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RESEARCH ARTICLE

Exploring communication barriers in bridge-teams: An innovative fuzzy-Bayesian approach

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ABSTRACT

The bridge teams on merchant vessels have a grave responsibility to guarantee the safe navigation and management of ships in the critical waterways of the world. In addition to maintaining effective communication between external stations (other ships-Vessel Traffic Service), it is crucial to ensure continuous internal collaboration among the bridge team in order to fulfil this important task to the highest standard. Nevertheless, the challenging working conditions and harsh environmental factors may impede the uninterrupted flow of information between bridge teams and disrupt the communication. Communication issues among team members are frequently mentioned as a root cause in maritime accident investigation reports. The aim of this research is to propose a novel model for identifying the factors that may cause to inadequate communication among bridge team members, employing a fuzzy Bayesian network (FBN) approach. As indicated by the findings, attitudinal and behavioural barriers exert a greater influence (43.3%) on communication than language barriers (41.5%), representing the most significant factors affecting communication. Environmental barriers and cultural barriers, on the other hand, have comparatively less impact, at 38.7% and 31.2%, respectively. The sensivity analysis also revealed that the root nodes exhibiting the highest degree of impacts were cultural barriers (31.2%), age differences (20.6%), and workplace issues (20.2%). The findings suggest that bridge communication refresher training programs are essential for the mitigation of the aforementioned barriers, and are expected to lead to the development of new strategies for the overcoming of these communication barriers.

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Introduction

The major maritime decision-making mechanisms such as International Maritime Organization (IMO) and the European Maritime Safety Agency (EMSA) are working to make maritime transportation safer, more ecologically friendly, and more efficient. A review of contemporary advancements in maritime engineering reveals a number of innovative solutions, particularly in the domains of energy efficiency and environmental protection, which are aligned with the IMO's 2030 and 2050 targets for reducing greenhouse gas emissions from ships (Mallouppas & Yfantis 2021; Islam Rony et al., 2023). In spite of technological advances, the maritime transport industry is still primarily a human-centred sector (Mallam et al., 2020; Wu et al., 2022). A review of the relevant literature on maritime accident investigations reveals that the human factor is identified as the primary root cause of accidents (Yıldırım et al., 2019; Shi et al., 2021; Paolo et al., 2021; EMSA, 2023). It is well known that seafarers work in harsh conditions; fatigue, static electricity, motion, noise and vibration have a negative impact on these key workers at their working environment. Despite these challenging conditions, seafarers shall complete their daily tasks as a well-organized team in strong coordination. It is of the utmost importance that those responsible for the ship's navigation and management, in particular the master and deck officers, work in harmony as a team in order to ensure the safety of navigation and thus, the protection of the environment. The notion of bridge team management (BTM) appears in maritime literature as a concept that has grown in importance in recent years, and critical positions such as the master, officers, lookout and helmsman are defined as members of this team (Aylward et al., 2020; Cavaleiro et al., 2020; UK Chamber of Shipping, 2020; Danielsen et al., 2022).

Communication, defined as a two-way process that involves the exchange of information, thoughts, and comments between the speaker and the listener, is the most critical factor influencing team cohesion (Sutter & Strassmair, 2009; Gervits et al., 2016; Yusof et al., 2020). A considerable number of studies have demonstrated a correlation between high levels of solidarity, collaboration, and harmony within organizational units and the efficacy of communication (Halis, 2000; Crant, 2000; Butchibabu et al., 2016). However, a multitude of factors may obstruct the efficacy of communication, and restrict members of a group from communicating and understanding each other clearly (Gürüz & Eğinli, 2008). It is a well-documented fact that communication issues are frequently cited as a cause of human error in maritime accidents and risks (Sotiralis et al., 2016; Kee et al., 2017; Zhang et al., 2019; Coraddu et al., 2020; Tunçel & Arslan, 2022, Güzel et al., 2023).

It is the responsibility of the bridge team to maintain the navigational safety of the ship (ICS, 2022), and this team is in charge of the most vital tasks in ship navigation and manoeuvring such as position fixing and course altering especially in restricted waters. The team is primarily composed of deck crew, and may also include a maritime pilot, who may be invited to join the team on a temporary basis, in order to provide local expertise and experience of the navigational hazards of the waterways. Team members shall comply with various conventions and policies that govern their responsibilities, including Convention on the International Regulations for Preventing Collisions at Sea (COLREG), the International Convention on Maritime Search and Rescue (SAR), and the International Convention for the Safety of Life at Sea (SOLAS). In this context, effective communication between the bridge team is of paramount importance for the successful completion of these challenging tasks.

Despite the abundance of studies that have identified communication problems in maritime accidents, it is notable that interrelations between the variables responsible for communication problems have been inadequately addressed. The aim of this research is to determine the variables that impede communication between bridge team members, and to determine the relationships between these variables and their respective influences, using the FBN approach. A systematic review of existing literature revealed a number of studies investigating communication difficulties in various occupational settings. Notably, no studies were identified that examined communication challenges specifically within the context of bridge teams on ships, to the best of our knowledge.

The current study consists of four sections. The introduction section places particular emphasis on the importance of effective communication within the bridge team, as evidenced by the analysis of maritime accident investigation reports. The following section, designated as "Methodology," will elucidate the flowchart of the study and the Fuzzy Bayesian Network method employed. Additionally, this section will present information concerning the experts involved in the study and the procedures utilized for their evaluations. The results and discussion are presented in the third section of the study, and finally the fourth chapter presents the study's conclusions and limitations, as well as priorities and advice for minimizing communication issues within the bridge team.

Material and Methods

Bayesian Network

The Bayes network is a dynamic and effective graphical model for revealing the probabilistic relationships between variables (Chang et al., 2021; Aydın & Kamal, 2022). The approach aids in the analysing and explaining of the sequence of complex interactions between system variables, allowing variables' impact to be accurately evaluated (Yang et al., 2008). For this reason, it is considered that this technique can reveal all the causes of inadequate bridge communication and the weights of the factors that can contribute to failure in this process. This section describes the Fuzzy-Bayesian network approach, as well as the methodology's conceptual structure as shown in Figure 1.

BNs are comprised of qualitative and quantitative components. The qualitative part comprises a network structure called a Directed Acyclic Graph (DAG) (Rostamabadi et al., 2019). The network consisted of nodes and directed arcs. The quantitative part of the BN is created using a number of conditional probability distributions. The arcs describe the variables' probabilistic causal connection, and Conditional Probability Tables (CPTs) are attached to the nodes to illustrate conditional dependencies (Yazdi & Kabir, 2017). In BNs, if an arrow begins from a node, that node is referred to as the parent node and the node to which the arrows point is referred to as the child node. The Root nodes are nodes that have no parents, whereas the leaf nodes are nodes that have no children. The inference presumption of the BN approach relies on Bayes probability theory. The following equations demonstrate the inference algorithms (Mahadevan et al., 2001).

The joint probability distribution of a set of variables $N = \{X_1, X_2, X_3 \ldots, X_n\}$ can be expressed as Eq. (1):

$$P(X_1, X_2, \ldots, X_n) = \prod_{i=1}^{n} P\left(X_i \setminus P_a(X_i)\right) \tag{1}$$

Based on Zarei et al. (2019), The parent set of variables is denoted by $P_a(X_i)$. Eq. (2) expresses the posterior probability of the parent node X_j under the scenario of the child node Xi:

$$P\left(x_{\_j} \setminus Xi\right) = \frac{P(x_i, x_{\_j})}{P(x_i)} \tag{2}$$

Determining the probability of the root nodes is a critical step in achieving meaningful results from the BN structure. The CPTs and the marginal probability of the root nodes can be created based on statistical data, expert judgment, or a mix of the two (Chen et al., 2022). In accordance with the objectives of this study, a survey was conducted among the bridge team members of merchant ships, during which communication problems that negatively affect collaboration on the bridge were identified. These survey results were also used to ascertain the marginal probability of root nodes in the Bayesian network. Figure 2 illustrates the rank distribution of the bridge team members who participated in the study.

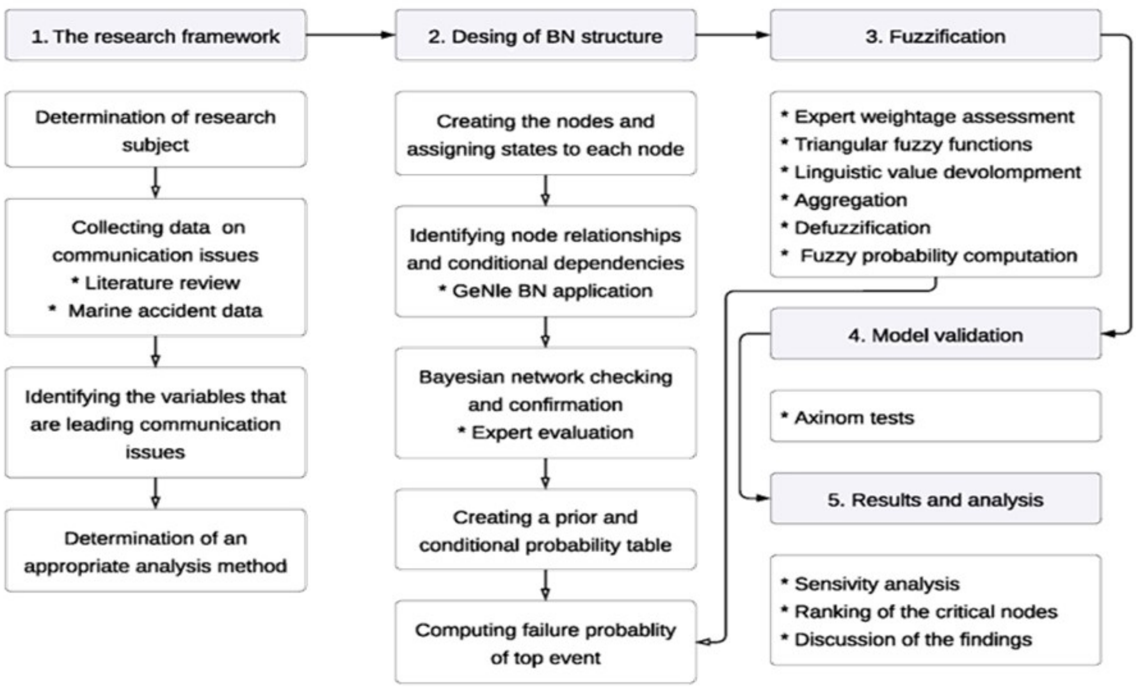

Figure 1. The research flow chart

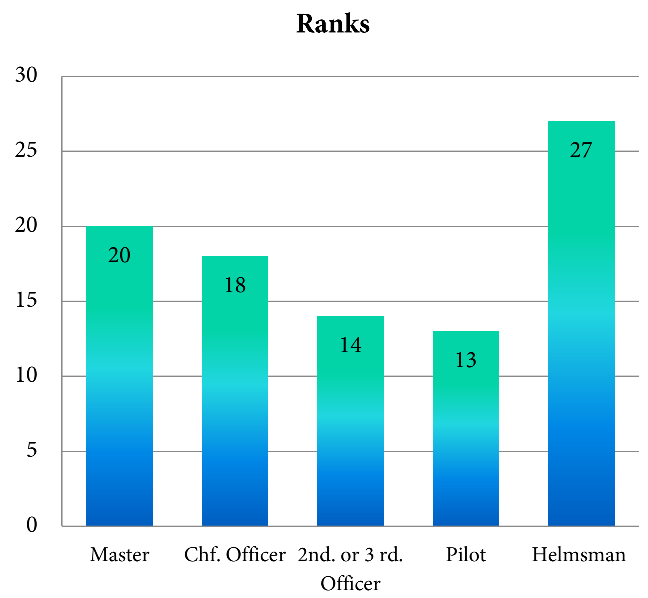

Figure 2. Distribution of participants of the survey

Prior Probabilities for a Node with Multiple Parents

The variables that have negative effects on communication have been categorized in BN structure. The final version of the BN network was determined in consultation with a heterogeneous expert group. Where the number of nodes used in the BN network is limited, experts are able to determine the probability directly, utilizing their expertise and knowledge. The assessment of probability combinations becomes more challenging when there are a large number of probabilities to be evaluated, particularly when the nodes have more than one parent, as is the case of the current study. To decrease complexity, the decomposition approach is used in this paper, which allows experts to extract the CPT by evaluating each parent node independently. The decomposition approach helps experts elicit the CPT more efficiently while reducing subjective prejudices (Wang et al., 2010, 2011; Ping et al., 2018).

Assume that node N has k states ($S_1, S_2, \ldots, S_k$) with n(n≥2) parents ($T^{(1)}, T^{(2)}, \ldots T^{(j)}, \ldots T^{(n)}$). The parent node T(j) has m states, which $T_1^{(j)}, T_2^{(j)}, \ldots T_m^{(j)}$ (J=1, …, m). Thus, the prior probability of each state of N under the various state combinations of its parent nodes can be described as:

$$P(N = S_i \mid T^{(1)} = T_u^{(1)}, T^{(2)} = T_u^{(2)}, \ldots, T^{(n)} = T_u^{(n)})\ i = 1, 2, \ldots, k;\ u = 1, 2, \ldots, m \quad (3)$$

When a node A has two parents B and C, its conditional probability on B and C can be approximated by means of:

$$P(A \backslash B, C) = \alpha P(A \backslash B) P(A \backslash C) \quad (4)$$

The normalizing constant (α) ensures that:

$$\sum_{\alpha \in A} \mathrm{P}(\alpha \backslash \mathrm{B}, \mathrm{C}) = 1 \quad (5)$$

Fuzzification

Language expressions that are unclear are translated into exact numerical expressions using linguistic variables. Fuzzy numbers, which generate values ranging from 0 to 1, indicate expert judgment uncertainty, whereas linguistic expressions express uncertain language expressions. The literature presents a variety of membership functions, most of which use triangle and trapezoidal functions. In maritime studies, triangular or trapezoidal fuzzy numbers are commonly used for assessing linguistic variables. The triangle membership function (TMF) is widely used because of its simplicity of use and accuracy in converting exact numbers to fuzzy numbers (Kamal et al., 2020; Akan & Bayar, 2022). Equation (6) illustrates the membership function of triangular fuzzy numbers. The triangular membership function (TMF) is used in this study because of its simplicity of use and accuracy.

$$\mu_{\tilde{A}}(x) = \begin{cases} 0, x \le a_1 \\ \frac{(x-a_1)}{(a_2-a_1)}, a_1 \le x \le a_2 \\ \frac{(a_3-x)}{(a_3-a_2)}, a_2 \le x \le a_3 \\ 0, x \ge a_3 \end{cases} \quad (6)$$

The equation for the triangular fuzzy number E (a1, a2, a3) is presented below:

$$X = \frac{\int_{a1}^{a2} \frac{x-a_1}{a_2-a_1} x\, dx + \int_{a2}^{a3} \frac{a_3-x}{a_3-a_2} x\, dx}{\int_{a1}^{a2} \frac{x-a_1}{a_2-a_1} x\, dx + \int_{a2}^{a3} \frac{a_3-x}{a_3-a_2} x\, dx} = \frac{1}{3}(a_1 + a_2 + a_3) \quad (7)$$

A higher level of precision can be achieved by splitting smaller probability ranges and applying the experts' probability decision to the fuzzy number. To evaluate nodes with unclear conditional probability, a seven-term linguistic scale was employed as shown in Table 1 (Rajakarunakaran et al., 2015).

Table 1. Linguistic scale

Linguistic terms	a_1	a_2	a_3
Very high (VH)	0.92	0.96	1.0
High (H)	0.81	0.87	0.93
Mildly high (MH)	0.63	0.73	0.83
Medium (M)	0.35	0.50	0.65
Mildly low (ML)	0.17	0.27	0.37
Low (L)	0.07	0.13	0.19
Very low (VL)	0.00	0.04	0.08

Expert Elicitation and Aggregation

Makridakis & Winkler (1983) and Clemen & Winkler (1999) highlights the negative marginal values associated with the large number of experts. Five experts have been selected who can assist with variable identification and the development of the Bayesian network at the highest level. Experts' risk perception differs due to variances in their knowledge structure and skills. A weighing process has been employed at this step, taking into account the positions, operational experience, and educational degrees of the chosen experts. Risk perceptions differ due to variances in the knowledge structure and skills of experts. Each expert's decision weight has been assessed by four objective criteria: professional position, competency, service time, and education level. Each parameter is ranked from 1 to 5. The decision weights of the experts chosen for this study were calculated using the criteria shown in Table 1. Table 2 provides the details for the experts as well as the weighting procedure calculations.

Table 3 indicates that the five experts are the Editor in chief, the Accident surveyor, the Senior pilot, the Communications consultant, and the Senior lecturer. For example, the chief editor is a communication expert with 11 years of experience in the field, demonstrating expertise across a range of media outlets. He provides consultancy services to companies as an experienced communication professional and also works as a field editor in a publishing organization. The senior lecturer who is a PhD-qualified maritime educator with 11 years of teaching experience and is an ocean goingmaster, is responsible for teaching maritime communication and maritime English.

Table 2. Weighting criteria of the experts

Attribute	Classification	Weighting Score (WS)
Occupational position	Marine accident surveyor	5
	Editor in chief	4
	Senior marine pilot	3
	Communication consultant	2
	Senior lecturer	1
Competency	Senior pilot	5
	Ocean going master (STCW II/2)	4
	Communications professional	3
	Chief officer & Chief engineer	2
	2nd officer	1
Service time	≥ 15	5
	11-15	4
	6-10	3
	3-5	2
	≤ 2	1
Educational level	Doctorate (PhD)	5
	Master of Science (MSc)	4
	Bachelor (BSc)	3
	Junior college	2
	High school	1

Table 3. Experts' background and decision weights

Expert	Profession title/WS	Competency/WS	Service time/WS	Education level/WS	TWS	Score (75)
E1	Editor in chief/4	Comm. Pro/3	11/4	BSc/3	14	0.186
E2	Accident surveyor/5	Master/4	16/5	PhD/5	19	0.253
E3	Senior pilot/3	Senior pilot/5	9/3	PhD/5	16	0.213
E4	Comm. consultant/2	Master/4	10/3	BSc/3	12	0.160
E5	Senior lecturer/1	Master/4	11/4	PhD/5	14	0.186

To aggregate judgments of these expert group, the Similarity Aggregation Method (SAM) proposed by Hsu & Chen (1996) was employed. The methodological framework is presented as follows:

E1, E2	: It represents a pair of expert opinions.
SUV (E1, E2)	: The degree of agreement (similarity level) between two different expert opinions,
S (E1, E2)	: It indicates the level of similarity between two fuzzy numbers
AA (EU)	: It denotes the average degree of agreement among experts
RA (EU)	: It refers experts' relative level of agreement
CC (EU)	: Consensus coefficient level of the experts
RAG	: It describes the aggregated outcome of the expert decisions.

Step (1): The level of similarity of judgements of the experts are determined. If the opinions of E1 and E2 experts are expressed by E1 = (a1, a2, a3) and E2 = (b1, b2, b3), The following equation illustrates the similarity function between expert E1 and expert E2.

$$S(E_1, E_2) = 1 - \frac{1}{3}\sum_{i=1}^{3}\lceil a1 - b1 \rceil \tag{8}$$

Step (2): The average agreement (AA) of M experts can be calculated as follows.

$$\text{AA}\ (E_U) = \frac{1}{M-1}\sum_{\substack{i=1 \\ n \neq m}}^{M} i\, S(E_1, E_2) \tag{9}$$

Step (3): The Relative Agreement Degree (RA) of M experts can be determined as follows.

$$RA(E_U) = \frac{\text{AA}\ (E_U)}{\sum_1^M \text{AA}\ (E_U)} \tag{10}$$

Step (4): The equation that follows can be used to figure out the consensus coefficient of M experts.

$$CC\ (E_U) = \beta . w\ (E_U\ ) + (1 - \ \beta).\ RA(E_U) \tag{11}$$

Step (5): The equation below is used to aggregate expert opinions.

$$R_{AG} = CC_1 x E_1 + CC_2 x E_2 + \cdots CC_{M1} x E_M \tag{12}$$

Defuzzification

To derive an inference from the Bayes network, the fuzzy numbers must be converted into crisp numbers (Aydin et al., 2024). Multiple methods for this conversion process have been provided in the literature, including the centre of sums, weighted average, centroid method, maximum membership degree, and centre of the largest area (Wang, 1997). The centre-of-area approach was adopted in this study because of its simplicity and versatility. This eliminates data corruption and leads to more accurate analysis. Equations (13) and (14) were employed to convert fuzzy numbers into crisp numbers.

Defuzzification equation:

$$X^* = \frac{\int \mu_{\mathrm{l}}(x)\, dx}{\int \mu_{\mathrm{l}}(x)} \tag{13}$$

For triangular fuzzy numbers;

$$\widetilde{A} = (a_1, a_2, a_3)$$

$$X = \frac{\int_{a_1}^{a_2} \frac{x - a_1}{a_2 - a_1} x\, dx + \int \int_{a_2}^{a_3} \frac{a_3 - x}{a_3 - a_2} x\, dx}{\int_{a_1}^{a_2} \frac{x - a_1}{a_2 - a_1} dx + \int \int_{a_2}^{a_3} \frac{a_3 - x}{a_3 - a_2} dx} = \frac{1}{3}(a_1 + a_2 + a_3) \tag{14}$$

Application of the Method to Bridge Team Communication Issues

It is evident that the safety of merchant ship port operations and navigation is highly dependent on the existence of a collaborative cooperative environment on board. In this section, the FBN approach was employed to simulate the potential barriers that may emerge during communication among bridge teams in these operations. Prior to implementing the proposed methodology, it is essential to identify the variables that hinder communication within the bridge team. A review of the literature revealed that studies on communication difficulties in different sectors have been conducted, but to the best of our knowledge, no study on the communication problems of the bridge team on ships has been found (Erven, 2002; John et al., 2013, 2016; Rani, 2016; Kapur, 2018; White et al., 2018; Salvation, 2019; Tunçel & Arslan, 2022; Güzel et al., 2023).

The following phase reviewed maritime accident investigation reports published in recent years by the Maritime Accident Investigation Branch (MAIB), Marine Casualty Investigation Board (MCIB), Japan Transport Safety Board (JTSB), and National Transportation Safety Board (NTSB) to identify bridge-team communication failures in collision-type accidents. The Bayesian network creation process commenced following the identification of the variables. Before commencing the interviews, the experts were instructed about the goal of the study, the Bayes network method, and the process for exposing probabilities. The data on bridge team communication issues were shared with the appointed experts, and the variables included in the framework were debated based on their structure. Before commencing the interviews, the experts were instructed about the goal of the study, the Bayes network method, and the process for exposing probabilities. The data pertaining to the communication issues encountered by bridge teams were presented to experts, and the specific variables included in the proposed framework were discussed. A Bayes network-based model was created using the academic software package GeNle 3.0 (Bayes Fusion LLC, 2021). The variables were connected in the BN in hierarchical order based on previous studies (Kapur, 2018; Salvation, 2019; Çakır & Kamal, 2021). The final version of the BN was established through the consensus of the experts. The marginal probabilities of the root nodes in the BN were calculated using data collected from a web-based survey of bridge team members. Before employing the software, the opinions of experts, represented in linguistic terms, were converted into triangular fuzzy sets. Expert opinions were reconciled using Hsu & Chen's (1996) similarity aggregation approach. Figure 3 illustrates the posterior probability for all nodes. The nodes in the BN are assigned colors according to their hierarchical order.

Table 4 describes the nodes that may cause bridge-team communication issues. The nodes of the network are based on the literature, expert judgments, and accident reports (MAIB, 2015, 2020; BSU, 2019; UEIM, 2019; JTSB, 2020; NTSB, 2020; MCIB, 2022; USCG, 2022).

Prior to entering the data in the GeNIe program, the expert views collected in linguistic form were fuzzified using the triangular fuzzy members listed in Table 1. Due to limited space, Tables 5 and 6 only provide expert verbal evaluations of the node "Language barriers" and conditional probabilities for the node "Personal barriers".

Validity of the Method

In the final step, the model that was created will be validated. Validation is an essential component of the BN model since it offers reasonable confidence in the findings. Based on the literature, there are various methods to assess the validity of the created model. Three axioms should be satisfied using a frequently utilized approach, which is also applied in this paper (Zhang et al., 2013; Chang et al., 2021). Axiom 1 states that increasing or decreasing the prior probability of each parent node by a particular percentage must result in a meaningful and significant rise or drop in the posterior probabilities of the linked child nodes (Table 7).

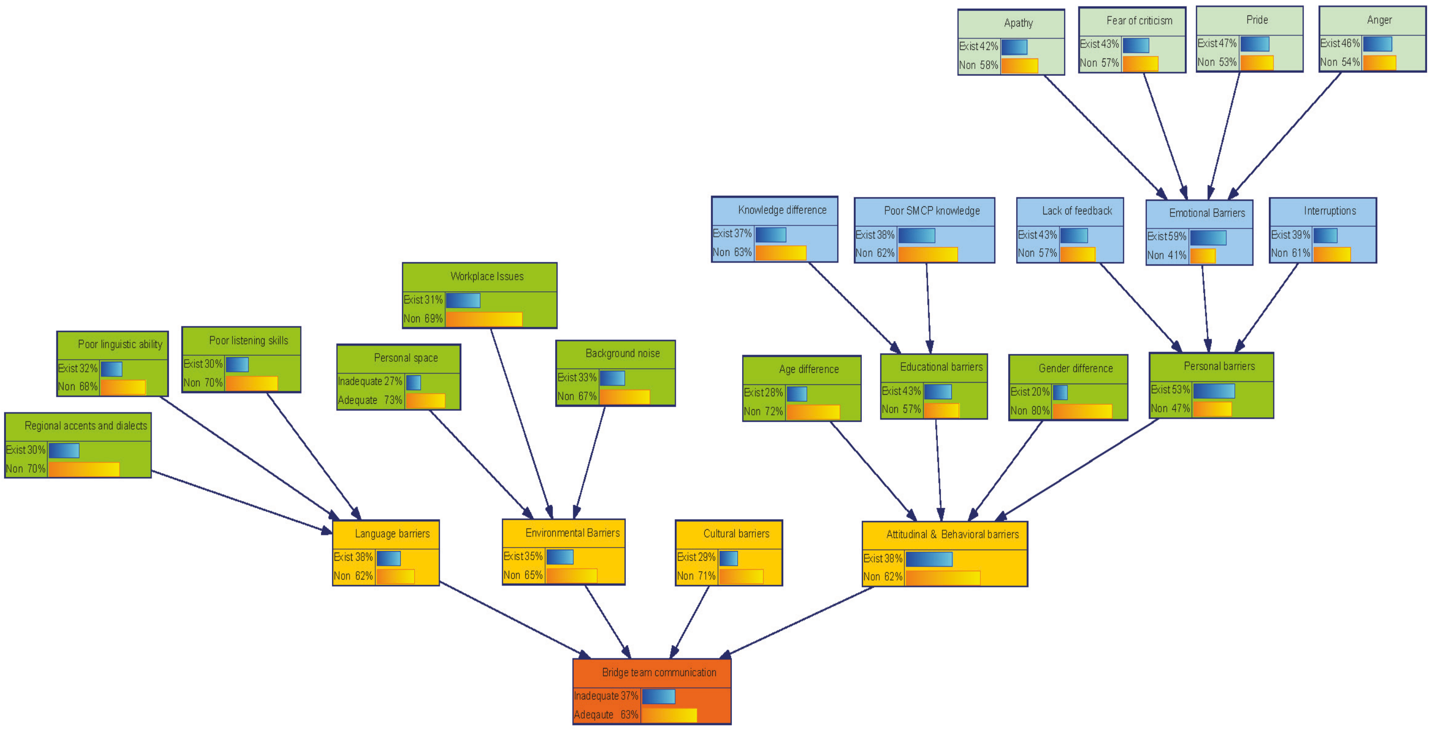

Figure 3. Nodes of bridge team communication issues in the FBN approach

Table 4. Details of the nodes

Node Description	Node Condition	Failure Reference	Definition
Bridge team communication	Leaf	AIR	The term is used to describe the process of exchanging information and instructions in a coordinated manner among the members of a ship's bridge team.
Language barriers	Parent	LR, AIR, EJ	It refers to the obstacles or challenges that arise when individuals or groups cannot effectively communicate due to the lack of a shared or common language.
Environmental barriers	Parent	LR	The term refers to obstacles in the physical environment that hinder people's ability to participate fully in activities or access services.
Cultural barriers	Root	LR	The term encompasses the discrepancies in norms, values, traditions, and communication styles that can impede comprehension and efficacious interaction between individuals from disparate cultural backgrounds.
Attitudinal & Behavioural barriers	Child	AIR, EJ	It refers obstacles that stem from people's attitudes and behaviors rather than physical or systemic issues.
Regional accents and dialects	Root	AIR	The term denotes a variation in the manner of linguistic expression, contingent upon the geographical region or area from which the speaker hails.
Poor linguistic ability	Root	LR	The term refers a lack of aptitude in the acquisition of language.
Poor listening skills	Root	EJ	The term is used to describe an individual's limited capacity to decode and interpret verbal messages and nonverbal cues, such as tone of voice, facial expressions, and physical posture.
Personal space	Root	LR	The term denotes the immediate physical environment of an individual, which may evoke feelings of encroachment and discomfort when perceived as a threat.
Workplace issues	Root	LR	The term is used to describe the difficulties encountered by employees in their professional environments.
Background noise	Root	LR	The term which is defined as any sound that is not the primary sound being monitored is a form of noise pollution. .
Age difference	Root	LR	It refers to the amount by which ages are different.
Educational barriers	Parent	EJ	It denotes obstacles that arise from differences in knowledge, skills, or educational background
Gender difference	Root	LR	The term is used to describe the range of behaviours and attitudes that are associated with being female or male.
Personal barriers	Parent	LR, EJ	The term refers to obstacles that stem from individual characteristics, affecting one's ability to communicate or participate effectively.
Knowledge difference	Root	EJ	The term denotes the level of information or awareness that an individual possesses regarding a specific topic area.
Poor SMCP knowledge	Root	AIR, EJ	The term denotes the low level of information that an individual possesses regarding SMCP.
Lack of feedback	Root	AIR	The term denotes the insufficient transmission of evaluative or corrective information regarding an action, event, or process to the original or controlling source.
Emotional barriers	Parent	LR, EJ	The term refers to communication and interaction barriers arising from an individual's emotional state.
Interruptions	Root	EJ	The term refers to disruptions during communication that break the flow of conversation, leading to potential misunderstandings and loss of key information.
Apathy	Root	EJ	It refers to lack of feeling or emotion
Fear of criticism	Root	LR, EJ	It refers to the apprehension of articulating disapproval of an individual or entity due to perceived imperfections or shortcomings.
Pride	Root	EJ	It can be defined as a feeling of positive affect associated with the accomplishment or acquisition of something perceived as beneficial.
Anger	Root	EJ	It signifies a powerful inclination to inflict harm or exhibit malevolence as a consequence of an unjust or unkind occurrence.

Note: AIR: Accident Investigation Report, LR: Literature Review, EJ: Expert judgment, SMCP: Standard Marine Communication Phrases

Table 5. Verbal evaluations by experts and fuzzy possibility scores (FPS) for State A of the node "Language barriers"

Language barriers	**States**		**Evaluations for states A**					**(FPS)**
	States A	***States B***	***Expert 1***	***Expert 2***	***Expert 3***	***Expert 4***	***Expert 5***	
Poor listening skills	Exist	Non	H	MH	H	H	H	0.896
Regional accents and dialects	Exist	Non	ML	M	M	ML	ML	0.858
Poor linguistic ability	Exist	Non	M	VH	VH	H	VH	0.903

Table 6. Conditional probabilities for the personal barriers' node

Emotional barriers	**Exist**				**Non**			
Interruptions	***Exist***		***Non***		***Exist***		***Non***	
Lack of feedback	***Exist***	***Non***	***Exist***	***Non***	***Exist***	***Non***	***Exist***	***Non***
Exist	0.998	0.940	0.828	0.091	0.984	0.577	0.293	0.008
Non	0.001	0.059	0.171	0.908	0.015	0.422	0.706	0.991

Table 7. Test of Axiom 1 for the node "Environmental barriers"

Condition	**Root Nodes**	**Parent node**
Exist	Workplace issues	Environmental barriers
	Prior %	34.8
	100 %	71.1
	0 %	18.8
Exist	Background noise	Environmental barriers
	Prior %	34.8
	100 %	53.5
	0 %	25.7
Exist	Personal space	Environmental barriers
	Prior %	34.8
	100 %	67.0
	0 %	22.8

Table 8. Axiom Test 3 for the node "Emotional barriers"

Parent nodes				**Child node**	**Percentage change**
Apathy (%)	***Fear of criticism (%)***	***Pride (%)***	***Anger (%)***	***Emotional barriers (%)***	
41.5	42.7	46.9	46.4	59.1	0%
100	42.7	46.9	46.4	81.9	22.8%
41.5	100	46.9	46.4	81.1	22.0%
41.5	42.7	100	46.4	80.1	21.0%
41.5	42.7	46.9	100	76.8	17.7%
100	100	100	100	99.9	40.8%

According to the Axiom 2, different levels of increase in a parent node's prior probability should have the coherent effect on the child node. Figure 4 shows the change in probability for the child node 'Environmental barriers' as a result of alterations to its parent variables 'Personal space', 'Workplace issues', and 'Background noise'. When examining child nodes with more than one parent, the combined influence of parents should be greater than the effect of each parent individually, according to Axiom 3 (Table 8).

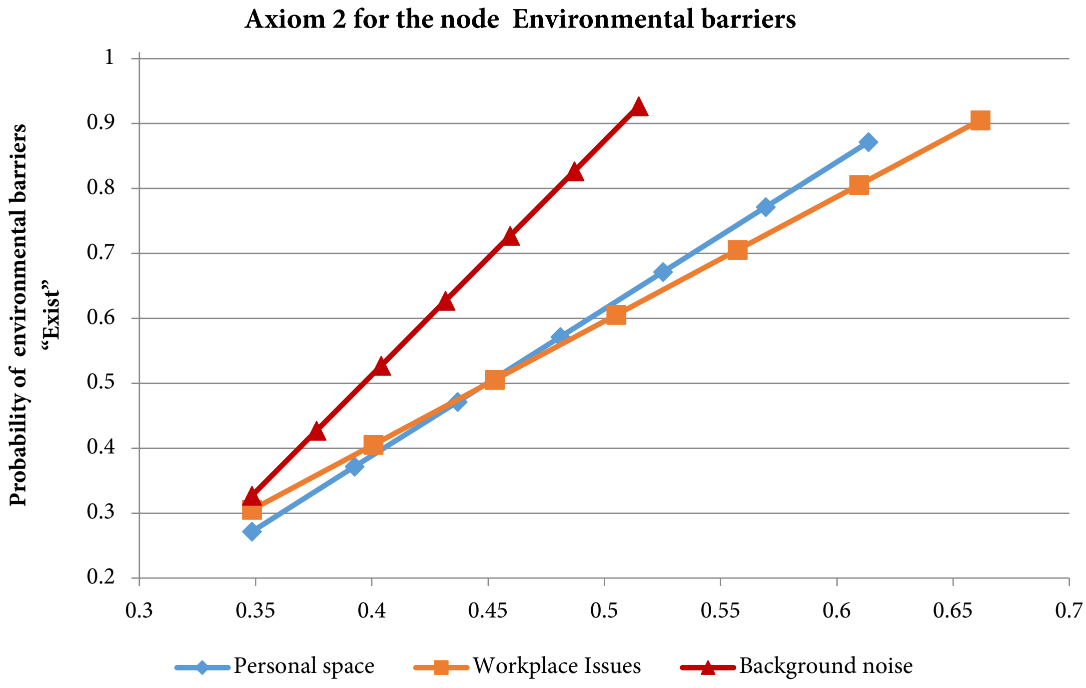

Figure 4. Test of Axiom 2 for the node "Environmental barriers"

Table 9. Sensivity analysis results of the top fifteen node's

Nodes affecting bridge-team communication	Condition	Prior (%)	Change 0%	Change 100%	Effect (%)
Attitudinal & behavioural barriers	Child	38.3	20.8	64.1	43.3
Language barriers	Parent	38.4	21.5	63.0	41.5
Environmental barriers	Parent	34.8	23.9	62.6	38.7
Cultural barriers	Root	28.6	28.5	59.7	31.2
Age difference	Root	27.7	31.7	52.3	20.6
Workplace issues	Root	30.5	31.2	51.4	20.2
Poor linguistic ability	Root	32.1	31.1	50.6	19.5
Poor listening skills	Root	30.2	31.7	50.5	18.8
Gender difference	Root	19.6	33.8	52.2	18.4
Personal space	Root	27.1	32.8	49.9	17.1
Personal barriers	Parent	52.5	28.4	45.5	17.1
Regional accents and dialects	Root	29.9	33.4	46.9	13.5
Educational barriers	Parent	43.3	32.4	44.0	11.6
Background noise	Root	32.6	33.9	44.6	10.7
Interruptions	Root	39.1	33.5	43.5	10.0

Table 10. Sensivity analysis results of the last three node's

Nodes affecting bridge-team communication	Condition 1st	Prior (%)	Change 0%	Change 100%	Effect (%)
Apathy	Exist	41.5	36.7	38.4	1.7
Pride	Exist	46.9	36.5	38.3	1.8
Fear of criticism	Exist	42.7	36.6	38.5	1.9

Sensivity Analysis

Sensivity analysis is a crucial technique in probabilistic assessment, employed to ascertain the behavioural patterns of a given BN model. This technique enables the discovery of discrepancies in the created model. Sensivity analysis determines which variables in the network have the greatest influence on the target node. The prior probability numbers for the variables in the network are changed during the Sensivity analysis, allowing the influence of each node on the target node to be explored. It also allows the network's preventative activities to be uncovered (Zhang et al., 2014). In this study, Sensivity analyses were conducted for all root and intermediate nodes, and the findings are presented in Tables 9 and 10.

Results and Discussion

According to the Figure 3, results, among the 92 seafarers engaged in various duties within the bridge teams of merchant ships, the probability of communication difficulties among bridge crew members was calculated to be 37%. The probability of the root causes identified as potential barriers to bridge communication was calculated, and the subsequent findings yielded the highest marginal probability ratio for emotional barriers (59%), pride (47%), and anger (46%). Furthermore, the root causes with the lowest marginal probability ratio were found to be "Gender difference, with a probability of 20%, "Personnel space", with a probability of 27%, and "Age difference", with a probability of 28%.

Based on the Sensivity analysis, the most significant three root nodes on bridge communication failures were identified as "Cultural barriers (31.2%)", "Age differences (20.6%)", and "Workplace issues (20.2%)". Moreover, the least effective root nodes of bridge communication barriers are the "Apathy (1.7%)", "Pride (1.8%)", and "Fear of criticism (1.9%)", respectively. It was revealed that "Attitudinal and behavioural barriers" had the highest impact (43.3%) on the leaf node, "Bridge team communication". Considering the Sensivity analysis results, it is observed that "Language barriers (41.5%)" and "Environmental barriers (38.7%)" have the most substantial impact on the occurrence of bridge-team communication issues after "Attitudinal and behavioural barriers". Upon examination of the intermediate nodes designated "Attitudinal & behavioural barriers," "Language barriers," "Environmental barriers," and "Cultural barriers," which impact the "Bridge team communication" leaf node in Figure 3, it becomes evident that the cultural barrier node exhibits the lowest efficacy, with an effect of 31.2%.

The outcomes of this study are in line with the results presented by Tunçel & Arslan (2022), as one of the greatest threats to communication on board is a lack of training, which we recognize as an educational barrier. Similarly, "Language barriers" node was determined to be the second most adverse barrier influencing bridge-team communication (41.5%) in the present study. Moreover, in the other study conducted by Güzel et al. (2023), the potential causes of communication failure during cargo operations and proposed countermeasures are discussed in detail. Although the research was conducted on the cargo operations of a cargo ship, the variables identified as affecting communication problems in cargo operations, including poor listening skills, insufficient knowledge of maritime English, and distraction and noise, are similar to those identified in the present study as root causes of communication problems. These include poor listening skills, poor SMCP knowledge, poor linguistic ability, and background noise. The study revealed that language barriers constitute a significant communication barrier in the context of cargo operations. This finding aligns with the results of the Sensivity analysis conducted in current study.

As discussed above, several studies have focused on human factors in maritime accidents or operations and highlighted the impact of communication issues (Chauvin et al., 2013; Barić et al., 2018; Yıldırım et al., 2019, Güzel et al., 2023). Marine accident reports highlight the significance of bridge team communication, which is the primary element of Bridge Resource Management (UK Chamber of Shipping, 2020). Based on the created model, the study's findings suggest that to prevent issues with communication, one should first address "Attitudinal and Behavioural barriers" that arise from working together. In terms of navigation safety, the effectiveness of communication within the bridge team is dependent upon a number of variables. The subject of monitoring and evaluation methods for these variables may be a future area of research.

Conclusion

Hybrid fuzzy Bayesian networks are an exceptionally beneficial method for identifying and evaluating the causes of marine accidents. This study explored the communication issues faced by 92 bridge team members, reviewed accident investigation reports, and sought expert opinion. The study examined ship bridge communication barriers, identifying 17 root causes. These root causes were grouped into four intermediate nodes: "Attitudinal & behavioural barriers," "Language barriers," "Environmental barriers," and "Cultural barriers." The model results revealed that the node with the greatest impact on bridge communication was the "Attitudinal & behavioural barriers" node. It is evident that addressing the key communication barriers identified in this study can significantly reduce the risk of accidents, and therefore should be a priority for all those concerned with safety of navigation.

Upon examination of the underlying factors contributing to the mentioned node (attitudinal and behavioural barriers), it became evident that the node pertaining to age differences exhibited a notable pattern. In this regard, the findings indicated that a significant age discrepancy between the members of the bridge team could potentially impede the flow of communication. This aspect should be recommended and taken into account during the personnel planning stage.

In addition, the following practical implications and suggestions can be drawn from the present study: Firstly, it is recommended that the communication and collaboration skills of the bridge team be evaluated on a regular basis. Prior research has indicated that the flow of information on the bridge can be quantified, with the development of a specific index for this purpose (John et al., 2013). In the event that professionals deem these skills to be inadequate, companies should provide training in communication skills to facilitate development. It is recommended that the obligation to adhere strictly to the standardized communication protocols defined under the SMCP be included in the duties and responsibilities section of the International Safety Management (ISM) manuals of maritime companies. It would be beneficial to implement refresher training programs for both the rating and the officers on this subject.

Secondly, crew satisfaction should be reviewed on a regular basis and its influence on retention rates monitored. It would be prudent to enhance the social facilities on board in order to enhance satisfaction among crew members. It would also be beneficial to prioritize social associations in order to facilitate enhanced communication between the crew.

Thirdly, in light of the considerable diversity of cultural backgrounds among the personnel involved in maritime shipping, it is recommended that shipping companies implement culturally sensitive educational programs designed to foster awareness of cultural differences.

Finally, it is also recommended that companies provide easily accessible psychological support, which can assist in reducing communication barriers by ensuring the crew's emotional well-being. While these decisions fall under the purview of the company's Safety Management System (SMS) and the company's overall safety culture, issues with communication should be addressed in depth, particularly during officer training, to promote good communication.

The generalisability of the results of this study is contingent upon certain limitations. For instance, the study employed expert evaluations as a data source. It is possible that evaluations conducted by experts working on diverse types of ships and engaged in disparate tasks may yield disparate results. In this direction, it is recommended that future studies employ different methods and engage experts working on different types of ships. It is postulated that a bridge communication problem study focusing on ships with a demanding work schedule, particularly chemical tankers and container ships, may yield more divergent results in terms of findings. Additionally, Further research could also examine the potential application of the fuzzy Bayesian network model to other maritime operations where effective communication is of paramount importance, such as cargo and mooring operations.

Compliance With Ethical Standards

Authors' Contributions

İT: Conceptualization, Visualization, Data curation, Formal analysis, Methodology, Investigation, Writing – original draft, Writing – review & editing,

OBÖ: Data curation, Methodology, Writing – review & editing

All authors read and approved the final manuscript.

Conflict of Interest

The authors declare that there is no conflict of interest.

Ethical Approval

This study was approved by the Social and Human Sciences Ethics Committee of Recep Tayyip Erdoğan University (Ethics approval number: 2023/026, Date: 25/01/2023).

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Data Availability

The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

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