Coughs is High **AND** Number of Passengers in Restaurant is Medium **AND** Time of Exposure is Medium **THEN** Transmission Risk is Medium
31. **IF** HVAC airflow is Medium **AND** Body Temperature is High **AND** Number of Coughs is High **AND** Number of Passengers in Restaurant is High **AND** Time of Exposure is Medium **THEN** Transmission Risk is High
32. **IF** HVAC airflow is Medium **AND** Body Temperature is High **AND** Number of Coughs is High **AND** Number of Passengers in Restaurant is High **AND** Time of Exposure is High **THEN** Transmission Risk is High
33. **IF** HVAC airflow is Medium **AND** Body Temperature is Medium **AND** Number of Coughs is High **AND** Number of Passengers in Restaurant is Medium **AND** Time of Exposure is Medium **THEN** Transmission Risk is Medium
34. **IF** HVAC airflow is Medium **AND** Body Temperature is Medium **AND** Number of Coughs is Medium **AND** Number of Passengers in Restaurant is High **AND** Time of Exposure is Medium **THEN** Transmission Risk is Medium
35. **IF** HVAC airflow is Medium **AND** Body Temperature is Medium **AND** Number of Coughs is Medium **AND** Number of Passengers in Restaurant is Medium **AND** Time of Exposure is High **THEN** Transmission Risk is Medium
36. **IF** HVAC airflow is Medium **AND** Body Temperature is Medium **AND** Number of Coughs is High **AND** Number of Passengers in Restaurant is High **AND** Time of Exposure is Medium **THEN** Transmission Risk is High
37. **IF** HVAC airflow is Medium **AND** Body Temperature is Medium **AND** Number of Coughs is Medium **AND** Number of Passengers in Restaurant is High **AND** Time of Exposure is High **THEN** Transmission Risk is High
38. **IF** HVAC airflow is Medium **AND** Body Temperature is Medium **AND** Number of Coughs is High **AND** Number of Passengers in Restaurant is High **AND** Time of Exposure is High **THEN** Transmission Risk is High



39. **IF** HVAC airflow is High **AND** Body Temperature is Low **AND** Number of Coughs is Low **AND** Number of Passengers in Restaurant is Low **AND** Time of Exposure is Low **THEN** Transmission Risk is Low
40. **IF** HVAC airflow is High **AND** Body Temperature is Medium **AND** Number of Coughs is Low **AND** Number of Passengers in Restaurant is Low **AND** Time of Exposure is Low **THEN** Transmission Risk is Low
41. **IF** HVAC airflow is High **AND** Body Temperature is Low **AND** Number of Coughs is Medium **AND** Number of Passengers in Restaurant is Low **AND** Time of Exposure is Low **THEN** Transmission Risk is Low
42. **IF** HVAC airflow is High **AND** Body Temperature is Low **AND** Number of Coughs is Low **AND** Number of Passengers in Restaurant is Medium **AND** Time of Exposure is Low **THEN** Transmission Risk is Low
43. **IF** HVAC airflow is High **AND** Body Temperature is Low **AND** Number of Coughs is Low **AND** Number of Passengers in Restaurant is Low **AND** Time of Exposure is Medium **THEN** Transmission Risk is Low
44. **IF** HVAC airflow is High **AND** Body Temperature is Medium **AND** Number of Coughs is Low **AND** Number of Passengers in Restaurant is Low **AND** Time of Exposure is Low **THEN** Transmission Risk is Low
45. **IF** HVAC airflow is High **AND** Body Temperature is Medium **AND** Number of Coughs is Medium **AND** Number of Passengers in Restaurant is Low **AND** Time of Exposure is Low **THEN** Transmission Risk is Medium
46. **IF** HVAC airflow is High **AND** Body Temperature is Medium **AND** Number of Coughs is Medium **AND** Number of Passengers in Restaurant is Medium **AND** Time of Exposure is Medium **THEN** Transmission Risk is Medium
47. **IF** HVAC airflow is High **AND** Body Temperature is High **AND** Number of Coughs is Medium **AND** Number of Passengers in Restaurant is Medium **AND** Time of Exposure is Medium **THEN** Transmission Risk is High
48. **IF** HVAC airflow is High **AND** Body Temperature is High **AND** Number of Coughs is Medium **AND** Number of Passengers in Restaurant is Medium **AND** Time of Exposure is Medium **THEN** Transmission Risk is Medium
49. **IF** HVAC airflow is High **AND** Body Temperature is High **AND** Number of Coughs is High **AND** Number of Passengers in Restaurant is Medium **AND** Time of Exposure is Medium **THEN** Transmission Risk is High
50. **IF** HVAC airflow is High **AND** Body Temperature is High **AND** Number of Coughs is High **AND** Number of Passengers in Restaurant is High **AND** Time of Exposure is Medium **THEN** Transmission Risk is High



- 51. **IF** HVAC airflow is High **AND** Body Temperature is High **AND** Number of Coughs is High **AND** Number of Passengers in Restaurant is High **AND** Time of Exposure is High **THEN** Transmission Risk is High
- 52. **IF** HVAC airflow is High **AND** Body Temperature is Medium **AND** Number of Coughs is High **AND** Number of Passengers in Restaurant is Medium **AND** Time of Exposure is Medium **THEN** Transmission Risk is High
- 53. **IF** HVAC airflow is High **AND** Body Temperature is Medium **AND** Number of Coughs is Medium **AND** Number of Passengers in Restaurant is High **AND** Time of Exposure is Medium **THEN** Transmission Risk is High
- 54. **IF** HVAC airflow is High **AND** Body Temperature is Medium **AND** Number of Coughs is Medium **AND** Number of Passengers in Restaurant is Medium **AND** Time of Exposure is High **THEN** Transmission Risk is High
- 55. **IF** HVAC airflow is High **AND** Body Temperature is Medium **AND** Number of Coughs is High **AND** Number of Passengers in Restaurant is High **AND** Time of Exposure is Medium **THEN** Transmission Risk is High
- 56. **IF** HVAC airflow is High **AND** Body Temperature is Medium **AND** Number of Coughs is Medium **AND** Number of Passengers in Restaurant is High **AND** Time of Exposure is High **THEN** Transmission Risk is High
- 57. **IF** HVAC airflow is High **AND** Body Temperature is Medium **AND** Number of Coughs is High **AND** Number of Passengers in Restaurant is High **AND** Time of Exposure is High **THEN** Transmission Risk is High



Rule (No)	HVAC Airflow	Body Temperature	Number of Coughs	Number of Passengers	Time exposure	Risk
1	LOW	LOW	LOW	LOW	LOW	LOW
2	LOW	MEDIUM	LOW	LOW	LOW	LOW
3	LOW	LOW	MEDIUM	LOW	LOW	LOW
4	LOW	LOW	LOW	MEDIUM	LOW	LOW
5	LOW	LOW	LOW	LOW	MEDIUM	LOW
6	LOW	MEDIUM	MEDIUM	LOW	LOW	LOW
7	LOW	MEDIUM	MEDIUM	MEDIUM	MEDIUM	MEDIUM
8	LOW	HIGH	MEDIUM	MEDIUM	MEDIUM	MEDIUM
9	LOW	HIGH	HIGH	MEDIUM	MEDIUM	HIGH
10	LOW	HIGH	HIGH	HIGH	MEDIUM	HIGH
11	LOW	HIGH	HIGH	HIGH	HIGH	HIGH
12	LOW	MEDIUM	HIGH	MEDIUM	MEDIUM	HIGH
13	LOW	MEDIUM	MEDIUM	HIGH	MEDIUM	HIGH
14	LOW	MEDIUM	MEDIUM	MEDIUM	HIGH	HIGH
15	LOW	MEDIUM	HIGH	HIGH	MEDIUM	HIGH
16	LOW	MEDIUM	MEDIUM	HIGH	HIGH	HIGH
17	LOW	MEDIUM	HIGH	HIGH	HIGH	HIGH
18	MEDIUM	MEDIUM	MEDIUM	MEDIUM	MEDIUM	MEDIUM
19	MEDIUM	LOW	LOW	LOW	LOW	LOW
20	MEDIUM	MEDIUM	LOW	LOW	LOW	LOW
21	HIGH	HIGH	LOW	LOW	LOW	LOW
22	MEDIUM	HIGH	LOW	LOW	LOW	LOW
23	MEDIUM	LOW	MEDIUM	LOW	LOW	LOW
24	MEDIUM	LOW	LOW	MEDIUM	LOW	LOW
25	MEDIUM	LOW	LOW	LOW	MEDIUM	LOW
26	MEDIUM	MEDIUM	LOW	LOW	LOW	LOW
27	MEDIUM	MEDIUM	MEDIUM	LOW	LOW	LOW
28	MEDIUM	MEDIUM	MEDIUM	MEDIUM	MEDIUM	MEDIUM
29	MEDIUM	HIGH	MEDIUM	MEDIUM	MEDIUM	MEDIUM
30	MEDIUM	HIGH	HIGH	MEDIUM	MEDIUM	MEDIUM
31	MEDIUM	HIGH	HIGH	HIGH	MEDIUM	HIGH
32	MEDIUM	HIGH	HIGH	HIGH	HIGH	HIGH
33	MEDIUM	MEDIUM	HIGH	MEDIUM	MEDIUM	MEDIUM
34	MEDIUM	MEDIUM	MEDIUM	HIGH	MEDIUM	MEDIUM
35	MEDIUM	MEDIUM	MEDIUM	MEDIUM	HIGH	MEDIUM
36	MEDIUM	MEDIUM	HIGH	HIGH	MEDIUM	HIGH
37	MEDIUM	MEDIUM	MEDIUM	HIGH	HIGH	HIGH
38	MEDIUM	MEDIUM	HIGH	HIGH	HIGH	HIGH
39	HIGH	LOW	LOW	LOW	LOW	LOW
40	HIGH	MEDIUM	LOW	LOW	LOW	LOW
41	HIGH	LOW	MEDIUM	LOW	LOW	LOW
42	HIGH	LOW	LOW	MEDIUM	LOW	LOW
43	HIGH	LOW	LOW	LOW	MEDIUM	LOW
44	HIGH	MEDIUM	LOW	LOW	LOW	LOW
45	HIGH	MEDIUM	MEDIUM	LOW	LOW	MEDIUM
46	HIGH	MEDIUM	MEDIUM	MEDIUM	MEDIUM	MEDIUM
47	HIGH	HIGH	HIGH	HIGH	HIGH	HIGH
48	HIGH	HIGH	MEDIUM	MEDIUM	MEDIUM	MEDIUM
49	HIGH	HIGH	HIGH	MEDIUM	MEDIUM	HIGH
50	HIGH	HIGH	HIGH	HIGH	MEDIUM	HIGH
51	HIGH	HIGH	HIGH	HIGH	HIGH	HIGH
52	HIGH	MEDIUM	HIGH	MEDIUM	MEDIUM	HIGH
53	HIGH	MEDIUM	MEDIUM	HIGH	MEDIUM	HIGH
54	HIGH	MEDIUM	MEDIUM	MEDIUM	HIGH	HIGH
55	HIGH	MEDIUM	HIGH	HIGH	MEDIUM	HIGH
56	HIGH	MEDIUM	MEDIUM	HIGH	HIGH	HIGH
57	HIGH	MEDIUM	HIGH	HIGH	HIGH	HIGH

Figure 33 Overview of the generated fuzzy rules for risk assessment of COVID-19 disease spread.

Experimental Cases

To evaluate the effectiveness of the defined fuzzy rules, 8 different scenarios comprising various values of input risk factors were examined for the two types of restaurants. For each of 8 scenarios, the input factors considered were the ventilation setting as well as the max body temperature, the total number of coughs and the total number of passengers detected over a certain period of time. These scenarios are summarized in Table 10, where the parentheses contain the respective linguistic values indicating the membership of a risk factor to a respective fuzzy set (L)ow, (M)edium, or (H)igh.

The proposed method was verified using the ABM framework Vadere (Rahn et al., 2022) and a risk index, hereinafter RiskABM, defined as the total number of infected people at the end of the simulation over the total number of people in the environment. Furthermore, the RiskABM is linguistically characterized using the fuzzy sets as illustrated in Figure 33(h). The ABM framework was used to simulate 100 iterations for each case that produced corresponding RiskABM values with a standard deviation ranging from 0.05 to 0.18.



Table 10 Input risk factors for risk assessment of COVID-19 transmission for e₁/e₂ eating areas.

No.	Ventilation (m ³ /h)	Max Body Temperature (°C)	Total Number of Coughs	Total Number of Passengers	Time (min)
1	1615 (L/L)	36.6 (L)	44 (M/M)	8 (M/L)	43 (M)
2	1615 (L/L)	38.0 (M)	44 (M/M)	8 (M/L)	43 (M)
3	2977 (M/M)	37.1 (L)	109 (H/H)	38 (H/M)	56 (M)
4	2977 (M/M)	37.1 (L)	50 (L/L)	38 (H/M)	56 (M)
5	2619 (M/M)	38.7 (H)	105 (H/H)	31 (H/M)	83 (H)
6	2619 (M/M)	38.7 (H)	105 (H/H)	31 (H/M)	31 (L)
7	2964 (M/M)	40.0 (H)	107 (H/H)	34 (H/M)	48 (M)
8	4017 (H/M)	38.7 (H)	50 (M/M)	25 (H/M)	32 (L)

Table 11 Risk assessment of COVID-19 transmission for e₁/e₂ eating areas using fuzzy rules.

No.	Risk	Confidence	Risk _{ABM}
1	0.15 (L)/ 0.15 (L)	0.78/ 0.78	0.18 (L) / 0.05(L)
2	0.38 (M)/ 0.45 (M)	0.61/ 0.78	0.15 (L) / 0.23(L)
3	0.76 (H)/ 0.71 (H)	0.69/ 0.53	0.81 (H) / 0.64(H)
4	0.64 (H)/ 0.60 (H)	0.37/ 0.36	0.54 (H) / 0.42(M)
5	0.79 (H)/ 0.41 (M)	0.73/ 0.70	0.81 (H) / 0.64(H)
6	0.75 (H)/ 0.58 (H)	0.64/ 0.25	0.80 (H) / 0.60(H)
7	0.15 (L)/ 0.15 (L)	0.78/ 0.78	0.80 (H) / 0.60(H)
8	0.38 (M)/ 0.45 (M)	0.61/ 0.78	0.58 (H) / 0.42(M)

Based on the results presented in Table 11, the following observations can be made:





An increase in the total **number of passengers** in a room, depending on the room capacity, results in an increase in the risk of the spread of the disease. For example, in Case 3, there is a greater risk, *i.e.*, $Risk\ 1 = 0.76$ in Restaurant 1 (e_1), where there is a *High* number of passengers, compared to the risk of Restaurant 2 (e_2), *i.e.*, $Risk\ 2 = 0.71$, where there is a *Medium* number of passengers.

Proper use of the **HVAC** system helps reduce the risk of disease spreading. For instance, in Case 8, where the system is properly configured for Restaurant 2, the risk is estimated to be lower than for Restaurant 1, *i.e.*, $Risk\ 1 = 0.63 > Risk\ 2 = 0.60$.

- An increased **number of coughs** increases the risk of disease spreading. This can be observed when comparing Case 3 with Case 4, where for 109 and 50 coughs, the risks are 0.76 and 0.64, respectively.
- An increased **body temperature** can lead to a higher risk of disease spreading on cruise ships. For example, a *Low* body temperature equal to 36.6°C is related to a $Risk\ 1 = 0.15$ (Case 1), which is lower than $Risk\ 1 = 0.38$ (Case 2) that is related to a *Medium* body temperature (38°C).

In addition, it can be observed that, in almost all cases, the proposed method is capable of assessing the TR in accordance with the ABM framework. Moreover, in most cases the estimated TR demonstrates high confidence ensuring the certainty of the result (Table 11). However, a difference can be observed between the calculated risks for the Case 5-Restaurant 2, where $Risk\ 2$ is assigned to a *High* TR with high confidence compared to the respective $Risk_{ABM}$ that indicates a *Medium* TR. This can be attributed to the fact that the ABM framework simulates pedestrian dynamics that are not represented in the fuzzy rules. The interactions of the passengers were not incorporated into the fuzzy rules, since they could not be detected by the available sensors.

Regarding cases where the confidence of the decision-making module (fuzzy rule-based system) is low the ABM was used to increase the confidence of the RA process. For example, in Case 4 of Table 11, the decision-making module has low confidence. By utilizing the output of the ABM, the risk predicted for e_1 is validated as high, whereas for e_2 is medium.

Effect of masks and vaccination on airborne disease transmission

Masks are a key countermeasure for reducing airborne disease transmission. Depending on the type of mask their efficiency may vary from 30% for cloth masks to 91% for surgical masks and up to 99.8% for N95 masks (A.-B. Wang et al., 2023). To account for this in the fuzzy rule-based system, the number of passengers wearing masks in an area is considered as an additional risk factor. Hence, a higher total number of people wearing masks is correlated with a reduced risk of transmission. Furthermore, vaccination is another crucial preventive measure. For COVID-19, vaccine effectiveness ranges from 50% to 70% (Harder et al., 2021; Law et al., 2023). Similar to masks, the total number of vaccinated people is included as an additional risk factor, where a higher number of vaccinated passengers is correlated with a reduced risk of disease transmission.

Fuzzy Rules with masks and vaccination

1. **IF** HVAC airflow is Low **AND** Fever is Low **AND** Cough is Low **AND** Number of Passengers wearing mask is Low **AND** Time Exposure is Low **AND** Number of Vaccinated Passengers is Low **THEN** Risk is Low
2. **IF** HVAC airflow is Low **AND** Fever is Low **AND** Cough is Low **AND** Number of Passengers wearing mask is Low **AND** Time Exposure is Low **AND** Number of Vaccinated Passengers is Medium **THEN** Risk is Low





3. **IF** HVAC airflow is Low **AND** Fever is Low **AND** Cough is Low **AND** Number of Passengers wearing mask is Low **AND** Time Exposure is Low **AND** Number of Vaccinated Passengers is High **THEN** Risk is Low
4. **IF** HVAC airflow is Low **AND** Fever is Medium **AND** Cough is Low **AND** Number of Passengers wearing mask is Low **AND** Time Exposure is Low **AND** Number of Vaccinated Passengers is Low **THEN** Risk is Low
5. **IF** HVAC airflow is Low **AND** Fever is Medium **AND** Cough is Low **AND** Number of Passengers wearing mask is Low **AND** Time Exposure is Low **AND** Number of Vaccinated Passengers is Medium **THEN** Risk is Low
6. **IF** HVAC airflow is Low **AND** Fever is Medium **AND** Cough is Low **AND** Number of Passengers wearing mask is Low **AND** Time Exposure is Low **AND** Number of Vaccinated Passengers is High **THEN** Risk is Low
7. **IF** HVAC airflow is Low **AND** Fever is Low **AND** Cough is Medium **AND** Number of Passengers wearing mask is Low **AND** Time Exposure is Low **AND** Number of Vaccinated Passengers is Low **THEN** Risk is Low
8. **IF** HVAC airflow is Low **AND** Fever is Low **AND** Cough is Medium **AND** Number of Passengers wearing mask is Low **AND** Time Exposure is Low **AND** Number of Vaccinated Passengers is Medium **THEN** Risk is Low
9. **IF** HVAC airflow is Low **AND** Fever is Low **AND** Cough is Medium **AND** Number of Passengers wearing mask is Low **AND** Time Exposure is Low **AND** Number of Vaccinated Passengers is High **THEN** Risk is Low
10. **IF** HVAC airflow is Low **AND** Fever is Low **AND** Cough is Low **AND** Number of Passengers wearing mask is Medium **AND** Time Exposure is Low **AND** Number of Vaccinated Passengers is Low **THEN** Risk is Low
11. **IF** HVAC airflow is Low **AND** Fever is Low **AND** Cough is Low **AND** Number of Passengers wearing mask is Medium **AND** Time Exposure is Low **AND** Number of Vaccinated Passengers is Medium **THEN** Risk is Low
12. **IF** HVAC airflow is Low **AND** Fever is Low **AND** Cough is Low **AND** Number of Passengers wearing mask is Medium **AND** Time Exposure is Low **AND** Number of Vaccinated Passengers is High **THEN** Risk is Low
13. **IF** HVAC airflow is Low **AND** Fever is Low **AND** Cough is Low **AND** Number of Passengers wearing mask is Low **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is Low **THEN** Risk is Low
14. **IF** HVAC airflow is Low **AND** Fever is Low **AND** Cough is Low **AND** Number of Passengers wearing mask is Low **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is Medium **THEN** Risk is Low
15. **IF** HVAC airflow is Low **AND** Fever is Low **AND** Cough is Low **AND** Number of Passengers wearing mask is Low **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is High **THEN** Risk is Low
16. **IF** HVAC airflow is Low **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers wearing mask is Low **AND** Time Exposure is Low **AND** Number of Vaccinated Passengers is Low **THEN** Risk is Low
17. **IF** HVAC airflow is Low **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers wearing mask is Low **AND** Time Exposure is Low **AND** Number of Vaccinated Passengers is Medium **THEN** Risk is Low
18. **IF** HVAC airflow is Low **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers wearing mask is Low **AND** Time Exposure is Low **AND** Number of Vaccinated Passengers is High **THEN** Risk is Low



19. **IF** HVAC airflow is Low **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers wearing mask is Medium **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is Low **THEN** Risk is Low
20. **IF** HVAC airflow is Low **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers wearing mask is Medium **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is Medium **THEN** Risk is Low
21. **IF** HVAC airflow is Low **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers wearing mask is Medium **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is High **THEN** Risk is Low
22. **IF** HVAC airflow is Low **AND** Fever is High **AND** Cough is Medium **AND** Number of Passengers wearing mask is Medium **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is Low **THEN** Risk is Low
23. **IF** HVAC airflow is Low **AND** Fever is High **AND** Cough is Medium **AND** Number of Passengers wearing mask is Medium **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is Medium **THEN** Risk is Low
24. **IF** HVAC airflow is Low **AND** Fever is High **AND** Cough is Medium **AND** Number of Passengers wearing mask is Medium **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is High **THEN** Risk is Low
25. **IF** HVAC airflow is Low **AND** Fever is High **AND** Cough is High **AND** Number of Passengers wearing mask is Medium **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is Low **THEN** Risk is Low
26. **IF** HVAC airflow is Low **AND** Fever is High **AND** Cough is High **AND** Number of Passengers wearing mask is Medium **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is Medium **THEN** Risk is Low
27. **IF** HVAC airflow is Low **AND** Fever is High **AND** Cough is High **AND** Number of Passengers wearing mask is Medium **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is High **THEN** Risk is Low
28. **IF** HVAC airflow is Low **AND** Fever is High **AND** Cough is High **AND** Number of Passengers wearing mask is High **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is Low **THEN** Risk is Low
29. **IF** HVAC airflow is Low **AND** Fever is High **AND** Cough is High **AND** Number of Passengers wearing mask is High **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is Medium **THEN** Risk is Low
30. **IF** HVAC airflow is Low **AND** Fever is High **AND** Cough is High **AND** Number of Passengers wearing mask is High **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is High **THEN** Risk is Low
31. **IF** HVAC airflow is Low **AND** Fever is High **AND** Cough is High **AND** Number of Passengers wearing mask is High **AND** Time Exposure is High **AND** Number of Vaccinated Passengers is Low **THEN** Risk is Low
32. **IF** HVAC airflow is Low **AND** Fever is High **AND** Cough is High **AND** Number of Passengers wearing mask is High **AND** Time Exposure is High **AND** Number of Vaccinated Passengers is Medium **THEN** Risk is Low
33. **IF** HVAC airflow is Low **AND** Fever is High **AND** Cough is High **AND** Number of Passengers wearing mask is High **AND** Time Exposure is High **AND** Number of Vaccinated Passengers is High **THEN** Risk is Low
34. **IF** HVAC airflow is Low **AND** Fever is Medium **AND** Cough is High **AND** Number of Passengers wearing mask is Medium **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is Low **THEN** Risk is Low



35. **IF** HVAC airflow is Low **AND** Fever is Medium **AND** Cough is High **AND** Number of Passengers wearing mask is Medium **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is Medium **THEN** Risk is Low
36. **IF** HVAC airflow is Low **AND** Fever is Medium **AND** Cough is High **AND** Number of Passengers wearing mask is Medium **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is High **THEN** Risk is Low
37. **IF** HVAC airflow is Low **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers wearing mask is High **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is Low **THEN** Risk is Low
38. **IF** HVAC airflow is Low **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers wearing mask is High **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is Medium **THEN** Risk is Low
39. **IF** HVAC airflow is Low **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers wearing mask is High **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is High **THEN** Risk is Low
40. **IF** HVAC airflow is Low **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers wearing mask is Medium **AND** Time Exposure is High **AND** Number of Vaccinated Passengers is Low **THEN** Risk is Medium
41. **IF** HVAC airflow is Low **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers wearing mask is Medium **AND** Time Exposure is High **AND** Number of Vaccinated Passengers is Medium **THEN** Risk is Low
42. **IF** HVAC airflow is Low **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers wearing mask is Medium **AND** Time Exposure is High **AND** Number of Vaccinated Passengers is High **THEN** Risk is Low
43. **IF** HVAC airflow is Low **AND** Fever is Medium **AND** Cough is High **AND** Number of Passengers wearing mask is High **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is Low **THEN** Risk is Low
44. **IF** HVAC airflow is Low **AND** Fever is Medium **AND** Cough is High **AND** Number of Passengers wearing mask is High **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is Medium **THEN** Risk is Low
45. **IF** HVAC airflow is Low **AND** Fever is Medium **AND** Cough is High **AND** Number of Passengers wearing mask is High **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is High **THEN** Risk is Low
46. **IF** HVAC airflow is Low **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers wearing mask is High **AND** Time Exposure is High **AND** Number of Vaccinated Passengers is Low **THEN** Risk is Medium
47. **IF** HVAC airflow is Low **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers wearing mask is High **AND** Time Exposure is High **AND** Number of Vaccinated Passengers is Medium **THEN** Risk is Low
48. **IF** HVAC airflow is Low **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers wearing mask is High **AND** Time Exposure is High **AND** Number of Vaccinated Passengers is High **THEN** Risk is Low
49. **IF** HVAC airflow is Low **AND** Fever is Medium **AND** Cough is High **AND** Number of Passengers wearing mask is High **AND** Time Exposure is High **AND** Number of Vaccinated Passengers is Low **THEN** Risk is Medium
50. **IF** HVAC airflow is Low **AND** Fever is Medium **AND** Cough is High **AND** Number of Passengers wearing mask is High **AND** Time Exposure is High **AND** Number of Vaccinated Passengers is Medium **THEN** Risk is Low



51. **IF** HVAC airflow is Low **AND** Fever is Medium **AND** Cough is High **AND** Number of Passengers wearing mask is High **AND** Time Exposure is High **AND** Number of Vaccinated Passengers is High **THEN** Risk is Low
52. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers wearing mask is Medium **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is Low **THEN** Risk is Medium
53. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers wearing mask is Medium **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is Medium **THEN** Risk is Low
54. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers wearing mask is Medium **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is High **THEN** Risk is Low
55. **IF** HVAC airflow is Medium **AND** Fever is Low **AND** Cough is Low **AND** Number of Passengers wearing mask is Low **AND** Time Exposure is Low **AND** Number of Vaccinated Passengers is Low **THEN** Risk is Low
56. **IF** HVAC airflow is Medium **AND** Fever is Low **AND** Cough is Low **AND** Number of Passengers wearing mask is Low **AND** Time Exposure is Low **AND** Number of Vaccinated Passengers is Medium **THEN** Risk is Low
57. **IF** HVAC airflow is Medium **AND** Fever is Low **AND** Cough is Low **AND** Number of Passengers wearing mask is Low **AND** Time Exposure is Low **AND** Number of Vaccinated Passengers is High **THEN** Risk is Low
58. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is Low **AND** Number of Passengers wearing mask is Low **AND** Time Exposure is Low **AND** Number of Vaccinated Passengers is Low **THEN** Risk is Low
59. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is Low **AND** Number of Passengers wearing mask is Low **AND** Time Exposure is Low **AND** Number of Vaccinated Passengers is Medium **THEN** Risk is Low
60. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is Low **AND** Number of Passengers wearing mask is Low **AND** Time Exposure is Low **AND** Number of Vaccinated Passengers is High **THEN** Risk is Low
61. **IF** HVAC airflow is High **AND** Fever is High **AND** Cough is Low **AND** Number of Passengers wearing mask is Low **AND** Time Exposure is Low **AND** Number of Vaccinated Passengers is Low **THEN** Risk is Low
62. **IF** HVAC airflow is High **AND** Fever is High **AND** Cough is Low **AND** Number of Passengers wearing mask is Low **AND** Time Exposure is Low **AND** Number of Vaccinated Passengers is Medium **THEN** Risk is Low
63. **IF** HVAC airflow is High **AND** Fever is High **AND** Cough is Low **AND** Number of Passengers wearing mask is Low **AND** Time Exposure is Low **AND** Number of Vaccinated Passengers is High **THEN** Risk is Low
64. **IF** HVAC airflow is Medium **AND** Fever is High **AND** Cough is Low **AND** Number of Passengers wearing mask is Low **AND** Time Exposure is Low **AND** Number of Vaccinated Passengers is Low **THEN** Risk is Low
65. **IF** HVAC airflow is Medium **AND** Fever is High **AND** Cough is Low **AND** Number of Passengers wearing mask is Low **AND** Time Exposure is Low **AND** Number of Vaccinated Passengers is Medium **THEN** Risk is Low
66. **IF** HVAC airflow is Medium **AND** Fever is High **AND** Cough is Low **AND** Number of Passengers wearing mask is Low **AND** Time Exposure is Low **AND** Number of Vaccinated Passengers is High **THEN** Risk is Low



67. **IF** HVAC airflow is Medium **AND** Fever is Low **AND** Cough is Medium **AND** Number of Passengers wearing mask is Low **AND** Time Exposure is Low **AND** Number of Vaccinated Passengers is Low **THEN** Risk is Low
68. **IF** HVAC airflow is Medium **AND** Fever is Low **AND** Cough is Medium **AND** Number of Passengers wearing mask is Low **AND** Time Exposure is Low **AND** Number of Vaccinated Passengers is Medium **THEN** Risk is Low
69. **IF** HVAC airflow is Medium **AND** Fever is Low **AND** Cough is Medium **AND** Number of Passengers wearing mask is Low **AND** Time Exposure is Low **AND** Number of Vaccinated Passengers is High **THEN** Risk is Low
70. **IF** HVAC airflow is Medium **AND** Fever is Low **AND** Cough is Low **AND** Number of Passengers wearing mask is Medium **AND** Time Exposure is Low **AND** Number of Vaccinated Passengers is Low **THEN** Risk is Low
71. **IF** HVAC airflow is Medium **AND** Fever is Low **AND** Cough is Low **AND** Number of Passengers wearing mask is Medium **AND** Time Exposure is Low **AND** Number of Vaccinated Passengers is Medium **THEN** Risk is Low
72. **IF** HVAC airflow is Medium **AND** Fever is Low **AND** Cough is Low **AND** Number of Passengers wearing mask is Medium **AND** Time Exposure is Low **AND** Number of Vaccinated Passengers is High **THEN** Risk is Low
73. **IF** HVAC airflow is Medium **AND** Fever is Low **AND** Cough is Low **AND** Number of Passengers wearing mask is Low **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is Low **THEN** Risk is Low
74. **IF** HVAC airflow is Medium **AND** Fever is Low **AND** Cough is Low **AND** Number of Passengers wearing mask is Low **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is Medium **THEN** Risk is Low
75. **IF** HVAC airflow is Medium **AND** Fever is Low **AND** Cough is Low **AND** Number of Passengers wearing mask is Low **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is High **THEN** Risk is Low
76. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is Low **AND** Number of Passengers wearing mask is Low **AND** Time Exposure is Low **AND** Number of Vaccinated Passengers is Low **THEN** Risk is Low
77. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is Low **AND** Number of Passengers wearing mask is Low **AND** Time Exposure is Low **AND** Number of Vaccinated Passengers is Medium **THEN** Risk is Low
78. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is Low **AND** Number of Passengers wearing mask is Low **AND** Time Exposure is Low **AND** Number of Vaccinated Passengers is High **THEN** Risk is Low
79. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers wearing mask is Low **AND** Time Exposure is Low **AND** Number of Vaccinated Passengers is Low **THEN** Risk is Low
80. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers wearing mask is Low **AND** Time Exposure is Low **AND** Number of Vaccinated Passengers is Medium **THEN** Risk is Low
81. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers wearing mask is Low **AND** Time Exposure is Low **AND** Number of Vaccinated Passengers is High **THEN** Risk is Low
82. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers wearing mask is Medium **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is Low **THEN** Risk is Medium



83. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers wearing mask is Medium **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is Medium **THEN** Risk is Low
84. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers wearing mask is Medium **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is High **THEN** Risk is Low
85. **IF** HVAC airflow is Medium **AND** Fever is High **AND** Cough is Medium **AND** Number of Passengers wearing mask is Medium **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is Low **THEN** Risk is Low
86. **IF** HVAC airflow is Medium **AND** Fever is High **AND** Cough is Medium **AND** Number of Passengers wearing mask is Medium **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is Medium **THEN** Risk is Low
87. **IF** HVAC airflow is Medium **AND** Fever is High **AND** Cough is Medium **AND** Number of Passengers wearing mask is Medium **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is High **THEN** Risk is Low
88. **IF** HVAC airflow is Medium **AND** Fever is High **AND** Cough is High **AND** Number of Passengers wearing mask is Medium **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is Low **THEN** Risk is Medium
89. **IF** HVAC airflow is Medium **AND** Fever is High **AND** Cough is High **AND** Number of Passengers wearing mask is Medium **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is Medium **THEN** Risk is Low
90. **IF** HVAC airflow is Medium **AND** Fever is High **AND** Cough is High **AND** Number of Passengers wearing mask is Medium **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is High **THEN** Risk is Low
91. **IF** HVAC airflow is Medium **AND** Fever is High **AND** Cough is High **AND** Number of Passengers wearing mask is High **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is Low **THEN** Risk is Low
92. **IF** HVAC airflow is Medium **AND** Fever is High **AND** Cough is High **AND** Number of Passengers wearing mask is High **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is Medium **THEN** Risk is Low
93. **IF** HVAC airflow is Medium **AND** Fever is High **AND** Cough is High **AND** Number of Passengers wearing mask is High **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is High **THEN** Risk is Low
94. **IF** HVAC airflow is Medium **AND** Fever is High **AND** Cough is High **AND** Number of Passengers wearing mask is High **AND** Time Exposure is High **AND** Number of Vaccinated Passengers is Low **THEN** Risk is Low
95. **IF** HVAC airflow is Medium **AND** Fever is High **AND** Cough is High **AND** Number of Passengers wearing mask is High **AND** Time Exposure is High **AND** Number of Vaccinated Passengers is Medium **THEN** Risk is Low
96. **IF** HVAC airflow is Medium **AND** Fever is High **AND** Cough is High **AND** Number of Passengers wearing mask is High **AND** Time Exposure is High **AND** Number of Vaccinated Passengers is High **THEN** Risk is Low
97. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is High **AND** Number of Passengers wearing mask is Medium **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is Low **THEN** Risk is Low
98. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is High **AND** Number of Passengers wearing mask is Medium **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is Medium **THEN** Risk is Low



99. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is High **AND** Number of Passengers wearing mask is Medium **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is High **THEN** Risk is Low
100. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers wearing mask is High **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is Low **THEN** Risk is Low
101. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers wearing mask is High **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is Medium **THEN** Risk is Low
102. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers wearing mask is High **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is High **THEN** Risk is Low
103. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers wearing mask is Medium **AND** Time Exposure is High **AND** Number of Vaccinated Passengers is Low **THEN** Risk is Low
104. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers wearing mask is Medium **AND** Time Exposure is High **AND** Number of Vaccinated Passengers is Medium **THEN** Risk is Low
105. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers wearing mask is Medium **AND** Time Exposure is High **AND** Number of Vaccinated Passengers is High **THEN** Risk is Low
106. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is High **AND** Number of Passengers wearing mask is High **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is Low **THEN** Risk is Low
107. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is High **AND** Number of Passengers wearing mask is High **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is Medium **THEN** Risk is Low
108. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is High **AND** Number of Passengers wearing mask is High **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is High **THEN** Risk is Low
109. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers wearing mask is High **AND** Time Exposure is High **AND** Number of Vaccinated Passengers is Low **THEN** Risk is Low
110. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers wearing mask is High **AND** Time Exposure is High **AND** Number of Vaccinated Passengers is Medium **THEN** Risk is Low
111. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers wearing mask is High **AND** Time Exposure is High **AND** Number of Vaccinated Passengers is High **THEN** Risk is Low
112. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is High **AND** Number of Passengers wearing mask is High **AND** Time Exposure is High **AND** Number of Vaccinated Passengers is Low **THEN** Risk is Low
113. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is High **AND** Number of Passengers wearing mask is High **AND** Time Exposure is High **AND** Number of Vaccinated Passengers is Medium **THEN** Risk is Low
114. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is High **AND** Number of Passengers wearing mask is High **AND** Time Exposure is High **AND** Number of Vaccinated Passengers is High **THEN** Risk is Low



115. **IF** HVAC airflow is High **AND** Fever is Low **AND** Cough is Low **AND** Number of Passengers wearing mask is Low **AND** Time Exposure is Low **AND** Number of Vaccinated Passengers is Low **THEN** Risk is Low
116. **IF** HVAC airflow is High **AND** Fever is Low **AND** Cough is Low **AND** Number of Passengers wearing mask is Low **AND** Time Exposure is Low **AND** Number of Vaccinated Passengers is Medium **THEN** Risk is Low
117. **IF** HVAC airflow is High **AND** Fever is Low **AND** Cough is Low **AND** Number of Passengers wearing mask is Low **AND** Time Exposure is Low **AND** Number of Vaccinated Passengers is High **THEN** Risk is Low
118. **IF** HVAC airflow is High **AND** Fever is Medium **AND** Cough is Low **AND** Number of Passengers wearing mask is Low **AND** Time Exposure is Low **AND** Number of Vaccinated Passengers is Low **THEN** Risk is Low
119. **IF** HVAC airflow is High **AND** Fever is Medium **AND** Cough is Low **AND** Number of Passengers wearing mask is Low **AND** Time Exposure is Low **AND** Number of Vaccinated Passengers is Medium **THEN** Risk is Low
120. **IF** HVAC airflow is High **AND** Fever is Medium **AND** Cough is Low **AND** Number of Passengers wearing mask is Low **AND** Time Exposure is Low **AND** Number of Vaccinated Passengers is High **THEN** Risk is Low
121. **IF** HVAC airflow is High **AND** Fever is Low **AND** Cough is Medium **AND** Number of Passengers wearing mask is Low **AND** Time Exposure is Low **AND** Number of Vaccinated Passengers is Low **THEN** Risk is Low
122. **IF** HVAC airflow is High **AND** Fever is Low **AND** Cough is Medium **AND** Number of Passengers wearing mask is Low **AND** Time Exposure is Low **AND** Number of Vaccinated Passengers is Medium **THEN** Risk is Low
123. **IF** HVAC airflow is High **AND** Fever is Low **AND** Cough is Medium **AND** Number of Passengers wearing mask is Low **AND** Time Exposure is Low **AND** Number of Vaccinated Passengers is High **THEN** Risk is Low
124. **IF** HVAC airflow is High **AND** Fever is Low **AND** Cough is Low **AND** Number of Passengers wearing mask is Medium **AND** Time Exposure is Low **AND** Number of Vaccinated Passengers is Low **THEN** Risk is Low
125. **IF** HVAC airflow is High **AND** Fever is Low **AND** Cough is Low **AND** Number of Passengers wearing mask is Medium **AND** Time Exposure is Low **AND** Number of Vaccinated Passengers is Medium **THEN** Risk is Low
126. **IF** HVAC airflow is High **AND** Fever is Low **AND** Cough is Low **AND** Number of Passengers wearing mask is Medium **AND** Time Exposure is Low **AND** Number of Vaccinated Passengers is High **THEN** Risk is Low
127. **IF** HVAC airflow is High **AND** Fever is Low **AND** Cough is Low **AND** Number of Passengers wearing mask is Low **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is Low **THEN** Risk is Low
128. **IF** HVAC airflow is High **AND** Fever is Low **AND** Cough is Low **AND** Number of Passengers wearing mask is Low **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is Medium **THEN** Risk is Low
129. **IF** HVAC airflow is High **AND** Fever is Low **AND** Cough is Low **AND** Number of Passengers wearing mask is Low **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is High **THEN** Risk is Low
130. **IF** HVAC airflow is High **AND** Fever is Medium **AND** Cough is Low **AND** Number of Passengers wearing mask is Low **AND** Time Exposure is Low **AND** Number of Vaccinated Passengers is Low **THEN** Risk is Low



131. **IF** HVAC airflow is High **AND** Fever is Medium **AND** Cough is Low **AND** Number of Passengers wearing mask is Low **AND** Time Exposure is Low **AND** Number of Vaccinated Passengers is Medium **THEN** Risk is Low
132. **IF** HVAC airflow is High **AND** Fever is Medium **AND** Cough is Low **AND** Number of Passengers wearing mask is Low **AND** Time Exposure is Low **AND** Number of Vaccinated Passengers is High **THEN** Risk is Low
133. **IF** HVAC airflow is High **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers wearing mask is Low **AND** Time Exposure is Low **AND** Number of Vaccinated Passengers is Low **THEN** Risk is Low
134. **IF** HVAC airflow is High **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers wearing mask is Low **AND** Time Exposure is Low **AND** Number of Vaccinated Passengers is Medium **THEN** Risk is Low
135. **IF** HVAC airflow is High **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers wearing mask is Low **AND** Time Exposure is Low **AND** Number of Vaccinated Passengers is High **THEN** Risk is Low
136. **IF** HVAC airflow is High **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers wearing mask is Medium **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is Low **THEN** Risk is Medium
137. **IF** HVAC airflow is High **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers wearing mask is Medium **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is Medium **THEN** Risk is Low
138. **IF** HVAC airflow is High **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers wearing mask is Medium **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is High **THEN** Risk is Low
139. **IF** HVAC airflow is High **AND** Fever is High **AND** Cough is High **AND** Number of Passengers wearing mask is High **AND** Time Exposure is High **AND** Number of Vaccinated Passengers is Low **THEN** Risk is Medium
140. **IF** HVAC airflow is High **AND** Fever is High **AND** Cough is High **AND** Number of Passengers wearing mask is High **AND** Time Exposure is High **AND** Number of Vaccinated Passengers is Medium **THEN** Risk is Medium
141. **IF** HVAC airflow is High **AND** Fever is High **AND** Cough is High **AND** Number of Passengers wearing mask is High **AND** Time Exposure is High **AND** Number of Vaccinated Passengers is High **THEN** Risk is Medium
142. **IF** HVAC airflow is High **AND** Fever is High **AND** Cough is Medium **AND** Number of Passengers wearing mask is Medium **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is Low **THEN** Risk is Medium
143. **IF** HVAC airflow is High **AND** Fever is High **AND** Cough is Medium **AND** Number of Passengers wearing mask is Medium **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is Medium **THEN** Risk is Low
144. **IF** HVAC airflow is High **AND** Fever is High **AND** Cough is Medium **AND** Number of Passengers wearing mask is Medium **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is High **THEN** Risk is Low
145. **IF** HVAC airflow is High **AND** Fever is High **AND** Cough is High **AND** Number of Passengers wearing mask is Medium **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is Low **THEN** Risk is Medium
146. **IF** HVAC airflow is High **AND** Fever is High **AND** Cough is High **AND** Number of Passengers wearing mask is Medium **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is Medium **THEN** Risk is Low



147. **IF** HVAC airflow is High **AND** Fever is High **AND** Cough is High **AND** Number of Passengers wearing mask is Medium **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is High **THEN** Risk is Low
148. **IF** HVAC airflow is High **AND** Fever is High **AND** Cough is High **AND** Number of Passengers wearing mask is High **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is Low **THEN** Risk is Medium
149. **IF** HVAC airflow is High **AND** Fever is High **AND** Cough is High **AND** Number of Passengers wearing mask is High **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is Medium **THEN** Risk is Low
150. **IF** HVAC airflow is High **AND** Fever is High **AND** Cough is High **AND** Number of Passengers wearing mask is High **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is High **THEN** Risk is Low
151. **IF** HVAC airflow is High **AND** Fever is High **AND** Cough is High **AND** Number of Passengers wearing mask is High **AND** Time Exposure is High **AND** Number of Vaccinated Passengers is Low **THEN** Risk is Medium
152. **IF** HVAC airflow is High **AND** Fever is High **AND** Cough is High **AND** Number of Passengers wearing mask is High **AND** Time Exposure is High **AND** Number of Vaccinated Passengers is Medium **THEN** Risk is Medium
153. **IF** HVAC airflow is High **AND** Fever is High **AND** Cough is High **AND** Number of Passengers wearing mask is High **AND** Time Exposure is High **AND** Number of Vaccinated Passengers is High **THEN** Risk is Low
154. **IF** HVAC airflow is High **AND** Fever is Medium **AND** Cough is High **AND** Number of Passengers wearing mask is Medium **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is Low **THEN** Risk is Medium
155. **IF** HVAC airflow is High **AND** Fever is Medium **AND** Cough is High **AND** Number of Passengers wearing mask is Medium **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is Medium **THEN** Risk is Low
156. **IF** HVAC airflow is High **AND** Fever is Medium **AND** Cough is High **AND** Number of Passengers wearing mask is Medium **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is High **THEN** Risk is Low
157. **IF** HVAC airflow is High **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers wearing mask is High **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is Low **THEN** Risk is Low
158. **IF** HVAC airflow is High **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers wearing mask is High **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is Medium **THEN** Risk is Low
159. **IF** HVAC airflow is High **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers wearing mask is High **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is High **THEN** Risk is Low
160. **IF** HVAC airflow is High **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers wearing mask is Medium **AND** Time Exposure is High **AND** Number of Vaccinated Passengers is Low **THEN** Risk is Medium
161. **IF** HVAC airflow is High **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers wearing mask is Medium **AND** Time Exposure is High **AND** Number of Vaccinated Passengers is Medium **THEN** Risk is Low
162. **IF** HVAC airflow is High **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers wearing mask is Medium **AND** Time Exposure is High **AND** Number of Vaccinated Passengers is High **THEN** Risk is Low



163. **IF** HVAC airflow is High **AND** Fever is Medium **AND** Cough is High **AND** Number of Passengers wearing mask is High **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is Low **THEN** Risk is Low
164. **IF** HVAC airflow is High **AND** Fever is Medium **AND** Cough is High **AND** Number of Passengers wearing mask is High **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is Medium **THEN** Risk is Low
165. **IF** HVAC airflow is High **AND** Fever is Medium **AND** Cough is High **AND** Number of Passengers wearing mask is High **AND** Time Exposure is Medium **AND** Number of Vaccinated Passengers is High **THEN** Risk is Low
166. **IF** HVAC airflow is High **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers wearing mask is High **AND** Time Exposure is High **AND** Number of Vaccinated Passengers is Low **THEN** Risk is Low
167. **IF** HVAC airflow is High **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers wearing mask is High **AND** Time Exposure is High **AND** Number of Vaccinated Passengers is Medium **THEN** Risk is Low
168. **IF** HVAC airflow is High **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers wearing mask is High **AND** Time Exposure is High **AND** Number of Vaccinated Passengers is High **THEN** Risk is Low
169. **IF** HVAC airflow is High **AND** Fever is Medium **AND** Cough is High **AND** Number of Passengers wearing mask is High **AND** Time Exposure is High **AND** Number of Vaccinated Passengers is Low **THEN** Risk is Low
170. **IF** HVAC airflow is High **AND** Fever is Medium **AND** Cough is High **AND** Number of Passengers wearing mask is High **AND** Time Exposure is High **AND** Number of Vaccinated Passengers is Medium **THEN** Risk is Low
171. **IF** HVAC airflow is High **AND** Fever is Medium **AND** Cough is High **AND** Number of Passengers wearing mask is High **AND** Time Exposure is High **AND** Number of Vaccinated Passengers is High **THEN** Risk is Low



Experimental cases with masks and vaccination

Several combinations of risk factor values were examined for both monitored environments e_1 and e_2 . This experimental setup can be observed in Table 12.

Table 12 Experimental cases with enhanced risk factors for e_1/e_2 .

No.	Ventilation (m ³ /h)	Max Body Temperature (°C)	Total Number of Coughs	Total Number of Passengers with	Time	Passengers with vaccination
1	1617 (L)	36.6 (L)	48 (M)	10 (M)	40 (M)	10 (M)
2	1617 (L)	38.3 (M)	48 (M)	20 (H)	50 (M)	35 (H)
3	2972 (M)	37.3 (M)	43 (M)	37 (H)	80 (H)	21 (H)
4	2611 (M)	39 (H)	115 (H)	30 (H)	91 (H)	20 (H)
5	2599 (M)	39 (H)	124 (H)	13 (M)	56 (M)	17 (H)

Based on the results observed in Table 13, it can be inferred that the use of masks is an important countermeasure to disease transmission. In addition, increased number of vaccinated passengers may mitigate the risk of disease transmission, since vaccination increases the infection resistance of the passengers.

Table 13 Risk assessment of COVID-19 transmission using enhanced fuzzy rules.

No.	Risk	Confidence	Risk _{ABM}
1	0.1512 (L)	0.75	0.155 (L)
2	0.16 (L)	0.81	0.25 (L)
3	0.16 (L)	0.80	0.14 (L)
4	0.19 (L)	0.98	0.157 (L)
5	0.20 (L)	0.93	0.12 (L)

5.1.2 Vessel's other high-risk public spaces

Two representative bar areas of the World Dream ship were selected for the experiments related to high-risk public spaces of the ship. These areas, due to increased mobility and relaxed safe distance policies between the passengers, can lead to scenarios of high transmission risk (Figures 7-9). The bar areas examined are presented in Figure 34. The two examined indoor environments, *i.e.*, e_1 and e_2 had surface areas of 351 m² and 250 m², respectively. The capacity of e_1 and e_2 was set to 81 and 44 people, respectively. Both of the bar areas had a height of 3.2 m.

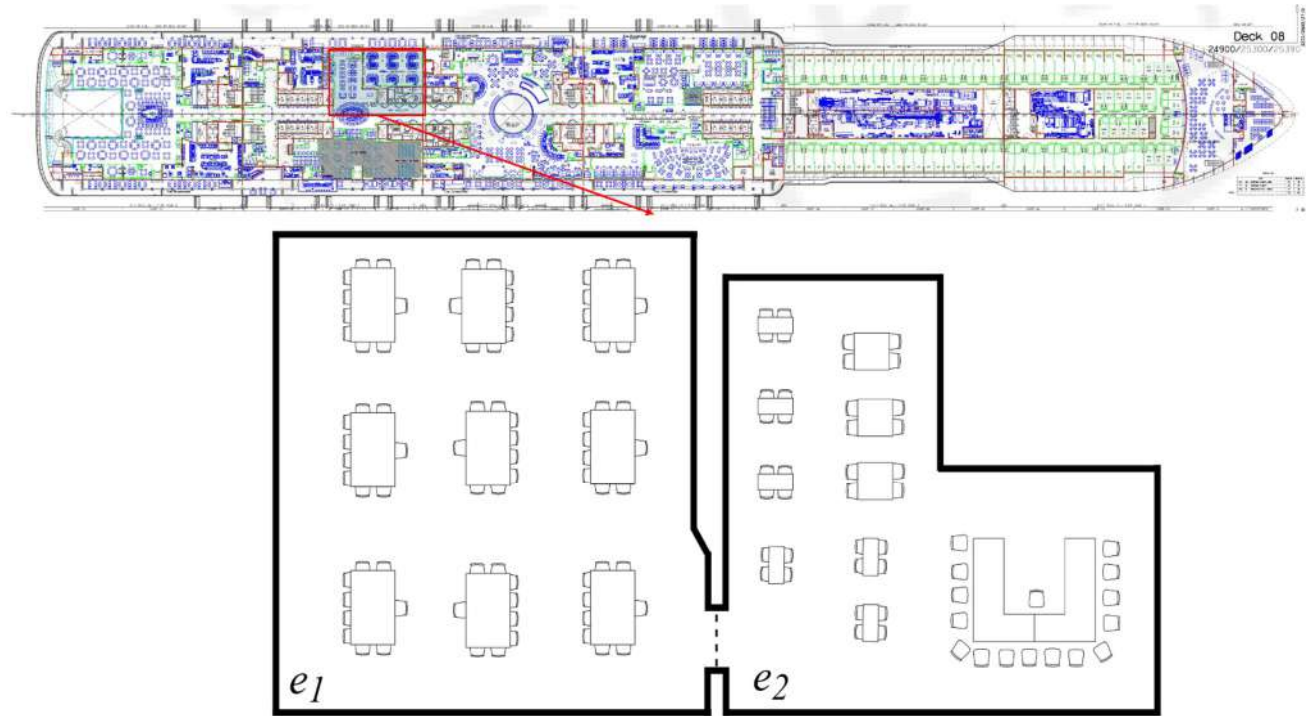


Figure 34 Topography of the two examined bar areas e_1 and e_2 residing in Deck 08, highlighted with red.

Analysis of Risk factors

The risk factors considered in these experiments were the same as in Subsection 5.1.1. An additional risk factor was considered to accommodate the poor distancing conditions in such scenarios. This risk factor, hereinafter contact distance, considers the dynamics of droplet dispersion in the area based on CFD studies that examined the maximum reach of droplets for different ventilation settings in a public indoor area. (Triantafyllou, Kalozoumis, et al., 2024). The area occupied by a person is defined by a surface, D (m²), of a circle with a radius, r (m), similarly to the Subsection 5.1.1. Since the surface area of the room is constant r depends on the number of people inside the room. Therefore, considering that each person occupies a surface area of $D = 1$ m², the radius r is defined as the contact distance between the individuals in a room. Therefore, considering that droplets emitted through coughing can spread up to 1 m (Ritos et al., 2023, 2024), the risk increases when $2 \cdot r < 1$ m and decreases when $2 \cdot r \geq 1$ m (Figure 35). When $2 \cdot r \geq 2$ m the individuals are considered safely distanced (Organization & others, 2020a).

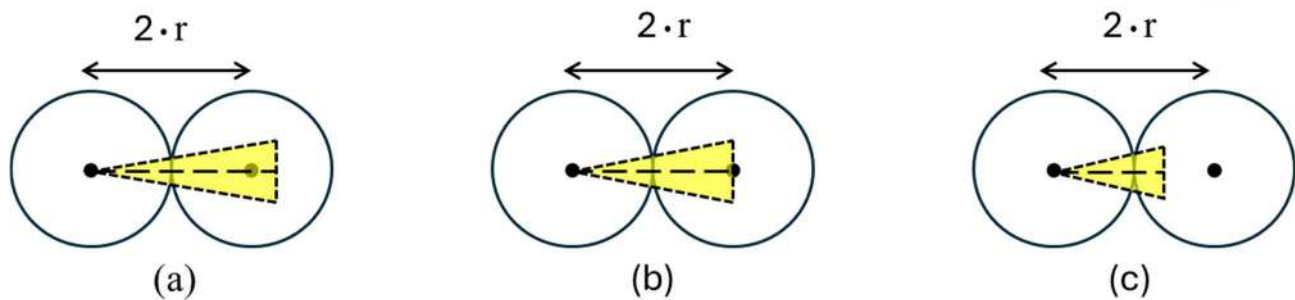


Figure 35 TR in a room depending on the distance between r and d_c . For the cases (a) $2 \cdot r < 1$, (b) $2 \cdot r = 1$, and (c) $2 \cdot r > 1$.

The correlation between the Contact Distance risk factor and the risk of COVID-19 transmission can be summarized in Table 14.

Table 14 Correlation of risk of COVID-19 transmission with Contact Distance.

Risk factors	Impact on Transmission Risk	
1. Contact Distance	Lower $\uparrow$	Higher $\downarrow$

Fuzzy Rules

Appropriate fuzzy rules were generated based on experts' knowledge resulting in 154 fuzzy rules. This set contained more rules due to the additional risk factors. The fuzzy rule set is presented as follows:

1. IF HVAC airflow is Low **ANDAND** Fever is Low **ANDAND** Cough is Low **ANDAND** Number of Passengers is Low **ANDAND** Time Exposure is Low **AND** Contact Distance is Medium **THEN** Risk is Low
2. IF HVAC airflow is Low **ANDAND** Fever is Low **ANDAND** Cough is Low **AND** Number of Passengers is Low **AND** Time Exposure is Low **AND** Contact Distance is High **THEN** Risk is Low
3. IF HVAC airflow is Low **AND** Fever is Medium **AND** Cough is Low **AND** Number of Passengers is Low **AND** Time Exposure is Low **AND** Contact Distance is Medium **THEN** Risk is Low
4. IF HVAC airflow is Low **AND** Fever is Medium **AND** Cough is Low **AND** Number of Passengers is Low **AND** Time Exposure is Low **AND** Contact Distance is High **THEN** Risk is Low
5. IF HVAC airflow is Low **AND** Fever is Low **AND** Cough is Medium **AND** Number of Passengers is Low **AND** Time Exposure is Low **AND** Contact Distance is Medium **THEN** Risk is Low
6. IF HVAC airflow is Low **AND** Fever is Low **AND** Cough is Medium **AND** Number of Passengers is Low **AND** Time Exposure is Low **AND** Contact Distance is High **THEN** Risk is Low
7. IF HVAC airflow is Low **AND** Fever is Low **AND** Cough is Low **AND** Number of Passengers is Medium **AND** Time Exposure is Low **AND** Contact Distance is Low **THEN** Risk is Low
8. IF HVAC airflow is Low **AND** Fever is Low **AND** Cough is Low **AND** Number of Passengers is Medium **AND** Time Exposure is Low **AND** Contact Distance is Medium **THEN** Risk is Low



9. **IF** HVAC airflow is Low **AND** Fever is Low **AND** Cough is Low **AND** Number of Passengers is Medium **AND** Time Exposure is Low **AND** Contact Distance is High **THEN** Risk is Low
10. **IF** HVAC airflow is Low **AND** Fever is Low **AND** Cough is Low **AND** Number of Passengers is Low **AND** Time Exposure is Medium **AND** Contact Distance is Medium **THEN** Risk is Low
11. **IF** HVAC airflow is Low **AND** Fever is Low **AND** Cough is Low **AND** Number of Passengers is Low **AND** Time Exposure is Medium **AND** Contact Distance is High **THEN** Risk is Low
12. **IF** HVAC airflow is Low **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers is Low **AND** Time Exposure is Low **AND** Contact Distance is Medium **THEN** Risk is Medium
13. **IF** HVAC airflow is Low **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers is Low **AND** Time Exposure is Low **AND** Contact Distance is High **THEN** Risk is High
14. **IF** HVAC airflow is Low **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers is Medium **AND** Time Exposure is Medium **AND** Contact Distance is Low **THEN** Risk is Medium
15. **IF** HVAC airflow is Low **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers is Medium **AND** Time Exposure is Medium **AND** Contact Distance is Medium **THEN** Risk is Medium
16. **IF** HVAC airflow is Low **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers is Medium **AND** Time Exposure is Medium **AND** Contact Distance is High **THEN** Risk is Medium
17. **IF** HVAC airflow is Low **AND** Fever is High **AND** Cough is Medium **AND** Number of Passengers is Medium **AND** Time Exposure is Medium **AND** Contact Distance is Low **THEN** Risk is Medium
18. **IF** HVAC airflow is Low **AND** Fever is High **AND** Cough is Medium **AND** Number of Passengers is Medium **AND** Time Exposure is Medium **AND** Contact Distance is Medium **THEN** Risk is Medium
19. **IF** HVAC airflow is Low **AND** Fever is High **AND** Cough is Medium **AND** Number of Passengers is Medium **AND** Time Exposure is Medium **AND** Contact Distance is High **THEN** Risk is Medium
20. **IF** HVAC airflow is Low **AND** Fever is High **AND** Cough is High **AND** Number of Passengers is Medium **AND** Time Exposure is Medium **AND** Contact Distance is Low **THEN** Risk is High
21. **IF** HVAC airflow is Low **AND** Fever is High **AND** Cough is High **AND** Number of Passengers is Medium **AND** Time Exposure is Medium **AND** Contact Distance is Medium **THEN** Risk is High
22. **IF** HVAC airflow is Low **AND** Fever is High **AND** Cough is High **AND** Number of Passengers is Medium **AND** Time Exposure is Medium **AND** Contact Distance is High **THEN** Risk is Medium
23. **IF** HVAC airflow is Low **AND** Fever is High **AND** Cough is High **AND** Number of Passengers is High **AND** Time Exposure is Medium **AND** Contact Distance is Low **THEN** Risk is High
24. **IF** HVAC airflow is Low **AND** Fever is High **AND** Cough is High **AND** Number of Passengers is High **AND** Time Exposure is Medium **AND** Contact Distance is Medium **THEN** Risk is High
25. **IF** HVAC airflow is Low **AND** Fever is High **AND** Cough is High **AND** Number of Passengers is High **AND** Time Exposure is Medium **AND** Contact Distance is High **THEN** Risk is Medium
26. **IF** HVAC airflow is Low **AND** Fever is High **AND** Cough is High **AND** Number of Passengers is High **AND** Time Exposure is High **THEN AND** Contact Distance is Low **THEN** Risk is High
27. **IF** HVAC airflow is Low **AND** Fever is High **AND** Cough is High **AND** Number of Passengers is High **AND** Time Exposure is High **THEN AND** Contact Distance is Medium **THEN** Risk is High



28. **IF** HVAC airflow is Low **AND** Fever is High **AND** Cough is High **AND** Number of Passengers is High **AND** Time Exposure is High **THEN AND** Contact Distance is High **THEN** Risk is High
29. **IF** HVAC airflow is Low **AND** Fever is Medium **AND** Cough is High **AND** Number of Passengers is Medium **AND** Time Exposure is Medium **AND** Contact Distance is Low **THEN** Risk is High
30. **IF** HVAC airflow is Low **AND** Fever is Medium **AND** Cough is High **AND** Number of Passengers is Medium **AND** Time Exposure is Medium **AND** Contact Distance is Medium **THEN** Risk is Medium
31. **IF** HVAC airflow is Low **AND** Fever is Medium **AND** Cough is High **AND** Number of Passengers is Medium **AND** Time Exposure is Medium **AND** Contact Distance is High **THEN** Risk is Medium
32. **IF** HVAC airflow is Low **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers is High **AND** Time Exposure is Medium **AND** Contact Distance is Low **THEN** Risk is Medium
33. **IF** HVAC airflow is Low **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers is High **AND** Time Exposure is Medium **AND** Contact Distance is Medium **THEN** Risk is Medium
34. **IF** HVAC airflow is Low **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers is High **AND** Time Exposure is Medium **AND** Contact Distance is High **THEN** Risk is Medium
35. **IF** HVAC airflow is Low **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers is Medium **AND** Time Exposure is High **THEN AND** Contact Distance is Low **THEN** Risk is High
36. **IF** HVAC airflow is Low **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers is Medium **AND** Time Exposure is High **THEN AND** Contact Distance is Medium **THEN** Risk is High
37. **IF** HVAC airflow is Low **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers is Medium **AND** Time Exposure is High **THEN AND** Contact Distance is High **THEN** Risk is Medium
38. **IF** HVAC airflow is Low **AND** Fever is Medium **AND** Cough is High **AND** Number of Passengers is High **AND** Time Exposure is Medium **AND** Contact Distance is Low **THEN** Risk is High
39. **IF** HVAC airflow is Low **AND** Fever is Medium **AND** Cough is High **AND** Number of Passengers is High **AND** Time Exposure is Medium **AND** Contact Distance is Medium **THEN** Risk is High
40. **IF** HVAC airflow is Low **AND** Fever is Medium **AND** Cough is High **AND** Number of Passengers is High **AND** Time Exposure is Medium **AND** Contact Distance is High **THEN** Risk is High
41. **IF** HVAC airflow is Low **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers is High **AND** Time Exposure is High **THEN AND** Contact Distance is Low **THEN** Risk is High
42. **IF** HVAC airflow is Low **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers is High **AND** Time Exposure is High **THEN AND** Contact Distance is Medium **THEN** Risk is High
43. **IF** HVAC airflow is Low **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers is High **AND** Time Exposure is High **THEN AND** Contact Distance is High **THEN** Risk is Medium
44. **IF** HVAC airflow is Low **AND** Fever is Medium **AND** Cough is High **AND** Number of Passengers is High **AND** Time Exposure is High **THEN AND** Contact Distance is Low **THEN** Risk is High



45. **IF** HVAC airflow is Low **AND** Fever is Medium **AND** Cough is High **AND** Number of Passengers is High **AND** Time Exposure is High **THEN AND** Contact Distance is Medium **THEN** Risk is High
46. **IF** HVAC airflow is Low **AND** Fever is Medium **AND** Cough is High **AND** Number of Passengers is High **AND** Time Exposure is High **THEN AND** Contact Distance is High **THEN** Risk is High
47. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers is Medium **AND** Time Exposure is Medium **AND** Contact Distance is Low **THEN** Risk is Medium
48. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers is Medium **AND** Time Exposure is Medium **AND** Contact Distance is Medium **THEN** Risk is Medium
49. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers is Medium **AND** Time Exposure is Medium **AND** Contact Distance is High **THEN** Risk is Medium
50. **IF** HVAC airflow is Medium **AND** Fever is Low **AND** Cough is Low **AND** Number of Passengers is Low **AND** Time Exposure is Low **AND** Contact Distance is Medium **THEN** Risk is Low
51. **IF** HVAC airflow is Medium **AND** Fever is Low **AND** Cough is Low **AND** Number of Passengers is Low **AND** Time Exposure is Low **AND** Contact Distance is High **THEN** Risk is Low
52. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is Low **AND** Number of Passengers is Low **AND** Time Exposure is Low **AND** Contact Distance is Low **THEN** Risk is Low
53. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is Low **AND** Number of Passengers is Low **AND** Time Exposure is Low **AND** Contact Distance is Medium **THEN** Risk is Low
54. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is Low **AND** Number of Passengers is Low **AND** Time Exposure is Low **AND** Contact Distance is High **THEN** Risk is Low
55. **IF** HVAC airflow is High **AND** Fever is High **AND** Cough is Low **AND** Number of Passengers is Low **AND** Time Exposure is Low **AND** Contact Distance is Medium **THEN** Risk is Low
56. **IF** HVAC airflow is High **AND** Fever is High **AND** Cough is Low **AND** Number of Passengers is Low **AND** Time Exposure is Low **AND** Contact Distance is High **THEN** Risk is Low
57. **IF** HVAC airflow is Medium **AND** Fever is High **AND** Cough is Low **AND** Number of Passengers is Low **AND** Time Exposure is Low **AND** Contact Distance is Medium **THEN** Risk is Low
58. **IF** HVAC airflow is Medium **AND** Fever is High **AND** Cough is Low **AND** Number of Passengers is Low **AND** Time Exposure is Low **AND** Contact Distance is High **THEN** Risk is Low
59. **IF** HVAC airflow is Medium **AND** Fever is Low **AND** Cough is Medium **AND** Number of Passengers is Low **AND** Time Exposure is Low **AND** Contact Distance is Medium **THEN** Risk is Low
60. **IF** HVAC airflow is Medium **AND** Fever is Low **AND** Cough is Medium **AND** Number of Passengers is Low **AND** Time Exposure is Low **AND** Contact Distance is High **THEN** Risk is Low
61. **IF** HVAC airflow is Medium **AND** Fever is Low **AND** Cough is Low **AND** Number of Passengers is Medium **AND** Time Exposure is Low **AND** Contact Distance is Low **THEN** Risk is Low



62. **IF** HVAC airflow is Medium **AND** Fever is Low **AND** Cough is Low **AND** Number of Passengers is Medium **AND** Time Exposure is Low **AND** Contact Distance is Medium **THEN** Risk is Low
63. **IF** HVAC airflow is Medium **AND** Fever is Low **AND** Cough is Low **AND** Number of Passengers is Medium **AND** Time Exposure is Low **AND** Contact Distance is High **THEN** Risk is Low
64. **IF** HVAC airflow is Medium **AND** Fever is Low **AND** Cough is Low **AND** Number of Passengers is Low **AND** Time Exposure is Medium **AND** Contact Distance is Medium **THEN** Risk is Low
65. **IF** HVAC airflow is Medium **AND** Fever is Low **AND** Cough is Low **AND** Number of Passengers is Low **AND** Time Exposure is Medium **AND** Contact Distance is High **THEN** Risk is Low
66. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is Low **AND** Number of Passengers is Low **AND** Time Exposure is Low **AND** Contact Distance is Medium **THEN** Risk is Low
67. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is Low **AND** Number of Passengers is Low **AND** Time Exposure is Low **AND** Contact Distance is High **THEN** Risk is Low
68. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers is Low **AND** Time Exposure is Low **AND** Contact Distance is Low **THEN** Risk is Low
69. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers is Low **AND** Time Exposure is Low **AND** Contact Distance is Medium **THEN** Risk is Low
70. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers is Low **AND** Time Exposure is Low **AND** Contact Distance is High **THEN** Risk is Low
71. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers is Medium **AND** Time Exposure is Medium **AND** Contact Distance is Low **THEN** Risk is Medium
72. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers is Medium **AND** Time Exposure is Medium **AND** Contact Distance is Medium **THEN** Risk is Medium
73. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers is Medium **AND** Time Exposure is Medium **AND** Contact Distance is High **THEN** Risk is Medium
74. **IF** HVAC airflow is Medium **AND** Fever is High **AND** Cough is Medium **AND** Number of Passengers is Medium **AND** Time Exposure is Medium **AND** Contact Distance is Low **THEN** Risk is Medium
75. **IF** HVAC airflow is Medium **AND** Fever is High **AND** Cough is Medium **AND** Number of Passengers is Medium **AND** Time Exposure is Medium **AND** Contact Distance is Medium **THEN** Risk is Medium
76. **IF** HVAC airflow is Medium **AND** Fever is High **AND** Cough is Medium **AND** Number of Passengers is Medium **AND** Time Exposure is Medium **AND** Contact Distance is High **THEN** Risk is Medium
77. **IF** HVAC airflow is Medium **AND** Fever is High **AND** Cough is High **AND** Number of Passengers is Medium **AND** Time Exposure is Medium **AND** Contact Distance is Low **THEN** Risk is High



78. **IF** HVAC airflow is Medium **AND** Fever is High **AND** Cough is High **AND** Number of Passengers is Medium **AND** Time Exposure is Medium **AND** Contact Distance is Medium **THEN** Risk is High
79. **IF** HVAC airflow is Medium **AND** Fever is High **AND** Cough is High **AND** Number of Passengers is Medium **AND** Time Exposure is Medium **AND** Contact Distance is High **THEN** Risk is High
80. **IF** HVAC airflow is Medium **AND** Fever is High **AND** Cough is High **AND** Number of Passengers is High **AND** Time Exposure is Medium **AND** Contact Distance is Low **THEN** Risk is High
81. **IF** HVAC airflow is Medium **AND** Fever is High **AND** Cough is High **AND** Number of Passengers is High **AND** Time Exposure is Medium **AND** Contact Distance is Medium **THEN** Risk is High
82. **IF** HVAC airflow is Medium **AND** Fever is High **AND** Cough is High **AND** Number of Passengers is High **AND** Time Exposure is Medium **AND** Contact Distance is High **THEN** Risk is High
83. **IF** HVAC airflow is Medium **AND** Fever is High **AND** Cough is High **AND** Number of Passengers is High **AND** Time Exposure is High **THEN AND** Contact Distance is Low **THEN** Risk is High
84. **IF** HVAC airflow is Medium **AND** Fever is High **AND** Cough is High **AND** Number of Passengers is High **AND** Time Exposure is High **THEN AND** Contact Distance is Medium **THEN** Risk is High
85. **IF** HVAC airflow is Medium **AND** Fever is High **AND** Cough is High **AND** Number of Passengers is High **AND** Time Exposure is High **THEN AND** Contact Distance is High **THEN** Risk is High
86. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is High **AND** Number of Passengers is Medium **AND** Time Exposure is Medium **AND** Contact Distance is Low **THEN** Risk is High
87. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is High **AND** Number of Passengers is Medium **AND** Time Exposure is Medium **AND** Contact Distance is Medium **THEN** Risk is High
88. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is High **AND** Number of Passengers is Medium **AND** Time Exposure is Medium **AND** Contact Distance is High **THEN** Risk is High
89. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers is High **AND** Time Exposure is Medium **AND** Contact Distance is Low **THEN** Risk is High
90. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers is High **AND** Time Exposure is Medium **AND** Contact Distance is Medium **THEN** Risk is Medium
91. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers is High **AND** Time Exposure is Medium **AND** Contact Distance is High **THEN** Risk is Medium
92. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers is Medium **AND** Time Exposure is High **THEN AND** Contact Distance is Low **THEN** Risk is High
93. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers is Medium **AND** Time Exposure is High **THEN AND** Contact Distance is Medium **THEN** Risk is High



94. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers is Medium **AND** Time Exposure is High **THEN AND** Contact Distance is High **THEN** Risk is High
95. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is High **AND** Number of Passengers is High **AND** Time Exposure is Medium **AND** Contact Distance is Low **THEN** Risk is Medium
96. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is High **AND** Number of Passengers is High **AND** Time Exposure is Medium **AND** Contact Distance is Medium **THEN** Risk is Medium
97. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is High **AND** Number of Passengers is High **AND** Time Exposure is Medium **AND** Contact Distance is High **THEN** Risk is High
98. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers is High **AND** Time Exposure is High **THEN AND** Contact Distance is Low **THEN** Risk is High
99. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers is High **AND** Time Exposure is High **THEN AND** Contact Distance is Medium **THEN** Risk is High
100. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers is High **AND** Time Exposure is High **THEN AND** Contact Distance is High **THEN** Risk is Medium
101. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is High **AND** Number of Passengers is High **AND** Time Exposure is High **THEN AND** Contact Distance is Low **THEN** Risk is High
102. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is High **AND** Number of Passengers is High **AND** Time Exposure is High **THEN AND** Contact Distance is Medium **THEN** Risk is High
103. **IF** HVAC airflow is Medium **AND** Fever is Medium **AND** Cough is High **AND** Number of Passengers is High **AND** Time Exposure is High **THEN AND** Contact Distance is High **THEN** Risk is High
104. **IF** HVAC airflow is High **AND** Fever is Low **AND** Cough is Low **AND** Number of Passengers is Low **AND** Time Exposure is Low **AND** Contact Distance is Medium **THEN** Risk is Low
105. **IF** HVAC airflow is High **AND** Fever is Low **AND** Cough is Low **AND** Number of Passengers is Low **AND** Time Exposure is Low **AND** Contact Distance is High **THEN** Risk is Low
106. **IF** HVAC airflow is High **AND** Fever is Medium **AND** Cough is Low **AND** Number of Passengers is Low **AND** Time Exposure is Low **AND** Contact Distance is Medium **THEN** Risk is Low
107. **IF** HVAC airflow is High **AND** Fever is Medium **AND** Cough is Low **AND** Number of Passengers is Low **AND** Time Exposure is Low **AND** Contact Distance is High **THEN** Risk is Low
108. **IF** HVAC airflow is High **AND** Fever is Low **AND** Cough is Medium **AND** Number of Passengers is Low **AND** Time Exposure is Low **AND** Contact Distance is Medium **THEN** Risk is Low
109. **IF** HVAC airflow is High **AND** Fever is Low **AND** Cough is Medium **AND** Number of Passengers is Low **AND** Time Exposure is Low **AND** Contact Distance is High **THEN** Risk is Low



110. IF HVAC airflow is High **AND** Fever is Low **AND** Cough is Low **AND** Number of Passengers is Medium **AND** Time Exposure is Low **AND** Contact Distance is Low **THEN** Risk is Low
111. IF HVAC airflow is High **AND** Fever is Low **AND** Cough is Low **AND** Number of Passengers is Medium **AND** Time Exposure is Low **AND** Contact Distance is Medium **THEN** Risk is Low
112. IF HVAC airflow is High **AND** Fever is Low **AND** Cough is Low **AND** Number of Passengers is Medium **AND** Time Exposure is Low **AND** Contact Distance is High **THEN** Risk is Low
113. IF HVAC airflow is High **AND** Fever is Low **AND** Cough is Low **AND** Number of Passengers is Low **AND** Time Exposure is Medium **AND** Contact Distance is Medium **THEN** Risk is Low
114. IF HVAC airflow is High **AND** Fever is Low **AND** Cough is Low **AND** Number of Passengers is Low **AND** Time Exposure is Medium **AND** Contact Distance is High **THEN** Risk is Low
115. IF HVAC airflow is High **AND** Fever is Medium **AND** Cough is Low **AND** Number of Passengers is Low **AND** Time Exposure is Low **AND** Contact Distance is Medium **THEN** Risk is Low
116. IF HVAC airflow is High **AND** Fever is Medium **AND** Cough is Low **AND** Number of Passengers is Low **AND** Time Exposure is Low **AND** Contact Distance is High **THEN** Risk is Low
117. IF HVAC airflow is High **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers is Low **AND** Time Exposure is Low **AND** Contact Distance is Medium **THEN** Risk is Low
118. IF HVAC airflow is High **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers is Low **AND** Time Exposure is Low **AND** Contact Distance is High **THEN** Risk is Low
119. IF HVAC airflow is High **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers is Medium **AND** Time Exposure is Medium **AND** Contact Distance is Low **THEN** Risk is High
120. IF HVAC airflow is High **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers is Medium **AND** Time Exposure is Medium **AND** Contact Distance is Medium **THEN** Risk is Medium
121. IF HVAC airflow is High **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers is Medium **AND** Time Exposure is Medium **AND** Contact Distance is High **THEN** Risk is Medium
122. IF HVAC airflow is High **AND** Fever is High **AND** Cough is High **AND** Number of Passengers is High **AND** Time Exposure is High **THEN** **AND** Contact Distance is Low **THEN** Risk is High
123. IF HVAC airflow is High **AND** Fever is High **AND** Cough is High **AND** Number of Passengers is High **AND** Time Exposure is High **THEN** **AND** Contact Distance is Medium **THEN** Risk is High
124. IF HVAC airflow is High **AND** Fever is High **AND** Cough is High **AND** Number of Passengers is High **AND** Time Exposure is High **THEN** **AND** Contact Distance is High **THEN** Risk is High
125. IF HVAC airflow is High **AND** Fever is High **AND** Cough is Medium **AND** Number of Passengers is Medium **AND** Time Exposure is Medium **AND** Contact Distance is Low **THEN** Risk is High



126. IF HVAC airflow is High **AND** Fever is High **AND** Cough is Medium **AND** Number of Passengers is Medium **AND** Time Exposure is Medium **AND** Contact Distance is Medium **THEN** Risk is Medium
127. IF HVAC airflow is High **AND** Fever is High **AND** Cough is Medium **AND** Number of Passengers is Medium **AND** Time Exposure is Medium **AND** Contact Distance is High **THEN** Risk is Medium
128. IF HVAC airflow is High **AND** Fever is High **AND** Cough is High **AND** Number of Passengers is Medium **AND** Time Exposure is Medium **AND** Contact Distance is Low **THEN** Risk is High
129. IF HVAC airflow is High **AND** Fever is High **AND** Cough is High **AND** Number of Passengers is Medium **AND** Time Exposure is Medium **AND** Contact Distance is Medium **THEN** Risk is Medium
130. IF HVAC airflow is High **AND** Fever is High **AND** Cough is High **AND** Number of Passengers is Medium **AND** Time Exposure is Medium **AND** Contact Distance is High **THEN** Risk is Medium
131. IF HVAC airflow is High **AND** Fever is High **AND** Cough is High **AND** Number of Passengers is High **AND** Time Exposure is Medium **AND** Contact Distance is Low **THEN** Risk is High
132. IF HVAC airflow is High **AND** Fever is High **AND** Cough is High **AND** Number of Passengers is High **AND** Time Exposure is Medium **AND** Contact Distance is Medium **THEN** Risk is High
133. IF HVAC airflow is High **AND** Fever is High **AND** Cough is High **AND** Number of Passengers is High **AND** Time Exposure is Medium **AND** Contact Distance is High **THEN** Risk is High
134. IF HVAC airflow is High **AND** Fever is High **AND** Cough is High **AND** Number of Passengers is High **AND** Time Exposure is High **THEN AND** Contact Distance is Low **THEN** Risk is High
135. IF HVAC airflow is High **AND** Fever is High **AND** Cough is High **AND** Number of Passengers is High **AND** Time Exposure is High **THEN AND** Contact Distance is Medium **THEN** Risk is High
136. IF HVAC airflow is High **AND** Fever is High **AND** Cough is High **AND** Number of Passengers is High **AND** Time Exposure is High **THEN AND** Contact Distance is High **THEN** Risk is High
137. IF HVAC airflow is High **AND** Fever is Medium **AND** Cough is High **AND** Number of Passengers is Medium **AND** Time Exposure is Medium **AND** Contact Distance is Low **THEN** Risk is High
138. IF HVAC airflow is High **AND** Fever is Medium **AND** Cough is High **AND** Number of Passengers is Medium **AND** Time Exposure is Medium **AND** Contact Distance is Medium **THEN** Risk is High
139. IF HVAC airflow is High **AND** Fever is Medium **AND** Cough is High **AND** Number of Passengers is Medium **AND** Time Exposure is Medium **AND** Contact Distance is High **THEN** Risk is Medium
140. IF HVAC airflow is High **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers is High **AND** Time Exposure is Medium **AND** Contact Distance is Low **THEN** Risk is Medium
141. IF HVAC airflow is High **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers is High **AND** Time Exposure is Medium **AND** Contact Distance is Medium **THEN** Risk is Medium



142. IF HVAC airflow is High **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers is High **AND** Time Exposure is Medium **AND** Contact Distance is High **THEN** Risk is Medium
143. IF HVAC airflow is High **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers is Medium **AND** Time Exposure is High **THEN AND** Contact Distance is Low **THEN** Risk is High
144. IF HVAC airflow is High **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers is Medium **AND** Time Exposure is High **THEN AND** Contact Distance is Medium **THEN** Risk is Medium
145. IF HVAC airflow is High **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers is Medium **AND** Time Exposure is High **THEN AND** Contact Distance is High **THEN** Risk is Medium
146. IF HVAC airflow is High **AND** Fever is Medium **AND** Cough is High **AND** Number of Passengers is High **AND** Time Exposure is Medium **AND** Contact Distance is Low **THEN** Risk is High
147. IF HVAC airflow is High **AND** Fever is Medium **AND** Cough is High **AND** Number of Passengers is High **AND** Time Exposure is Medium **AND** Contact Distance is Medium **THEN** Risk is High
148. IF HVAC airflow is High **AND** Fever is Medium **AND** Cough is High **AND** Number of Passengers is High **AND** Time Exposure is Medium **AND** Contact Distance is High **THEN** Risk is Medium
149. IF HVAC airflow is High **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers is High **AND** Time Exposure is High **THEN AND** Contact Distance is Low **THEN** Risk is High
150. IF HVAC airflow is High **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers is High **AND** Time Exposure is High **THEN AND** Contact Distance is Medium **THEN** Risk is High
151. IF HVAC airflow is High **AND** Fever is Medium **AND** Cough is Medium **AND** Number of Passengers is High **AND** Time Exposure is High **THEN AND** Contact Distance is High **THEN** Risk is Medium
152. IF HVAC airflow is High **AND** Fever is Medium **AND** Cough is High **AND** Number of Passengers is High **AND** Time Exposure is High **THEN AND** Contact Distance is Low **THEN** Risk is High
153. IF HVAC airflow is High **AND** Fever is Medium **AND** Cough is High **AND** Number of Passengers is High **AND** Time Exposure is High **THEN AND** Contact Distance is Medium **THEN** Risk is High
154. IF HVAC airflow is High **AND** Fever is Medium **AND** Cough is High **AND** Number of Passengers is High **AND** Time Exposure is High **THEN AND** Contact Distance is High **THEN** Risk is High

Experimental Cases

Following the fuzzy rule set generation, several cases that simulated varying conditions inside the examined areas were utilized to assess the validity of the generated fuzzy rule sets. The examined bar areas e_1 and e_2 were used to define different cases with varying ventilation, max body temperature, total number of coughs, total number of passengers and contact distance configurations over a period of up to 120 min. The method was evaluated in 20 cases, 6 of which are indicatively presented in Table 16, with three (L)ow, (M)edium and (H)igh fuzzy sets for each risk factor. Similarly with Subsection 5.1.1 the corresponding fuzzy sets were generated based on the



examined areas and the risk factor analysis. The ranges of the fuzzy sets corresponding to each risk factor for the bar areas examined can be observed in Table 15.

Table 15 Fuzzy sets for each risk factor corresponding to e_1 and e_2 bar areas.

Fuzzy Set		Room Ventilation	Body Temperature	Total Number of Coughs	Total Number of Passengers	Contact Distance	Exposure Time	Risk
Low	e_1	[0,3369]	[35,38]	[0,61]	[2,20]	[0,1]	[15,45]	[0,0.3]
	e_2	[0,2400]		[0,44]	[2,10]			
Med.	e_1	[1685,6738]	[36,39]	[25,97]	[10,40]	[0.5,1.5]	[30,60]	[0.1,0.5]
	e_2	[1200,4800]		[17,71]	[5,20]			
High	e_1	[3369,6738]	[38,42]	[61,250]	[20, 81]	[1,2]	[45,120]	[0.3,1]
	e_2	[2400,4800]		[44,200]	[10,44]			

Furthermore, for each scenario, the confidence score is defined as the degree of membership to the fuzzy set responsible for RA. The evaluation of the method was based on the results of the ABM framework that was also employed in Subsection 5.1.1, where similarly the Risk_{ABM} is defined as the total number of infected over the total number of passengers in the room.

Table 16 Experimental cases with varying input risk factors for e_1/e_2 bar areas.

No.	Ventilation (m ³ /h)	Max Body Temperature (°C)	Total Number of Coughs	Total Number of Passengers	Contact Distance (m)	Time (min)
1	L/L	L	M/M	L/M	M	M
2	L/L	M	M/M	L/M	M	M
3	M/M	M	H/H	H/H	L	H
4	M/M	H	H/H	M/H	M	H
5	M/M	H	H/H	H/H	H	H
6	M/M	M	H/H	H/H	H	H

The results presented in Table 17 show that the proposed method aligns with the ABM tool for RA, with high confidence in estimating the transmission risk across most cases. Despite that the ventilation is considered an important countermeasure for airborne disease transmission, it is not



sufficient for cases with high number of coughs, passengers and/or exposure time. In most cases, the RA performed by the proposed method is comparable to the results obtained from the ABM simulations, with 83.3% accuracy for 20 cases. The incorrectly predicted risk, i.e., for e_2 in Case 1 (Table 17), estimated by the proposed method can be attributed to the factors of passenger movement and interactions since they are not represented in the rules.

Regarding cases where the confidence of the decision-making module (fuzzy rule-based system) is low, the ABM was used to increase the confidence of the RA process. For example, in Case 2 of Table 17, the decision-making module has low confidence for the e_1 bar area. By utilizing the output of the ABM, the risk predicted for e_1 is validated as medium, effectively increasing the confidence of the RA process. Similarly, the ABM further validates the inferred risk in Case 3 for both bar areas and in Cases 5 & 6 for bar area e_1 .

Table 17 Risk assessment of COVID-19 transmission for e_1/e_2 bar areas using fuzzy rules.

No.	Risk	Confidence	Risk _{ABM}
1	L/H	0.88/0.26	L/L
2	M/M	0.36/0.79	M/M
3	H/H	0.39/0.38	H/H
4	H/H	0.71/0.75	H/H
5	H/H	0.43/0.74	H/H
6	H/H	0.58/0.74	H/H

5.1.3 Public toilet

Public toilets in cruise ships can create a conducive environment for infectious diseases. The small available surface area combined with poor air quality can accelerate the transmission of infectious diseases. An infectious passenger might cough on their hands or have contaminated hands after using the toilet. By touching other surfaces areas and especially fomites that are frequently used by other passengers, an infectious individual can contribute to an accelerated transmission of the disease. highly infectious. Several risk factors were identified in the literature, such as washing hands, number of passengers entering the public toilet and disinfection of surfaces. These factors were not sufficient to create a fuzzy rule-based system similar to the other cases. Thus, an agent-based probabilistic model was used to assess the risk of disease transmission in this scenario.

Surface-mediated disease transmission can be considered for both airborne and waterborne diseases, such as COVID-19 and norovirus. Therefore, in these experiments we considered one case where a passenger infected with COVID-19 used the public toilet with a contaminated hand and then touched the exit door handle (fomite) of room. The exit door handle is examined, since it is a fomite that is accessed by all passengers who enter the public toilet (Figure 36).

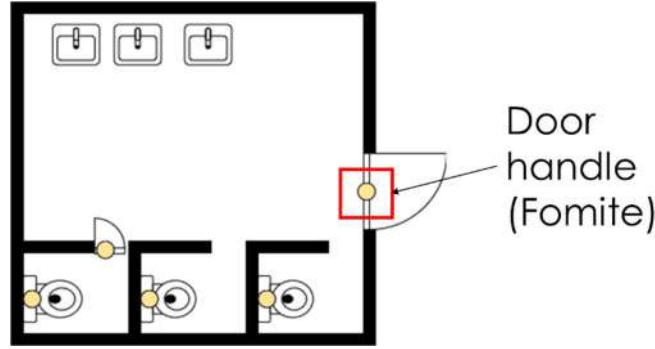


Figure 36 Representative schematic of a public toilet with pathogens denoted as yellow circles.

Dose-response model combined with surface-mediated disease transmission simulations

A dose-response model was used to calculate the risk of infection for each passenger based on:

$$P = 1 - \exp\left(-\frac{D}{ID_{50}}\right) \quad (9)$$

where D is the dose that each passenger is exposed and ID_{50} is the minimum infectious dose.

To determine the number of virus particles (D) that each healthy passenger is exposed to, surface-mediated disease transmission simulations were conducted using the ABM model in (Arav et al., 2021). According to this ABM model, each passenger that enters the public toilet is exposed to the virus based on:

$$D = S_{fi} * (e_{in} * C_{fi}) \quad (10)$$

where S_{fi} is the surface area of each finger of the passenger, e_{in} is the transfer efficiency of the pathogen from the hand to the orifice and C_{fi} is the concentration of pathogen per cm^2 on each finger. In this study, we consider that a passenger has equally distributed pathogens on each of their finger and D is based on a touching event involving one finger of the passenger.

The concentration of pathogen on the hand of each passenger C_{fi} is calculated based on:

$$C_{fi} = S_{fi} * e_{fh} * C_{fo} \quad (11)$$

where e_{fh} is the transfer efficiency of the pathogen from the fomite to the hand and C_{fo} is the concentration of pathogen per cm^2 on the fomite. In contrast to (Arav et al., 2021), we consider that the passengers do not have contaminated hands and pathogen is only transferred from the fomite to the hand and not vice versa.

Lastly, the concentration of pathogen of the fomite C_{fo} decreases after each touching event based on:

$$C_{fo} = C_{fo} - \frac{C_{fi}}{S_{fo}} \quad (12)$$

A summary of each parameter used in the RA model can be observed in Table 18.



Table 18 Description of each parameter used in the RA model.

Information		RA model parameters
Surface area (cm ²)	Finger	S_{fi}
	Fomite	S_{fo}
Transfer efficiency of pathogen	From fomite to hand	e_{fh}
	From hand to orifice	e_{in}
Concentration of pathogen per cm ²	Fomite	C_{fo}
	Finger	C_{fi}

Experimental Cases

Several experimental cases were examined based on the public toilet scenario for COVID-19 and norovirus. For each experiment S_{fi} was set to 2 cm² and S_{fo} was set to 13.33 cm² (Arav et al., 2021). For the COVID-19 experiments e_{in} was set to 0.35, e_{fh} was set to 0.24 (Arav et al., 2021) and ID_{50} was set to 1000 virus particles (Rahn et al., 2022). The initial pathogen on the fomite was set to 4500 pathogens/cm² based on measurements from the study in (Nicholls et al., 2023). This approximates the pathogen concentration on the fomite, due to lack of available data regarding the transfer mechanics of pathogen from mouth to hand due to coughing. For the norovirus experiments e_{in} was set to 0.339, e_{fh} was sampled from a uniform distribution [0.05,0.22] (Canales et al., 2019) and ID_{50} was set to 18 virus particles (Hall, 2012). As described in (Canales et al., 2019), different materials have different transfer efficiency. Since, the material type of the fomite is not always available, a uniform distribution with limits the minimum and maximum transfer efficiency of the probable fomite materials was used for the norovirus cases. Similarly to the COVID-19 experiments, the initial pathogen concentration was set to 243 cm² based on a previous surface-based transmission study of a norovirus outbreak (Canales et al., 2019). The results of the experiments can be observed in Table 19. Since in these simulated scenarios the ABM was effectively part of the decision-making process, the confidence of the RA process is sufficient, and no further simulations are required.

Table 19 Experimental cases for surface-based RA.

No.	Number of passengers	Risk _{COVID-19}	Risk _{Norovirus}
1.	10	0.72 (H)	0.9 (H)
2.	20	0.65 (H)	0.84 (H)
3.	30	0.59 (H)	0.83 (H)

5.1.4 Public Swimming Pool Area

In the swimming pool scenario, a decision-making module was examined, considering diseases that can be transmitted through water, such as norovirus, in an outdoor area. Similarly to Subsections 5.1.1 and 5.1.2, a fuzzy-rule system was generated based on risk factors derived from the literature. These factors were first analyzed, and the generated fuzzy rules were then validated based on an



outbreak of norovirus that was found in the literature (Paranthaman et al., 2018). Specifically, the following risk factors were considered for the RA of disease transmission in swimming pools of the cruise ship: chlorine levels, age, time of exposure and number of passengers. To detect the symptoms, the available sensors included in the smart ship design proposed in (Triantafyllou, Kalozoumis, et al., 2024) were used. In addition, the most probable symptoms of norovirus were identified by the partner **HPI** (Subsection 3.1.1 and Table 3).

Analysis of risk factors related to waterborne disease transmission

In the examined outbreak, chlorine levels ranged from 0.5 to 1 mg/L (Paranthaman et al., 2018). The epidemiological study concluded that these levels were insufficient for preventing outbreaks of highly transmissible viruses, falling into a "grey area." The risk of norovirus disease transmission is correlated with factors such as the chlorine levels (Sheet, 2024), the age (Paranthaman et al., 2018), and the exposure time of individuals in the contaminated water (Pintar et al., 2010). Based on the literature, the association between the risk factors and the risk of disease transmission was defined and is summarized in Table 20.

Table 20 Correlation of each risk factor with risk of norovirus transmission.

Risk factor correlation with Transmission Risk	
Chlorine Level	→ Positive correlation
Age	→ Positive correlation
Occupancy	→ Negative correlation
Time	→ Negative correlation

Fuzzy Rules

Following the analysis of the risk factors, respective fuzzy rules were generated:

1. **IF** Chlorine Level is Low **AND** Age is Low **AND** Number of Passengers is Low **AND** Time Exposure is Low **THEN** Risk is Medium
2. **IF** Chlorine Level is Low **AND** Age is Medium **AND** Number of Passengers is Low **AND** Time Exposure is Low **THEN** Risk is Medium
3. **IF** Chlorine Level is Low **AND** Age is Low **AND** Number of Passengers is Low **AND** Time Exposure is Low **THEN** Risk is Medium
4. **IF** Chlorine Level is Low **AND** Age is Low **AND** Number of Passengers is Low **AND** Time Exposure is Low **THEN** Risk is Medium
5. **IF** Chlorine Level is Low **AND** Age is Low **AND** Number of Passengers is Medium **AND** Time Exposure is Low **THEN** Risk is Medium
6. **IF** Chlorine Level is Low **AND** Age is Low **AND** Number of Passengers is Medium **AND** Time Exposure is Low **THEN** Risk is Medium
7. **IF** Chlorine Level is Low **AND** Age is Low **AND** Number of Passengers is Medium **AND** Time Exposure is Low **THEN** Risk is Medium
8. **IF** Chlorine Level is Low **AND** Age is Low **AND** Number of Passengers is Low **AND** Time Exposure is Medium **THEN** Risk is High



9. **IF** Chlorine Level is Low **AND** Age is Low **AND** Number of Passengers is Low **AND** Time Exposure is Medium **THEN** Risk is High
10. **IF** Chlorine Level is Low **AND** Age is Medium **AND** Number of Passengers is Low **AND** Time Exposure is Low **THEN** Risk is Medium
11. **IF** Chlorine Level is Low **AND** Age is Medium **AND** Number of Passengers is Low **AND** Time Exposure is Low **THEN** Risk is Medium
12. **IF** Chlorine Level is Low **AND** Age is Medium **AND** Number of Passengers is Medium **AND** Time Exposure is Medium **THEN** Risk is High
13. **IF** Chlorine Level is Low **AND** Age is Medium **AND** Number of Passengers is Medium **AND** Time Exposure is Medium **THEN** Risk is High
14. **IF** Chlorine Level is Low **AND** Age is Medium **AND** Number of Passengers is Medium **AND** Time Exposure is Medium **THEN** Risk is High
15. **IF** Chlorine Level is Low **AND** Age is High **AND** Number of Passengers is Medium **AND** Time Exposure is Medium **THEN** Risk is Medium
16. **IF** Chlorine Level is Low **AND** Age is High **AND** Number of Passengers is Medium **AND** Time Exposure is Medium **THEN** Risk is Medium
17. **IF** Chlorine Level is Low **AND** Age is High **AND** Number of Passengers is Medium **AND** Time Exposure is Medium **THEN** Risk is Medium
18. **IF** Chlorine Level is Low **AND** Age is Medium **AND** Number of Passengers is High **AND** Time Exposure is Medium **THEN** Risk is High
19. **IF** Chlorine Level is Low **AND** Age is Medium **AND** Number of Passengers is High **AND** Time Exposure is Medium **THEN** Risk is High
20. **IF** Chlorine Level is Low **AND** Age is Medium **AND** Number of Passengers is High **AND** Time Exposure is Medium **THEN** Risk is High
21. **IF** Chlorine Level is Low **AND** Age is Medium **AND** Number of Passengers is Medium **AND** Time Exposure is High **THEN** Risk is High
22. **IF** Chlorine Level is Low **AND** Age is Medium **AND** Number of Passengers is Medium **AND** Time Exposure is High **THEN** Risk is High
23. **IF** Chlorine Level is Low **AND** Age is Medium **AND** Number of Passengers is Medium **AND** Time Exposure is High **THEN** Risk is High
24. **IF** Chlorine Level is Low **AND** Age is Medium **AND** Number of Passengers is High **AND** Time Exposure is Medium **THEN** Risk is High
25. **IF** Chlorine Level is Low **AND** Age is Medium **AND** Number of Passengers is High **AND** Time Exposure is High **THEN** Risk is High
26. **IF** Chlorine Level is Low **AND** Age is Medium **AND** Number of Passengers is High **AND** Time Exposure is High **THEN** Risk is High
27. **IF** Chlorine Level is Low **AND** Age is Medium **AND** Number of Passengers is High **AND** Time Exposure is High **THEN** Risk is High
28. **IF** Chlorine Level is Low **AND** Age is Medium **AND** Number of Passengers is High **AND** Time Exposure is High **THEN** Risk is High
29. **IF** Chlorine Level is Low **AND** Age is Medium **AND** Number of Passengers is High **AND** Time Exposure is High **THEN** Risk is High
30. **IF** Chlorine Level is Medium **AND** Age is Medium **AND** Number of Passengers is Medium **AND** Time Exposure is Medium **THEN** Risk is Low
31. **IF** Chlorine Level is Medium **AND** Age is Medium **AND** Number of Passengers is Medium **AND** Time Exposure is Medium **THEN** Risk is Low



32. **IF** Chlorine Level is Medium **AND** Age is Medium **AND** Number of Passengers is Medium **AND** Time Exposure is Medium **THEN** Risk is Low
33. **IF** Chlorine Level is Medium **AND** Age is Low **AND** Number of Passengers is Low **AND** Time Exposure is Low **THEN** Risk is Low
34. **IF** Chlorine Level is Medium **AND** Age is Low **AND** Number of Passengers is Low **AND** Time Exposure is Low **THEN** Risk is Low
35. **IF** Chlorine Level is Medium **AND** Age is Medium **AND** Number of Passengers is Low **AND** Time Exposure is Low **THEN** Risk is Low
36. **IF** Chlorine Level is Medium **AND** Age is Medium **AND** Number of Passengers is Low **AND** Time Exposure is Low **THEN** Risk is Low
37. **IF** Chlorine Level is Medium **AND** Age is Medium **AND** Number of Passengers is Low **AND** Time Exposure is Low **THEN** Risk is Low
38. **IF** Chlorine Level is Medium **AND** Age is High **AND** Number of Passengers is Low **AND** Time Exposure is Low **THEN** Risk is Low
39. **IF** Chlorine Level is Medium **AND** Age is High **AND** Number of Passengers is Low **AND** Time Exposure is Low **THEN** Risk is Low
40. **IF** Chlorine Level is Medium **AND** Age is Low **AND** Number of Passengers is Low **AND** Time Exposure is Low **THEN** Risk is Low
41. **IF** Chlorine Level is Medium **AND** Age is Low **AND** Number of Passengers is Low **AND** Time Exposure is Low **THEN** Risk is Low
42. **IF** Chlorine Level is Medium **AND** Age is Low **AND** Number of Passengers is Medium **AND** Time Exposure is Low **THEN** Risk is Low
43. **IF** Chlorine Level is Medium **AND** Age is Low **AND** Number of Passengers is Medium **AND** Time Exposure is Low **THEN** Risk is Low
44. **IF** Chlorine Level is Medium **AND** Age is Low **AND** Number of Passengers is Medium **AND** Time Exposure is Low **THEN** Risk is Low
45. **IF** Chlorine Level is Medium **AND** Age is Low **AND** Number of Passengers is Low **AND** Time Exposure is Medium **THEN** Risk is Low
46. **IF** Chlorine Level is Medium **AND** Age is Low **AND** Number of Passengers is Low **AND** Time Exposure is Medium **THEN** Risk is Low
47. **IF** Chlorine Level is Medium **AND** Age is Medium **AND** Number of Passengers is Low **AND** Time Exposure is Low **THEN** Risk is Low
48. **IF** Chlorine Level is Medium **AND** Age is Medium **AND** Number of Passengers is Low **AND** Time Exposure is Low **THEN** Risk is Low
49. **IF** Chlorine Level is Medium **AND** Age is Medium **AND** Number of Passengers is Low **AND** Time Exposure is Low **THEN** Risk is Low
50. **IF** Chlorine Level is Medium **AND** Age is Medium **AND** Number of Passengers is Low **AND** Time Exposure is Low **THEN** Risk is Low
51. **IF** Chlorine Level is Medium **AND** Age is Medium **AND** Number of Passengers is Low **AND** Time Exposure is Low **THEN** Risk is Low
52. **IF** Chlorine Level is Medium **AND** Age is Medium **AND** Number of Passengers is Medium **AND** Time Exposure is Medium **THEN** Risk is Low
53. **IF** Chlorine Level is Medium **AND** Age is Medium **AND** Number of Passengers is Medium **AND** Time Exposure is Medium **THEN** Risk is Low
54. **IF** Chlorine Level is Medium **AND** Age is Medium **AND** Number of Passengers is Medium **AND** Time Exposure is Medium **THEN** Risk is Low

55. **IF** Chlorine Level is Medium **AND** Age is High **AND** Number of Passengers is Medium **AND** Time Exposure is Medium **THEN** Risk is Low
56. **IF** Chlorine Level is Medium **AND** Age is High **AND** Number of Passengers is Medium **AND** Time Exposure is Medium **THEN** Risk is Low
57. **IF** Chlorine Level is Medium **AND** Age is High **AND** Number of Passengers is Medium **AND** Time Exposure is Medium **THEN** Risk is Low
58. **IF** Chlorine Level is Medium **AND** Age is Medium **AND** Number of Passengers is High **AND** Time Exposure is Medium **THEN** Risk is Low
59. **IF** Chlorine Level is Medium **AND** Age is Medium **AND** Number of Passengers is High **AND** Time Exposure is Medium **THEN** Risk is Low
60. **IF** Chlorine Level is Medium **AND** Age is Medium **AND** Number of Passengers is High **AND** Time Exposure is Medium **THEN** Risk is Low
61. **IF** Chlorine Level is Medium **AND** Age is Medium **AND** Number of Passengers is Medium **AND** Time Exposure is High **THEN** Risk is Low
62. **IF** Chlorine Level is Medium **AND** Age is Medium **AND** Number of Passengers is Medium **AND** Time Exposure is High **THEN** Risk is Low
63. **IF** Chlorine Level is Medium **AND** Age is Medium **AND** Number of Passengers is Medium **AND** Time Exposure is High **THEN** Risk is Low
64. **IF** Chlorine Level is Medium **AND** Age is Medium **AND** Number of Passengers is High **AND** Time Exposure is High **THEN** Risk is Medium
65. **IF** Chlorine Level is Medium **AND** Age is Medium **AND** Number of Passengers is High **AND** Time Exposure is High **THEN** Risk is Medium
66. **IF** Chlorine Level is Medium **AND** Age is Medium **AND** Number of Passengers is High **AND** Time Exposure is High **THEN** Risk is Medium

Experimental Cases

Following the validation of the generated fuzzy rules, several experiments were conducted by considering various combinations of risk factors for a swimming pool, hereinafter ship pool, found in the provided ship schematics (Figure 1). The selected swimming pool can also be observed in Figure 37.



Figure 37 Schematics of the selected swimming pool on Deck 16, highlighted with red.

These experiments aimed to observe the impact of a norovirus outbreak for different conditions and the results are provided in Table 21, where Risk denotes the risk predicted by the fuzzy rule-based system. It can be inferred from the results that chlorine levels are a crucial factor in the RA process and greatly affect the risk of disease transmission. For medium and high chlorine levels the risk of disease transmission is low even for low age and high exposure time, whereas for low chlorine levels the risk is high even for low exposure time and high number of passengers. The validation of the defined fuzzy rules was performed based on the research of (Paranthaman et al., 2018).

Table 21 Input risk factors and RA for various cases in the cruise ship pool.

No.	Chlorine Level	Age	Number of Passengers	Time	Risk
1	L	L	M	H	H
2	M	L	M	L	L
3	M	H	L	L	L
4	L	M	L	H	M
5	M	M	M	H	H
6	L	L	H	H	H

5.1.5 Risk assessment of COVID-19 for multiple spaces

For experiments regarding RA of COVID-19 for multiple spaces, 7 representative areas were selected from the ship schematics of the World Dream cruise ship, presented in Section 2, that was provided by the partners of the HS4U project. In addition to the two adjacent eating areas examined in Subsection 5.1.1, four nearby rooms were selected. Specifically, a bar area (e_3), a lounge area (e_4), a public toilet (e_5) and a cabin (e_6) were selected (Figure 38). These areas were selected due to their proximity to each other and to further examine the RA capabilities of the system on different types of spaces, including vessel's low-risk public spaces (Subsection 3.4.3), public toilets and cabins (Subsection 3.4.6) in accord with the simulated scenarios defined in Subsection 3.4, as well as the empirical data provided in Figures 7-9.

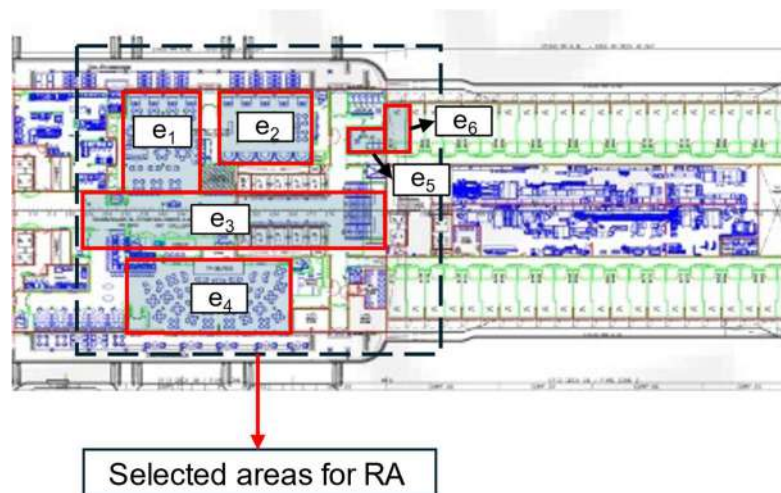


Figure 38 Overview of the rooms, e_1 , e_2 , e_3 , e_4 , e_5 , e_6 , that were selected from Deck 8 of the provided ship schematics for multi-space RA.

In this scenario, we consider that an infectious passenger travels through the monitored environments ($e_1 - e_6$). The infectious passenger has symptoms of an airborne infection, *i.e.*, coughing and fever, that are classified as COVID-19 by the data analysis module and the DNA/RNA sensors in the HVAC system. The RA system assesses the risk of COVID-19 transmission for each of them and the total risk for all the activated environments (Figure 39).

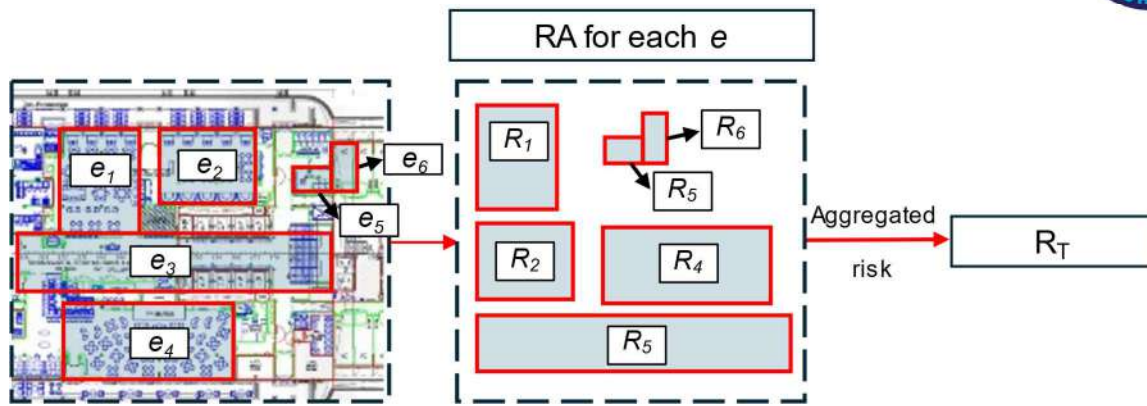


Figure 39 Overview of the RA workflow for the examined multiple-spaces scenario.

Similarly to the experiments conducted in Subsections 5.1.1 and 5.1.2, a fuzzy rule-based system was created, based on the characteristics of the examined monitored environments. Aiming to perform the disease transmission risk assessment, the following risk factors were identified in the literature: airflow rate, coughs, maximum body temperature, exposure time, number of people in a room, average distance of people in a room, number of people wearing masks and number of vaccinated people.

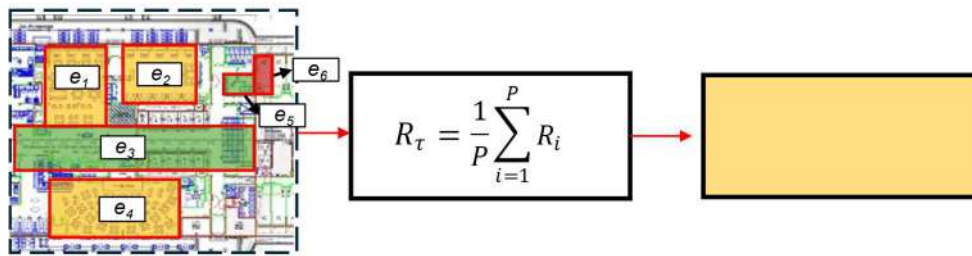
Experimental Cases

For each monitored environment a so-called sub-scenario was considered. This sub-scenario similar to the experiments in Subsections 5.1.1 and 5.1.2 represent a combination of risk factor values, representing a disease transmission event within each monitored environment. Then the risk predicted by the system for each sub-scenario was used to calculate the total risk of COVID-19 transmission using the average operator in Eq. (2). In the experiments, combinations of the risk factors were used to create RA sub-scenarios for each monitored environment. The system was tasked to assess the risk of disease transmission for each of these sub-scenarios and was validated using the Vadere ABM framework. The accuracy of the system was 84.2% for these experiments.

Representative results of these experiments can be observed in Figure 40, where the predicted risk for each monitored environment and the total risk are presented. The colors green, orange, and yellow denote low, medium, and high-risk levels, respectively. As can be observed, the fuzzy rule-based system agrees with the ABM, and the total risk predicted for this scenario is medium.

Monitored environments	e_1	e_2	e_3	e_4	e_5	e_6	Total Risk (R_T)
Predicted Risk (R_i)	M	M	L	M	L	H	M
ABM Risk (R_A)	M	M	L	M	L	H	M

a)



b)

Figure 40 Result of the experiments for RA of multiple spaces with a) Presenting the predicted and ABM risks for the examined scenario and b) Presenting a visualization of the workflow for predicting total risk.

Risk Mitigation

Based on the inferred risk level, the system proposes a set of actuations to mitigate the risk of transmission (Figure 41).

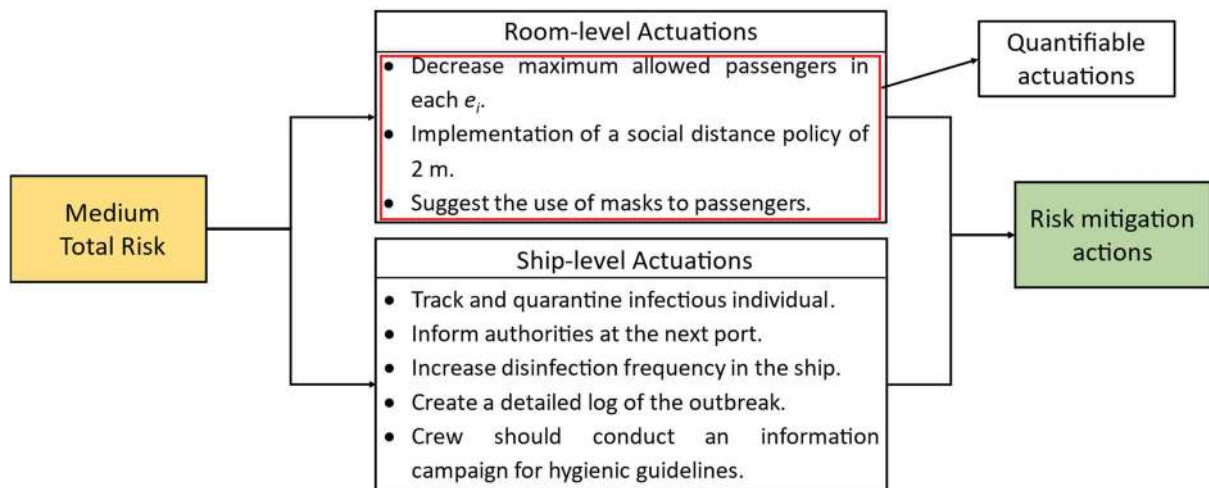


Figure 41 Risk mitigation actions proposed by the system.

Considering that the room-level actuations are implemented, another set of experiments were conducted to quantify their effect. In these experiments, all passengers wear masks, follow a strict social distance policy of 2 m and the maximum allowed passengers in each environment e are set as equal to 75% of the capacity of the room. Based on Table 22, these actuations resulted in a low total risk, further highlighting the advantages of the proposed system. In detail, the overall relative risk reduction when the risk mitigation actions were applied was ~30%.



Table 22 Comparison of predicted risk of transmission with and without actuations implemented.

Predicted Risk/ Monitored environments	e_1	e_2	e_3	e_4	e_5	e_6	Total Risk (R_T)
Without actuations	M	M	L	M	L	H	M
With actuations	L	L	L	L	L	H	L

5.2 SIMULATION MODULE

The Simulation Module is considered to be a complementary module to the RA Decision-Making module. For the purposes of this project, three different disease transmission mechanics were considered, namely airborne, waterborne, and surface.

The Vadere ABM framework is utilized to simulate the transmission mechanics of airborne diseases, through a dedicated peer-reviewed airborne disease transmission model. Apart from a complementary module, the airborne disease simulation tool was employed as a means to validate the RA models described in Subsections 5.1.1 and 5.1.2. This way the generated RA models are validated based on situations that approximate real-life scenarios, and the employed ABM framework can further be used to enhance the RA process. Representative simulation cases based on the examined scenarios are presented in the following Subsections 5.1.1 and 5.1.2. A passenger is regarded as infected when they have absorbed more than the minimum infectious dose, *i.e.*, 1000 virus particles. The infectious passenger is denoted with red color, the susceptible with blue and the exposed individuals with varying shades of purple. An increased degree of exposure corresponds to a darker shade of purple.

5.2.1 Eating Area

Airborne disease transmission simulations

Snapshots of the ABM simulations for Case 5 (Table 10 & Table 11) are depicted in Figure 42. Healthy individuals are denoted with blue, exposed with purple, and infectious with red. Based on these visualizations, It can be derived that a higher population density (Restaurant 1) is associated with increased exposure of healthy individuals resulting in more infections. In addition, the high number of coughs identified by the smart sensors result in an increased risk of disease transmission for both monitored environments despite that Restaurant 2 (left area) has a lower population density.



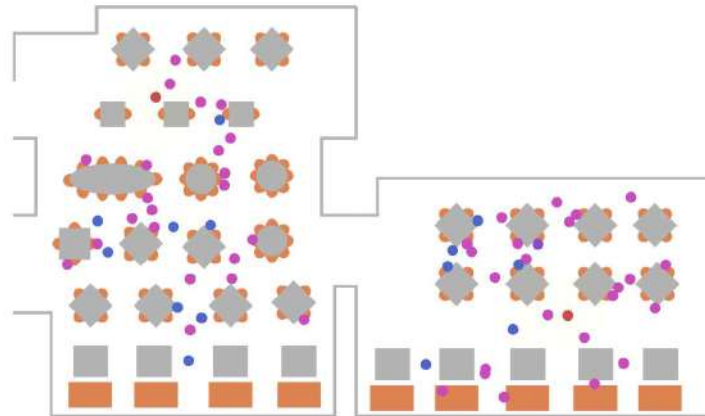


Figure 42 Result of the simulated scenarios for Case 5 (Table 10 & Table 11).

5.2.2 Vessel's other high-risk public spaces

Airborne disease transmission simulations

Snapshots of the ABM simulations for Cases 2 and 6 (Table 17) are depicted in Figures 43 & 44. In addition to the examined infectious, susceptible, and exposed passengers, yellow circles are designed to represent the probable spread of emitted droplets deriving from a cough. These circles are associated with the Contact Distance risk factor and are utilized to demonstrate its correlation with the spread of disease. From observing Figure 44, it can be derived that closer interaction between infected and healthy individuals is more probable in cases with a high number of passengers inside the indoor area.

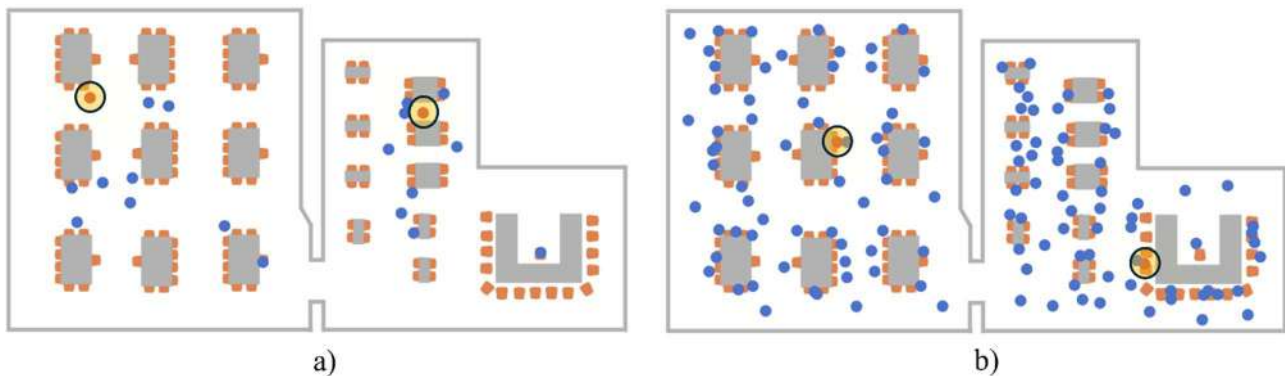


Figure 43 Initial setup of the simulated scenarios for a) Case 2 and b) Case 6 (Table 17).

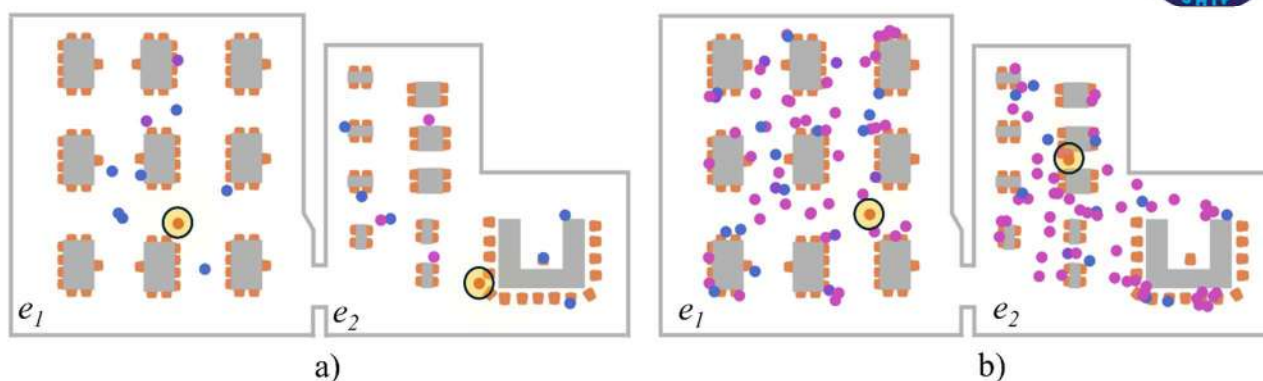


Figure 44 Result of the simulated scenarios for a) Case 2, and b) Case 6 (Table 17).

5.2.3 Public Swimming Pool Area

Waterborne disease transmission simulations

For the simulations related to waterborne disease transmission a dose-response model was combined with an agent-based approach. The simulations were aimed at examining the transmission of norovirus in the swimming pool scenario. Each passenger was treated as an agent that was exposed to norovirus based on the Wells-Riley dose-response model (Arav et al., 2021).

The minimum infectious dose is set to 18 particles for norovirus (Hall, 2012) and the exposure dose D is calculated based on (Pintar et al., 2010). A mapping between available information utilized by the Simulation Module and the parameters used in (Pintar et al., 2010) can be observed in Table 23.

Table 23 Mapping of the information obtain by the system with the waterborne RA ABM model parameters.

Information → ABM parameters
Chlorine Level → V_i
Age → Water Consumption (mL/min)
Mass of faecal matter released → M_f
Concentration per g of faecal matter → C_o
Total concentration of pathogen per L → C_w
Exposure Time → t
Pool volume in L → V_p

The experiments considered the asymptomatic case of a norovirus passenger in the swimming pool as examined in Subsection 5.1.4. Considering that a person has 0.14 g of fecal matter in their body while swimming, M_f was set to 0.14 g (Paranthaman et al., 2018) and C_o to 10^8 virus particles per g of fecal matter (Hall, 2012). In addition, the volume of the pool was calculated based on the characteristics of the swimming pool in Figure 37 (Subsection 5.1.4). The average water consumption of water (mL/min) was defined based on (Schets et al., 2011) and was set as 0.64 mL/min for children and 0.43 mL/min for adults. These findings were then used to set V depending on the average age in each case scenario. Specifically, for age above 16 the $V = 0.43$ corresponding to adults was used, whereas for age lower than 16 the $V = 0.64$ corresponding to children.

Several cases were examined for the cruise ship swimming pool that was presented in Figure 37. These results can be observed in Table 24, where $Risk_f$ corresponds to the risk assessment of the biomedical RA model described in Subsection 5.1.4 and $Risk_{ABM}$ corresponds to the calculated risk of the agent-based dose-response model. Based on the findings in Table 24, the results of the fuzzy rule-based RA model are similar to the ones of the AMB model. In addition, the median age of exposed passengers and the exposure time are important risk factors for both models examined. In Case 4, the confidence of the decision-making module is low. By using the output of the waterborne ABM, the confidence of the RA process is increased, and the risk is considered medium.

Table 24 Calculated risk of the agent-based dose-response model.

No.	Chlorine Level	Age	Number of Passengers	Time	$Risk_f$	$Risk_{ABM}$
1	L	L	H	H	H	H
2	M	L	M	L	L	L
3	M	H	L	L	L	L
4	L	M	L	H	M	H
5	M	M	M	H	H	H

5.3 CASE STUDY ON CELESTYAL DISCOVERY

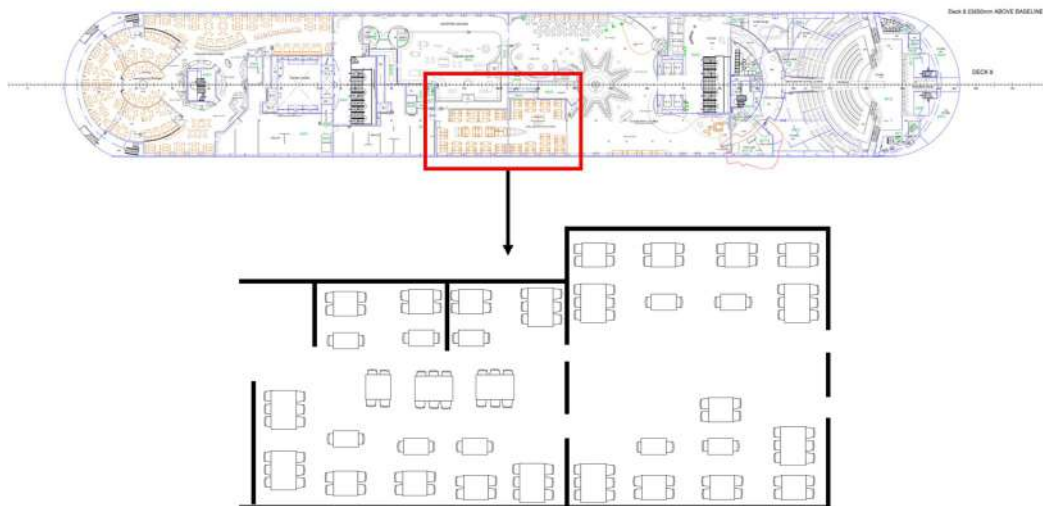


Figure 45 Overview of the selected eating area from Deck 8 of the Celestyal Discovery.

The RA system that was created from the experiments conducted in Subsection 5.1.5 was also used in a case study on the Celestyal Discovery. In these experiments an eating area in Deck 8 was selected (Figure 45). These areas were considered as monitored environments and appropriate fuzzy sets were created based on their characteristics, *i.e.*, surface area, max capacity, airflow rate. These characteristics were based on the ship schematics and the air-filtration and ventilation system schematics provided in Subsection 2. According to air-filtration and ventilation system schematics the average airflow rate of the room is set to 4000 m³/h, which is classified as high according to our analysis. In this scenario, the adherence of passengers to hygienic guidelines is low. Only a small portion of passengers is considered vaccinated with the newest covid vaccine that provides efficient protection not new variants of COVID-19. The scope of these experiments is to present a use case but also try to bridge our research with CDF as an example of how our RA system could be used to optimize the design of the rooms in a ship to minimize risk.



In these experiments, the infectious passenger is coughing inside the room with a detected body temperature of 38.0°C for 120 min, while the environment is operating at full capacity, *i.e.*, number of passengers are equal to maximum capacity. The risk of disease was then calculated, and two additional experiments were conducted to determine the effect of reduced occupancy and calibration of the airflow rate to an optimal value, *i.e.*, 3000 m³/h or 3 ACH. As can be observed in Table 25, the risk of disease transmission is high even for a medium number of coughs detected. Furthermore, an optimal airflow rate combined with a reduced occupancy equal to half of the maximum capacity seems to reduce the risk of disease transmission to a low risk level. This can be quantified as an up to 32% relative risk decrease when an optimal airflow rate is implemented and a reduced capacity equal to 50% of the max capacity is enforced.

Table 25 Experiments conducted in an eating area of the Celestyal Discovery.

Scenario	HVAC	NC	mBT	ET	NP	SD	NM	NV	Predicted Risk
1	4000(H)	60 (M)	38.0 (L)	120 (H)	110 (H)	1 (L)	0 (L)	20 (L)	0.78 (H)
2	4000(H)	60 (M)	38.0 (L)	120 (H)	55 (M)	1 (L)	0 (L)	10 (L)	0.37 (M)
3	3000 (M)	60 (M)	38.0 (L)	120 (H)	55 (M)	1 (L)	0 (L)	10(L)	0.25 (L)

6. DISCUSSION

In this deliverable, models, methodologies and frameworks were investigated, studied and developed with the aim of calculating the risk of disease transmission in indoor spaces of cruise ships. In the case of cruise ships, outbreaks are frequently associated with either airborne diseases, *e.g.*, COVID-19 or waterborne diseases, *e.g.*, gastrointestinal diseases. During outbreaks, cruise ships are often quarantined until the source is identified and the spread is controlled. As a result, modelling and predicting the evolution of disease outbreaks in closed environments is crucial for effective mitigation. Considering the need for short-term disease prediction, novel risk assessment systems designed to monitor and control the spread of diseases on cruise ships were proposed.

Analyzing signals from various sensors can offer valuable insights into the spread of infectious diseases in enclosed environments. By interpreting the data from these analyses, decision support systems can contribute to perform risk assessment of the disease spread aiming at its mitigation. In the context of the HS4U project, several types of sensors have been integrated into the smart ship design. These sensors were selected based on the valuable information they provide to the RA model. Audio sensors, for example, can capture vital information related to symptomatic passengers, such as using microphones to detect coughing in public areas on the cruise ship. Furthermore, pathogen detection sensors for air and water—referred to as air DNA/RNA sensors and water DNA/RNA sensors—can be incorporated into the HVAC and blackwater systems, or/and public restrooms, to identify pathogens in wastewater, such as norovirus. These sensors can also be placed in the ship's swimming pools and paired with chlorine level sensors. This combination helps monitor the risk of disease outbreaks, especially in scenarios where low chlorine levels coincide with the presence of highly contagious pathogens like norovirus. Additionally, monitoring





passengers' body temperatures in public areas can be important for assessing disease transmission risk. Thermal camera sensors integrated into the smart ship can help identify passengers showing signs of fever. RFID sensors are capable of providing extra data for disease transmission risk assessment, especially when symptoms are detected in monitored areas. These sensors track the number of passengers in a room and offer personalized data that can assist the RA process, such as identifying contact with infected individuals. The proposed approaches utilize information derived from sensors, aiming to perform risk assessment of the diseases.

A cruise ship typically has multiple decks with various areas accessible to passengers, such as cabin corridors, lounges with seating areas, shops, and outdoor spaces, such as swimming pools. The risk of infectious disease transmission can differ across these spaces; for instance, bathrooms and restrooms are likely to pose a higher risk than open areas. In this project, several scenarios were selected, including the movement of infectious passengers in high- and low-risk areas, under different conditions, e.g., with different ventilation settings, number of co-passengers in the room, and symptoms of disease. In order to perform the risk assessment, the process starts with monitoring, where sensors detect and identify pathogens on the ship. The data collected by these sensors, together with information from the ship's information system and information extracted from the literature and web sources, are then analyzed by our proposed systems. Based on the analysis, the introduced systems assess the risk of disease transmission. Depending on the estimated risk, the crew is notified and is required to take action to prevent the spread of the virus, in accordance with instructions and actuations given by the system.

Considering the above, in this chapter, regarding airborne disease outbreaks on ships, a knowledge-based RA system was proposed aimed at preventing COVID-19. Unlike previous studies, the proposed system incorporates a variety of smart sensors, such as thermal cameras, to detect early symptoms of diseases across different indoor areas of the ship and assess the risk of disease transmission. These sensors comply with the "privacy by design" policy, ensuring that passengers consented to being monitored in both public and private areas of the ship, including cabins. The RA process was facilitated by a decision-making module, specifically a fuzzy inference system, which is built on identified early indicators and risk factors for the study case, such as COVID-19. The proposed system leverages the smart ship design for early detection of infectious diseases and proposes a framework of actions for controlling outbreaks. Furthermore, in this context, a fuzzy rule-based decision-making module was developed based on an analysis of risk factors and early indicators of airborne infectious diseases, including coughing and fever, incorporating expert knowledge and information from relevant literature. The RA process within the decision-making module generated a risk index that was used to recommend appropriate control measures to the ship's crew. experiments conducted in multiple areas of representative cruise ships with various characteristics demonstrated the effectiveness of the system in real-world scenarios. Based on the results, the following conclusions were drawn regarding the risk factors and their impact on the risk of COVID-19 transmission:

- The risk of disease transmission increases as the number of passengers in a room increases, especially when the room capacity is exceeded. This highlights the importance of managing passengers' density to reduce the spread of infectious diseases.
- The efficient operation of the HVAC system plays a critical role in minimizing the risk of disease transmission. Proper configuration and maintenance of the system can significantly reduce the spread of pathogens, highlighting the need for optimized environmental control measures.





- The frequency of symptoms, such as coughing, is directly associated with an increased risk of disease transmission. This highlights the need for symptom monitoring and interventions to limit exposure to potentially infectious individuals.
- Elevated body temperatures are indicative of a higher risk of disease spread, further reinforcing the importance of monitoring passenger health as a means of early detection and mitigation.
- The effect of the masks and the vaccination has a great impact on the transmission of the disease, as it reduces the risk.

The proposed approach for assessing airborne transmission risk aligns with the results derived from the ABM framework, demonstrating high confidence in most cases and ensuring the reliability of the outputs. However, in some cases, deviations may arise due to the simulation of passenger dynamics in the ABM framework, which are not fully captured by the fuzzy rules.

Additional experiments were conducted to examine the risk of waterborne disease transmission of norovirus. Based on the experiments conducted in this chapter, it was concluded that the risk of norovirus transmission is influenced by the following factors:

- Chlorine level: As its level increases, the risk of transmission decreases.
- Age of individual: The increase in the age of individuals is associated with a decrease in the transmission of the disease.
- Exposure time: The longer the passengers remain in contaminated water, the greater the chance of them getting sick.
- Occupancy: The increase in the number of passengers causes an increase in the risk of transmission of the virus.

Experiments were conducted to examine the risk of fomite-mediated disease transmission for COVID-19 and norovirus. Based on the experiments conducted in this chapter, it was concluded that:

- Norovirus is more infectious than COVID-19 in terms of fomite-mediated transmission routes, which aligns with the literature.
- Risk of fomite-mediated transmission highly depends on the number of passengers that touch the contaminated surface.

To this end, this chapter introduced a smart sensor-based risk assessment system for disease transmission on cruise ships, demonstrating its effectiveness in real-world scenarios. Future work includes enhancing the RA process with deep learning methods and improving sensor fusion for real-time pathogen detection. Integrating passenger behavior modelling and social dynamics could also refine risk estimates, while privacy-preserving techniques like federated learning would ensure ethical compliance. These advancements will strengthen disease mitigation strategies in maritime and other enclosed environments. Overall, the proposed biomedical RA system paves the way for better outbreak preparedness, proactive disease mitigation, and safer environments in maritime and other enclosed settings.





7. CONCLUSIONS

In this document, which is a deliverable of the HS4U project describing the work performed and the results obtained by the research performed in the context of Task 3.2 (research and development of risk assessment methodologies, models and algorithms), a smart sensor-based biomedical risk assessment model was developed for disease transmission on cruise ships. The proposed biomedical risk assessment model integrates various sensors—including thermal cameras, audio sensors, and pathogen detection systems—to monitor early indicators of infectious diseases and assess real-time risk through a fuzzy inference system. To evaluate disease transmission dynamics for COVID-19 and norovirus, a structured mapping process linked ship infrastructural components—public areas, cabins, ventilation, and sewage systems—to disease spread, ensuring accurate risk estimation. Based on this mapping, the biomedical risk assessment model was evaluated through experiments in several representative simulated scenarios, covering eating areas, vessel's other high-risk areas (e.g., bars), low-risk public spaces (e.g., lounges), cabins, public toilets, outdoor swimming pools, and combination of these spaces for short-term COVID-19 and norovirus transmission. The biomedical risk assessment model was further enhanced by incorporating results from Computational Fluid Dynamics and Agent-Based Model simulations that were used to model airborne, waterborne, and surface-mediated transmission, improving the risk assessment process. These methods were used to simulate infection spread at a micro-scale, capturing the impact of human interactions and environmental factors on disease transmission

Evaluation of the model's performance against validated ABMs, confirmed that our approach reliably estimates transmission risks across different environments with an accuracy reaching up to 84%. The results demonstrated that the biomedical risk assessment model can effectively assess and mitigate disease spread by analyzing sensor data and providing actionable recommendations to the crew. The system is implemented in modular components, making it adaptable to different ship configurations and sensor setups. Within the HS4U project, this technology will be integrated into the CDF framework, ensuring its applicability for smart ship design and future maritime health monitoring initiatives.

Key Findings:

- The proposed biomedical risk assessment model accurately evaluates and mitigates infection spread using sensor data and a fuzzy rule-based decision-making process.
- Several disease transmission scenarios were simulated covering a wide range of ship infrastructural components that were selected based on available schematics, empirical data, and insights from project partners.
- Computational Fluid Dynamics and Agent-Based Model simulations were used to simulate airborne, waterborne, and surface-mediated infection transmission at a micro-scale, enhancing the confidence of the risk assessment process.
- Airborne transmission is significantly influenced by passenger density, HVAC efficiency, symptom monitoring, and protective measures such as masks and vaccination.
- Waterborne transmission is affected by chlorine levels, exposure duration, and occupancy.
- Norovirus shows a higher risk of fomite-mediated transmission compared to COVID-19.



- The system aligns closely with results from the validated ABM, confirming its accuracy (~84%) in real-world scenarios.
- The risk mitigation measures proposed by the biomedical RA model were capable of reducing the risk of disease transmission by 30% on average.
- The framework is adaptable and can be deployed on various ship types with different sensor configurations.
- Research outputs from this work have led to **10** publications in journal and conferences, demonstrating its impact on the field.

Based on these findings, it can be inferred that the use of a sensor-based biomedical RA model such as the one proposed in this deliverable can provide valuable information to ship operators. This information could be used to limit the spread of disease onboard. In addition, ship operators are advised to adopt the risk-level based mitigation measures (suggested actuations) proposed in this study, which enhance the established safeguards already in place. These measures have been proven effective in reducing the risk of disease transmission and allow for the gradual implementation of stricter policies based on the severity of the epidemic outbreak. Moreover, ship manufacturers are encouraged to incorporate smart sensors (such as those considered in this deliverable and investigated in D3.1) in the ship design process in order to provide timely detection of infectious diseases onboard. These sensors could also provide valuable feedback and improve the response of the crew. Furthermore, manufacturers are advised to consider the results of the experiments conducted in this deliverable which defined an optimal airflow rate configuration of 3 air changes per hour (ACH) for indoor areas of cruise ships. The proposed biomedical RA model including its simulation modules could be utilized by ship manufacturers to optimize the design of indoor areas of the ship, e.g., define optimal density to limit disease spread even in high-risk scenarios.

As part of the HS4U project, the system will be integrated into the CDF for enhanced risk assessment capabilities. Considering the generality of the proposed risk assessment model, its impact may extend to future applications in the tourist industry, e.g., hotels and restaurants, as well as in healthcare units, e.g., clinics and hospitals.





8. BIBLIOGRAPHY

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