

Fuzzy System for Norovirus Transmission Risk Assessment on Cruise Ships based on Sensor Data

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Abstract— Cruise ships are a popular means of vacation for millions of people every year. However, they present significant challenges, especially in terms of addressing the risk of outbreaks on board. Among various pathogens, norovirus is the most prevalent cause of gastrointestinal illness on cruise ships, posing serious health risks to both passengers and crew. Onboard recreational facilities such as swimming pools and pool parties can create conditions where standard hygiene protocols are not consistently enforced, increasing the risk of norovirus transmission. Motivated by these challenges, this paper presents a novel short-term risk assessment system for norovirus transmission in swimming pools of cruise ships using data from multiple sensors, and a fuzzy inference model. Traditional data-driven models are typically limited by the unavailability of training data in such environments. Instead, the proposed approach adopts a knowledge-based design, utilizing domain expertise and literature data, while incorporating sensor-driven inputs, in alignment with a recently introduced smart ship design. The system was validated using a real documented outbreak and tested under various simulated scenarios of a swimming pool derived from cruise ship schematics, demonstrating its practical relevance and adaptability across configurations.

Keywords—norovirus, waterborne disease, risk assessment, fuzzy logic, knowledge-based system, sensor-driven system.

I. INTRODUCTION

Norovirus is a leading cause of gastroenteritis outbreaks on cruise ships, where confined spaces and shared amenities facilitate rapid transmission [1]. Despite the fact that transmission of infectious agents through water is generally rare under normal circumstances, norovirus outbreaks on cruise ships are a significant public health concern [1], [2]. Moreover, norovirus is highly contagious, as even asymptomatic individuals can shed large quantities of the virus, with studies reporting that a single gram of feces may contain up to 100 billion viral particles [3], while only a few particles are sufficient to cause an infection [4]. Therefore, asymptomatic cases can be detrimental to the spread of a highly infectious virus such as norovirus, since they might not get detected by ship personnel [5].

Cruise ships include a variety of recreational activities, such as pool parties, that can create situations where standard safety protocols may not always be strictly followed [6]. Recreational water treated with chlorine levels above 1 mg/L can eliminate more than 99% of norovirus particles within seconds [7]. Nevertheless, outbreaks of norovirus have been attributed to chlorine levels below the safety guidelines that are designated by the Center for Diseases Control (CDC), such as in [8]. In this incident, reduced chlorine levels can

lead to a norovirus outbreak caused by an asymptomatic case. Specifically, the chlorine concentration dropped to a critical level (< 1 mg/L), placing it in a “gray zone” where disinfection proved ineffective, allowing the virus to thrive and spread [8]. Considering the above, it can be inferred that a smart system capable of monitoring the presence of waterborne infectious diseases in swimming pools could provide valuable assistance in reducing the risk of disease transmission onboard. Smart technologies, including smart sensors, have been proven to be useful tools for monitoring the transmission of infectious diseases [9]. These technologies can be utilized to identify early symptoms of a disease and automate the monitoring process, while providing valuable information to ship crew and manufacturers. This results in more informed and a daptive policy-making when considering safety guidelines related to waterborne diseases.

Data-driven approaches, such as machine learning models, are commonly used in health-related risk prediction tasks, yet they require extensive training datasets. As such, their application in assessing short-term disease transmission scenarios on cruise ships is constrained by the limited availability of outbreak data. In contrast, knowledge-based approaches offer a viable alternative in data-scarce environments. These methods leverage domain expertise, e.g., from domain experts and/or literature-derived insights to support decision-making and can be further enhanced through the integration of sensor-driven data, providing a more context-aware basis for risk assessment. Fuzzy logic is a powerful tool for handling uncertainty, incomplete data, and imprecise medical information [10]. Only a limited number of studies have been presented aiming to deal with waterborne infectious diseases using fuzzy approaches. Recent paradigms include, an adaptive neuro-fuzzy inference system was proposed for predicting norovirus in drinking water supply, based on water quality parameters such as water pH, turbidity, conductivity, temperature and rain [11]. A multi-criteria decision-making model that integrates Fuzzy Analytic Hierarchy Process (FAHP) with geospatial analysis was presented aiming to identify zones vulnerable to waterborne diseases [12]. However, the application of fuzzy logic to short-term disease transmission on cruise ships remains an open challenge.

To this end, considering the need for early prevention of norovirus spread in crowded environments with water facilities, such as in cruise ships, a novel system based on

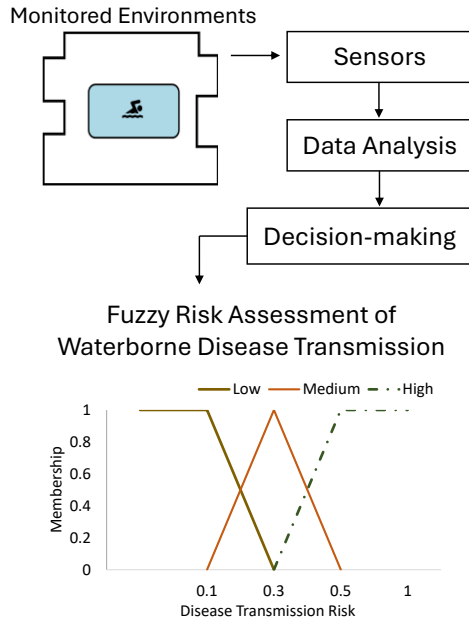


Fig. 1. Overview of the proposed system.

sensor data and knowledge-based fuzzy reasoning is proposed.

The system aims to assess the short-term transmission risk of norovirus in swimming pools, which can be very crowded, especially during the summertime. The proposed system utilizes data derived from different smart sensors, *e.g.*, RNA sensors and chlorine sensors, to assess the risk of waterborne diseases. These sensors are integrated into a novel smart ship design proposed in the context of the HS4U¹ project, which investigates methods for smart ship design, to provide enhanced passengers' health safety. The proposed fuzzy rule-based system considers several risk factors based on data provided by available smart sensors and information derived from the literature [9]. Compared to standard epidemiological studies that focus on long-term disease transmission and generic population dynamics [13], [14], this study analyzes the short-term effects of identified risk factors using a sensor-driven, fuzzy inference system, tailored to context-specific and operationally relevant conditions. To the best of our knowledge, this is the first time that a fuzzy rule-based system combined with smart sensors has been used to assess the risk of waterborne disease transmission in swimming pools. The main contributions of this study include the following:

- A novel knowledge-based system assessing the short-term risk of waterborne diseases in swimming pools.
- Identification of risk factors that are early indicators of waterborne infectious diseases and analysis of their impact on short-term transmission.
- Experiments for validating the proposed system on a real-case study and for different scenarios with various swimming pool configurations.

The remainder of this paper is organized into three sections. The proposed system is described in Section II. Section III includes the experimental setup, and the experiments

TABLE I. RISK FACTORS AND THEIR IMPACT ON WATERBORNE DISEASE TRANSMISSION.

Risk Factors	Impact on Transmission Risk	
	Lower ↓	Higher ↑
1. Chlorine Levels (mg/L)	Lower ↓	Higher ↑
2. Median Age (years)	Lower ↑	Higher ↓
3. Occupancy (number of passengers)	Lower ↓	Higher ↑
4. Time of Exposure (min)	Lower ↓	Higher ↑

↓ Reduces risk, ↑ Increases risk

conducted in this research are presented in Section IV. Finally, conclusions as well as future research directions are discussed in Section V.

II. METHODS

An overview of the proposed system is presented in Fig. 1. As illustrated, sensors, such as RNA sensors and chlorine sensors, are utilized to monitor areas of interest within the ship, (monitored environments). The system is also linked with the ships' information system that can provide further details of the passengers occupying each monitored environment. The collected data are analyzed, and the decision-making process is then performed, aiming to infer the risk of waterborne disease transmission. The resulting waterborne disease transmission risk is linguistically characterized using defined fuzzy sets, as presented in this section.

A. Risk Factor Analysis

Based on the available sensors included in the smart ship design proposed in [9], and information retrieved from the literature [15–18], the following risk factors were identified: i) chlorine levels (CL), ii) median age (MA), iii) time of exposure (ET) of passengers to the virus, and iv) occupancy (OCC), *i.e.*, number of passengers in a specific area. These factors constitute important indicators of norovirus transmission in water [18] and their impact is summarized in Table I.

Chlorine is the most important countermeasure against waterborne disease transmission in swimming pools. According to the literature, 99.2% of norovirus particles are eliminated after 4.2 s of contact with treated water that chlorine levels > 1 mg/L. However, concentrations below 1 mg/L have not been thoroughly investigated and, according to [8], are considered ineffective in preventing the transmission of highly infectious diseases like norovirus in swimming pool environments. In the investigated outbreak [8], chlorine levels were reported to vary between 0.5 and 1 mg/L, which were designated as a gray area. In addition, the CDC has also designated as safe, chlorine levels between 1 and 3 mg/L [17]. Chlorine concentrations above 3 mg/L are considered more effective at eliminating waterborne pathogens; however, levels exceeding 5 mg/L are deemed hazardous to human health [17].

Furthermore, the age of the passengers is correlated with the risk of waterborne disease transmission. Based on the

¹<https://hs4u.eu/>

No	CL	MA	OCC	ET	R _F	No	CL	MA	OCC	ET	R _F
34	MEDIUM	LOW	LOW	MEDIUM	LOW	1	LOW	LOW	LOW	LOW	MEDIUM
35	MEDIUM	LOW	LOW	MEDIUM	LOW	2	LOW	LOW	LOW	LOW	MEDIUM
36	MEDIUM	LOW	MEDIUM	LOW	LOW	3	LOW	LOW	LOW	LOW	MEDIUM
37	MEDIUM	LOW	MEDIUM	LOW	LOW	4	LOW	LOW	LOW	MEDIUM	HIGH
38	MEDIUM	LOW	MEDIUM	LOW	LOW	5	LOW	LOW	LOW	MEDIUM	HIGH
39	MEDIUM	MEDIUM	LOW	LOW	LOW	6	LOW	LOW	MEDIUM	LOW	MEDIUM
40	MEDIUM	MEDIUM	LOW	LOW	LOW	7	LOW	LOW	MEDIUM	LOW	MEDIUM
41	MEDIUM	MEDIUM	LOW	LOW	LOW	8	LOW	LOW	MEDIUM	LOW	MEDIUM
42	MEDIUM	MEDIUM	LOW	LOW	LOW	9	LOW	MEDIUM	LOW	LOW	MEDIUM
43	MEDIUM	MEDIUM	LOW	LOW	LOW	10	LOW	MEDIUM	LOW	LOW	MEDIUM
44	MEDIUM	MEDIUM	LOW	LOW	LOW	11	LOW	MEDIUM	LOW	LOW	MEDIUM
45	MEDIUM	MEDIUM	LOW	LOW	LOW	12	LOW	MEDIUM	MEDIUM	MEDIUM	HIGH
46	MEDIUM	MEDIUM	LOW	LOW	LOW	13	LOW	MEDIUM	MEDIUM	MEDIUM	HIGH
47	MEDIUM	MEDIUM	MEDIUM	MEDIUM	LOW	14	LOW	MEDIUM	MEDIUM	MEDIUM	HIGH
48	MEDIUM	MEDIUM	MEDIUM	MEDIUM	LOW	15	LOW	MEDIUM	MEDIUM	HIGH	HIGH
49	MEDIUM	MEDIUM	MEDIUM	MEDIUM	LOW	16	LOW	MEDIUM	MEDIUM	HIGH	HIGH
50	MEDIUM	MEDIUM	MEDIUM	MEDIUM	LOW	17	LOW	MEDIUM	MEDIUM	HIGH	HIGH
51	MEDIUM	MEDIUM	MEDIUM	MEDIUM	LOW	18	LOW	MEDIUM	HIGH	MEDIUM	HIGH
52	MEDIUM	MEDIUM	MEDIUM	MEDIUM	LOW	19	LOW	MEDIUM	HIGH	MEDIUM	HIGH
53	MEDIUM	MEDIUM	MEDIUM	HIGH	LOW	20	LOW	MEDIUM	HIGH	MEDIUM	HIGH
54	MEDIUM	MEDIUM	MEDIUM	HIGH	LOW	21	LOW	MEDIUM	HIGH	MEDIUM	HIGH
55	MEDIUM	MEDIUM	MEDIUM	HIGH	LOW	22	LOW	MEDIUM	HIGH	HIGH	HIGH
56	MEDIUM	MEDIUM	HIGH	MEDIUM	LOW	23	LOW	MEDIUM	HIGH	HIGH	HIGH
57	MEDIUM	MEDIUM	HIGH	MEDIUM	LOW	24	LOW	MEDIUM	HIGH	HIGH	HIGH
58	MEDIUM	MEDIUM	HIGH	MEDIUM	LOW	25	LOW	MEDIUM	HIGH	HIGH	HIGH
59	MEDIUM	MEDIUM	HIGH	HIGH	MEDIUM	26	LOW	MEDIUM	HIGH	HIGH	HIGH
60	MEDIUM	MEDIUM	HIGH	HIGH	MEDIUM	27	LOW	HIGH	MEDIUM	MEDIUM	MEDIUM
61	MEDIUM	MEDIUM	HIGH	HIGH	MEDIUM	28	LOW	HIGH	MEDIUM	MEDIUM	MEDIUM
62	MEDIUM	HIGH	LOW	LOW	LOW	29	LOW	HIGH	MEDIUM	MEDIUM	MEDIUM
63	MEDIUM	HIGH	LOW	LOW	LOW	30	MEDIUM	LOW	LOW	LOW	LOW
64	MEDIUM	HIGH	MEDIUM	MEDIUM	LOW	31	MEDIUM	LOW	LOW	LOW	LOW
65	MEDIUM	HIGH	MEDIUM	MEDIUM	LOW	32	MEDIUM	LOW	LOW	LOW	LOW
66	MEDIUM	HIGH	MEDIUM	MEDIUM	LOW	33	MEDIUM	LOW	LOW	LOW	LOW

RISK LEVELS		
LOW	MEDIUM	HIGH

Fig. 2. Fuzzy rules for estimation of waterborne disease transmission on cruise ships.

outbreak analyzed in [8], the risk of infection was notably higher among individuals under the age of 16.

Moreover, several studies have also highlighted that children are more susceptible to water-mediated infections, since they consume more water while swimming, compared to adults [16], [18]. Furthermore, the exposure time of individuals in waters that are contaminated with pathogens is associated with higher risk of infection [15]. Therefore, in the cases of norovirus transmission, the longer the exposure of the individuals the higher the transmission risk of the virus. Furthermore, the occupancy, *i.e.*, the total number of passengers, is also a risk factor when investigating water-mediated transmission of infectious disease. In detail, the World Health Organization (WHO) has designated specific guidelines to ensure safety and suggests a maximum capacity of bathers for swimming pools. The WHO dictates the maximum capacity of a pool can be calculated based on the surface area and depth of the pool as follows [7]:

$$B = \frac{L \cdot W}{b_l} \quad (1)$$

where B is the maximum capacity of the pool, L is the length of the pool, W is the width of the pool. The bather load b_l can be defined as follows:

$$b_l = \begin{cases} 2.2 \text{ m}^2, & \text{for depth} < 1.0 \text{ m} \\ 2.7 \text{ m}^2, & \text{for } 1.0 < \text{depth} < 1.5 \text{ m} \\ 4.0 \text{ m}^2, & \text{for depth} > 1.5 \text{ m} \end{cases} \quad (2)$$

The risk regarding the waterborne transmission for the validation scenarios is calculated as follows:

$$R_{GT} = \frac{P}{T} \quad (3)$$

where P are the number of infected passengers, and T is the total number of passengers in a pool.

B. Decision-Making Process

The processed data are assessed using a decision-making module, which evaluates the waterborne disease transmission risk in the monitored environment based on the identified risk factors. Each monitored environment is then assigned with a risk level, such as “Low” (L), “Medium” (M), and “High” (H). In this paper, a decision-making system based on fuzzy logic is proposed, aiming to perform the risk assessment of norovirus in swimming pools of cruise ships. The proposed system is developed based on Mamdani fuzzy inference, which is used as a baseline yet effective methodology [19], [20]. Unlike other methods, the Mamdani’s method does not require extensive data and provides explanatory results that can be easily understood.

To define the transmission risk based on the Mamdani's method, the following process is performed; the input variables are initially fuzzified using membership functions designed considering domain knowledge, as described in the following section. This fuzzification process transforms crisp input values into degrees of membership, enabling the system to handle data uncertainty and imprecision. The relationships between the identified risk factors and the output risk are inferred, using 'IF-THEN' rules. In this study, the fuzzy rule base was constructed by systematically combining the selected input factors. In the current study, the fuzzy rules were generated through a combination of the considered factors as well as expert knowledge and information derived from the literature [19]. Finally, a total number of 66 rules have been elicited and empirically selected by domain experts (Fig. 2).

The activation of these fuzzy rules depends on the specific input values and the logical operators. Each rule contributes to the generation of output membership functions, denoted as (M_j) , which are aggregated and defuzzified, resulting in a crisp final output, using the following equation:

$$M_j = \bigvee_{i=1}^n (A(x) \wedge B(z) \wedge C(d) \wedge D(k))_i \quad (4)$$

where " $\vee$ " and " $\wedge$ " correspond to the fuzzy union and intersection operations. Furthermore, $j = 1, \dots, M$, where M is the total number of activated fuzzy rules; the variables x, z, d, k are the input risk factors, *i.e.*, chlorine levels, median age, time of exposure of passengers to the virus, and occupancy, respectively. Each variable is defined by a corresponding fuzzy set A_i, B_i, C_i, D_i , respectively, with $i = 1, \dots, n$.

An indicative example of a fuzzy rule is the following: **"IF Chlorine Level is Low AND Median Age is Low AND Occupancy is Low AND Time of Exposure is Low THEN Risk is Medium."**

III. EXPERIMENTAL SETUP

To assess the risk of waterborne disease transmission, scenarios with sensors placed in pool areas (subsection III-A) were considered. The effectiveness of the defined fuzzy rules was validated using a norovirus outbreak scenario reported in the literature (subsection III-B). Furthermore, fuzzy sets were defined for the linguistic characterization of the inferred transmission risks (subsection III-C) were defined.

A. Sensors

The deployment and impact of the sensors was simulated to evaluate the effectiveness of the proposed system, in different experimental scenarios. The simulation of sensor deployment was guided by cruise ship schematics to ensure a representative spatial configuration of pool areas. This approach reflects typical onboard conditions relevant to health risk assessment, while maintaining flexibility in how sensor integration could be realized in practice, and aligns with the broader smart ship design principles explored in the HS4U project [21]. Furthermore, the following three sensors were considered: a) an RNA sensor was deployed in the examined pool to detect the presence of pathogens, providing information regarding potential contamination events; b) a chlorine sensor was used to monitor the concentration levels

of chlorine in the water; c) a Radio-Frequency Identification (RFID) sensor was implemented to collect information of passengers, including the number of people in a monitored environment, their time duration of exposure, and their median age. The combined use of these sensors allowed for a more comprehensive and effective analysis of the identified risk factors influencing short-term waterborne disease transmission.

B. Swimming Pool Scenarios

The generated fuzzy rule set was validated based on the norovirus outbreak reported in a swimming pool area described in [8]. The dimensions of the pool of this validation scenario were 25 m length, 12.5 m width and 1.2 m depth. Subsequently, the surface area of the pool was 312.5 m² and b_l for a pool with 1.2 m depth is 2.7 m², thus using these parameters in (1), (2) the maximum capacity of the pool, in terms of number of passengers, is equal to 115.

The effectiveness of the proposed system was also evaluated in various test scenarios, using the same risk factors and a set of different pool characteristics, compared to the validation scenarios. Specifically, the size of the current pool was 16.5 m length, 8.5 m width and 1.6 m – 1.8 m depth. Given that the surface area of the pool is 140.25 m² and the b_l for a pool with an average depth of 1.7 m is 4.0 m², the maximum capacity, based on (1) and (2), is calculated to be 35 passengers. The resulting fuzzy sets for the pools used in the experiments are presented in the following subsection.

C. Fuzzy Set Construction

Based on the analysis conducted in subsection II.A, four risk factors were identified according to the available sensors and information provided by the considered smart ship design. Each risk factor is represented by fuzzy sets that correspond to linguistic values, such as "Low", "Medium", and "High". A higher degree of membership towards a specific fuzzy set signifies an increased or decreased risk of the waterborne disease transmission, based on the risk factor analysis (II-A). To linguistically characterize the transmission risk, the fuzzy sets presented in Tables II and III, were defined.

TABLE II. FUZZY SETS OF THE RISK FACTORS FOR THE POOL OF THE VALIDATION SCENARIOS.

Fuzzy Set	CL	MA	OCC	ET	Risk
Low	[0, 1]	[1, 33]	[2, 59]	[15, 45]	[0, 0.3]
Med.	[0.5, 1.5]	[17, 49]	[30, 87]	[30, 60]	[0.1, 0.5]
High	[1, 3]	[33, 65]	[59, 115]	[45, 120]	[0.3, 1]

TABLE III. DEFINED FUZZY SETS OF THE RISK FACTORS FOR THE POOL OF THE TESTING SCENARIOS.

Fuzzy Set	Chlorine Level (mg/L)	Median Age	Occupancy	Exposure Time	R
Low	[0, 1]	[1, 33]	[2, 12]	[15, 45]	[0, 0.3]
Med.	[0.5, 1.5]	[17, 49]	[6, 23]	[30, 60]	[0.1, 0.5]
High	[1, 3]	[33, 65]	[12, 35]	[45, 120]	[0.3, 1]

IV. EXPERIMENTS AND RESULTS

A. Validation Scenarios

To evaluate the effectiveness of the defined fuzzy rules, different scenarios comprising various values of the identified risk factors were examined for the two types of swimming pools. Experiments were conducted for all combinations of the four risk factors, each characterized by three possible linguistic values, resulting in a total of 81 different scenarios. A representative subset of these scenarios is presented in Tables V-VI. 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 (Tables II-III).

Using the outbreak data reported in [8] as a reference, the defined fuzzy rules were applied to validation scenarios; only the participants who attended the Halloween party were considered, as the scope of the present study is to assess the short-term risk of waterborne disease transmission. Subsequently, it was reported that 58 participants attended the Halloween party, which lasted 120 minutes. Out of the 58 participants, 46 were reported to be infected, resulting in a disease transmission risk of 0.79, using (3), linguistically characterized as “High” (Table II). The median age of participants was equal to 25, and during that time the chlorine levels were reported to be 0.29 mg/L. Furthermore, participants spent 60 to 120 minutes inside the pool, thus a median time of 90 minutes of exposure time was considered. Based on Table IV, it can be observed that for a chlorine level of 0.29 mg/L, a median age of 25, occupancy of 58 participants, and 90 minutes of exposure, the system inferred a risk equal to $R_F = 0.78$ (“High”), which was in close agreement with the ground truth, *i.e.*, $R_{GT} = 0.79$ (“High”).

Additional experiments were conducted to observe the response of the system for other scenarios of detection of norovirus in the same swimming pool (Table V). Regarding the chlorine level as a risk factor, its correct regulation significantly reduces the risk of disease transmission [8], as also confirmed by the experiments conducted in this study. Specifically, a adequate chlorine levels of 3 mg/L result to a “Low” risk of transmission, even in scenarios of a “Medium” pool occupancy with passengers of a “Low” median age (scenario no. 2), factors that have been shown to be associated with a “High” risk of transmission (Table I). In addition, a “Low” median age increases the transmission risk especially when combined with “High” occupancy and exposure time (scenarios no. 1 and 4). Furthermore, “High” exposure time result to “High” transmission risk (scenario no. 5), especially when combined with “High” occupancy (scenarios no. 1 and 4).

B. Experiments on Swimming Pools of Cruise Ships

Multiple experiments were also conducted on a ship pool of a cruise ship, described in III-B, using various risk factor combinations, and are presented in Table VI. The experiments revealed that “Low” chlorine levels consistently resulted in “Medium” and “High” risk values of disease transmission, even when the median age was “Low” or “Medium” (no 1, 4). For “Medium” chlorine levels, the system inferred “Low” risk value of waterborne disease transmission (no. 2, 3).

TABLE IV. VALIDATION RESULTS BASED ON THE CASE STUDY [8].

No	CL	MA	OCC	ET	R_F	R_{GT}
1	0.29 (L)	25 (L)	58 (M)	90 (H)	0.78 (H)	0.79 (H)

TABLE V. RISK ASSESSMENT OF NOROVIRUS DISEASE TRANSMISSION ON CRUISE SHIPS USING THE DEFINED FUZZY RULES (VALIDATION SCENARIOS).

No	CL	MA	OCC	ET	R_F
1	0.50 (L)	20 (L)	100 (H)	80 (H)	0.76 (H)
2	3 (M)	5 (L)	55 (M)	20 (L)	0.15 (L)
3	3 (M)	55 (H)	55 (M)	20 (L)	0.15 (L)
4	0.70 (L)	40 (M)	102 (H)	110 (H)	0.71 (H)
5	0.80 (M)	30 (M)	34 (L)	110 (H)	0.53 (H)
6	0.70 (L)	40 (M)	102 (H)	40 (M)	0.62 (H)
7	0.80 (M)	30 (M)	34 (L)	45 (M)	0.19 (L)
8	0.70 (L)	40 (M)	102 (H)	20 (L)	0.59 (H)
9	0.80 (M)	30 (M)	34 (L)	20 (L)	0.14 (L)
10	0.50 (L)	20 (L)	100 (H)	20 (L)	0.59 (H)

TABLE VI. RISK ASSESSMENT OF NOROVIRUS DISEASE TRANSMISSION IN A SHIP'S SWIMMING POOL USING THE DEFINED FUZZY RULES (TESTING SCENARIOS).

No	CL	MA	OCC	ET	R_F
1	0.50 (L)	20 (L)	21 (M)	80 (H)	0.76 (H)
2	3 (M)	5 (L)	21 (M)	20 (L)	0.15 (L)
3	3 (M)	65 (H)	10 (L)	20 (L)	0.15 (L)
4	0.70 (L)	40 (M)	9 (L)	110 (H)	0.57 (H)
5	0.80 (L)	30 (M)	31 (H)	110 (H)	0.59 (H)
6	0.90 (M)	10 (L)	15 (M)	45 (M)	0.26 (M)
7	0.92 (M)	30 (M)	15 (M)	45 (M)	0.15 (L)
8	0.50 (L)	20 (L)	21 (M)	20 (L)	0.53 (H)
9	1 (M)	5 (L)	21 (M)	40 (M)	0.21 (M)
10	1 (M)	65 (H)	21 (M)	40 (M)	0.19 (L)

For scenarios with improperly regulated chlorine levels, such as “Low” and “High” chlorine levels (scenarios no. 1, 4), norovirus transmission is “High”. Furthermore, “High” exposure time result to “High” waterborne transmission risk (no. 4, 5),

By comparing the results between the validation pool and the ship pool, we can see that the proposed fuzzy rule-based

approach adapts well to different physical settings. The experiments in the ship's swimming pool further emphasize that the system is robust across varying pool sizes and configurations, providing a practical tool for real-time risk management. The results of this study are consistent with known epidemiological patterns of waterborne disease transmission reported in the literature [6], [13], highlighting the effectiveness of the proposed system. Specifically, as presented in Tables V and VI, the risk of norovirus transmission increases with the increase in the duration of passengers spent in the contaminated water (time exposure) and the occupancy of the area, whereas the transmission risk can be decreased as the chlorine levels and the median age are increased.

V. DISCUSSION AND CONCLUSIONS

This paper presented a fuzzy risk assessment system based on sensor data for short-term norovirus transmission on cruise ships. The proposed rule-based system considered several risk factors based on data provided by available smart sensors, such as RNA and RFID sensors, in a lignment with a recently introduced smart ship design [21]. To address the challenges of imprecise and incomplete data, the system incorporated information from domain experts and the literature, to predict the short-term transmission risk of norovirus onboard, using fuzzy rules. The experiments were conducted in two different pools with various characteristics and the results were validated using a case study of an epidemic outbreak reported in the literature. Furthermore, the results confirmed the importance of the identified risk factors for the transmission of waterborne diseases on board.

Future work will focus on incorporating additional risk factors, and ultimately integrating the proposed sensor-driven system into a real operational cruise ship setting to support real-time monitoring and automated health safety interventions. Future extensions of the proposed fuzzy knowledge-based system may incorporate data-driven components, enabling hybrid modeling of complex transmission scenarios based on large-scale datasets.

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