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Article

Analysis of Navigator Decision Making through Cognitive Science for the Presentation of a Collision-Avoidance Algorithm for MASSs

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Abstract: The study of navigator behavior is important for the study of MASSs. This study analyzed navigator behavior through cognitive science, and it modeled the navigator decision-making process. Usually, the assessment of the collision risk for long-distance target ships is conducted through the distance (DCPA) and time (TCPA) to the closest point of approach. The navigator's decision-making process is carried out quantitatively based on numerical values. Although the angle of the rudder is presented as a numerical value (i.e., 5°, 10°, 15°, and so on), it is expected that the navigator's use of the rudder will depend on the conventional method rather than the quantitative one. Therefore, a scenario was constructed, and a simulation test was carried out through a ship-handling simulator. Our results confirmed that the rudder was used according to the conventional method. Moreover, the navigator decision-making process was analyzed through cognitive science. Cognitive science has revealed that human judgment is not logical, and that all decision making relies on memory. We identified the type of memory that affects the decision making of navigators: the DCPA and navigators' decision-making-criteria values were mainly formed by episodic memory. A decision-making model for the relationship between the navigator's episodic memory and the value of the DCPA was subsequently developed. This study took a scientific approach to analyze the process of the decision making of navigators, and an engineering approach to construct a decision-making model for application in MASSs.

Keywords: MASS; ship collision; collision avoidance; cognitive science; decision making

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1. Introduction

Despite continuous efforts through numerous studies and revisions of the regulations, ship-collision accidents still occur and can lead to secondary accidents (such as sinkings, fires, oil spills, and even casualties) [1]. Therefore, efforts to reduce ship-collision accidents are continuously required, and they have been delivered through various studies. Representatively, there is the "ship domain", which focuses exclusively on the safe distance between ships. The ship domain was first proposed by Fujii and Tanaka [2], and it is based on the trajectory data of the ship. Moreover, several studies on avoiding ship collisions through the use of the ship domain or the closest point of approach (CPA) have been conducted [3–6], while more and more ship-collision-avoidance studies have been based on artificial intelligence (AI) [7–11]. However, most of the studies have implemented only an engineering approach [12,13]. In the field of aviation, research on the decision making of air force pilots has already been extensively conducted [14]. Endsley [14] studied the decision making of airplane pilots in order to prevent airplane accidents caused by human error. Since then, Endsley's model has been applied to various fields [15,16]; however, it is difficult to design a collision-avoidance algorithm for maritime autonomous surface ships (MASSs) with navigator decision making based on the Endsley model. This is because there is no root-cause analysis on why people think and judge as they do, as the Ensley model explains the human decision-making mechanisms at a general level (in the form of awareness, decision, and behavior). Moreover, the factors of a person that influence decision making are simply explained as individual factors. Therefore, it is impossible to explain the underlying reason why humans reach such decisions.

Although it is difficult to apply autonomous-vehicle research to MASSs, looking at the research trends for reference, research on decision making for autonomous vehicles is also being actively conducted [17]. According to Schwarting et al. [17], the Markov decision process (MDP) has been widely used in the decision making of autonomous vehicles, and Li et al. [18] conducted a study on autonomous-driving decision making using a machine-learning model. Even in the studies mentioned, those based on human decision making are rare.

Unni et al. [19] conducted a study on the kinds of interactions between machines and humans that appear to humans in complex situations. However, this study was conducted only on the reciprocal process that appears in humans, and it did not study the modeling of human decision making.

Studies on decision making in MASSs are being conducted in various ways [20–26]. However, most of these studies are focused on how to avoid target ships by engineering methods, and no human-based analysis has been conducted. Fan et al. [27] analyzed how emotions work in the decision making of navigators. Although it is difficult to generalize because the number of sample test subjects was small (11), it was not a study on the decision-making process of the navigator. According to these studies, it is difficult to present a decision-making process of navigators that is specifically similar to the Endsley model.

We believe that a model that reflects the decision-making process of navigators is necessary for the development of a successful ship-collision-avoidance algorithm for MASSs. AI models, such as neural networks, have been presented by referring to the decision-making process in the human brain [28–33], while AlphaGo and DeepBlue surpassed the human ability after learning human Go and chess play [34,35]. Therefore, in order to develop a reliable collision-avoidance algorithm for MASSs, a decision-making model that is specialized for navigators should be implemented.

This study proposes specialized decision-making modeling for navigators, and it analyzes the characteristics of the mechanism involved, as well as the reason for having such a mechanism, through cognitive science.

In order to develop the navigator decision-making model, we first hypothesized the navigator ship-collision-avoidance decision-making procedure as follows. The navigator undertakes the decision making on how to avoid the target ship (TS). In order to avoid collision, the decision making is performed based on information such as the position, speed, course of the navigator's own ship (OS), and that of the TS. Automatic radar plotting aids (ARPAs) calculate the aforementioned parameters, and they provide the distance to the CPA (DCPA) and time to the CPA (TCPA) to the navigator. Subsequently, the navigator quantitatively assesses the risk of a collision with the TS through the DCPA and TCPA, and he/she takes action so as to avoid collision with the TS if required. In this case, the collision-avoidance action may be the result of qualitative decision making. This is because the use of the rudder is customarily operated at 5 degrees. At sea, the trajectory of the OS may be different (even though the same rudder angle is used) due to the waves, currents, wind, and difference in the draft of the ship. It is possible to use a rudder turn of 7 degrees or 13 degrees if humans accurately predict the trajectory of the OS according to the sea conditions that change every moment, but this is still a very difficult problem. Therefore, there are many things that need to be qualitatively evaluated in ships, while so much of a ship's navigation relies on customs (such as the passing port side to port side between two ships, how to use the rudder, etc.). Most representatively, the Convention on the International Regulations for Preventing Collisions at Sea (COLREGs) was enacted in order to regulate what has been conventionally passed down [36].

Navigator decision-making modeling is possible only when there is a fundamental analysis of the navigator's decision making. The collision-avoidance-action mechanism of the navigator can be considered a part of the human decision-making process. According to cognitive science, human decision making depends on the memories of individuals [37]. It has been proven, through brain studies, that humans can perform logical decision making in the wrong way [38,39]; this is because humans tend to make judgments based on similar memories of the past in new situations [40].

Memory, which is the basis of judgment, has been classified into two typical types: explicit memory (which can be explained by words) and implicit memory (which cannot be explained by words) [41–44]. We deal mainly with explicit memory in this study, and it is divided into semantic and episodic memory. Semantic memory is a memory that is stored through learning, while episodic memory is a memory in which experiences are stored [44].

Therefore, we selected test subjects in order to analyze the decision-making processes involved in the navigator maneuvering of ships and to establish a collision scenario, and we conducted the experiment through the ship-handling simulator. The quantitative data extracted from the avoidance behaviors of the navigators were also analyzed.

The paper is structured as follows. The methodology used herein is presented in Section 2. The result of this study is explained in Section 3, and it is discussed in Section 4. Finally, the conclusions are presented in Section 5.

2. Materials and Methods

The ship-handling simulator was used for the undertaking of the experiment, and cognitive science was employed to analyze the decision-making processes of the navigators. Figure 1 shows the flow and methodology of this study. As can be seen in Figure 1, the overall research protocol was simple, and the analysis of the results was based on cognitive science.

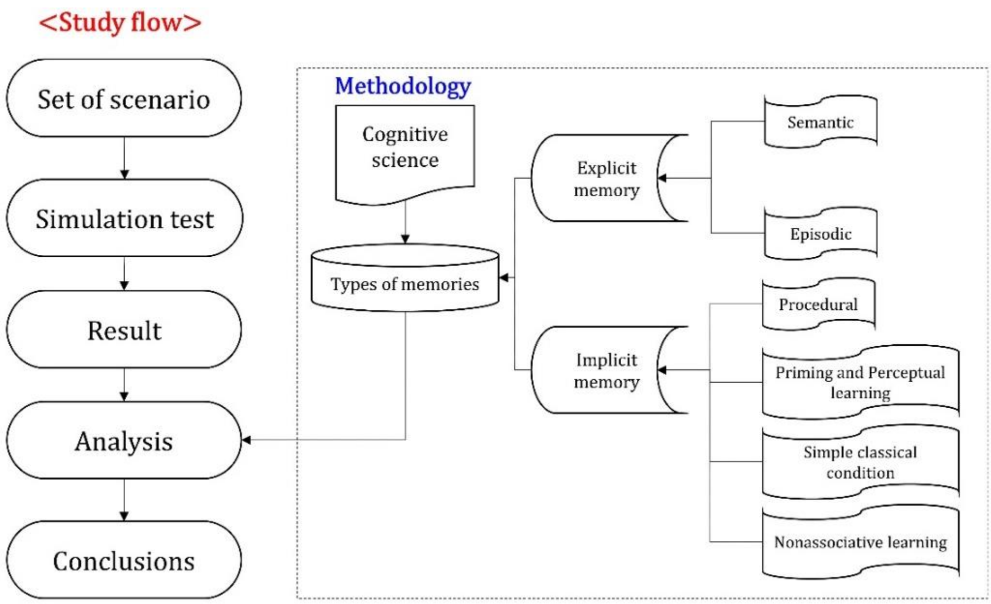

Figure 1. Flowchart of research protocol followed, and of cognitive-science-related methodology employed.

2.1. Cognitive Science and Decision Making

Cognitive science is a new form of study in which philosophy, psychology, anthropology, neuroscience, linguistics, and AI are fused in order to explore the human mind or intelligence [45–47]; it is, therefore, a multidisciplinary approach to the study of the human mind [46,48]. As with analyses that employ coding or software programs for complex calculations, this study used cognitive science as a research methodology to analyze the thinking of the navigators. As the human-thought process revealed through cognitive science has also influenced AI modeling [49–52], cognitive science can be a particularly important tool for the analysis and modeling of people.

2.1.1. The Human Brain and Decision Making

Before the development of neuroscience, the understanding of the human decision-making mechanisms depended heavily on philosophy. Therefore, the theories of decision making developed by philosophers such as Kant, Leibnich, and Descartes were accepted as orthodoxy [53]. However, with the development of neuroscience, the human brain was more thoroughly studied, and it was gradually revealed that our previous beliefs around the mechanisms of human decision making were wrong [37].

In the past, the human brain was thought to make decisions with logical operations [54–56], while it was widely believed that only rationality was necessary for wise judgment [38,39]; thus, logic-based AI emerged [57,58]. However, since the beginning of the study of brain-injury patients, it has been shown that the human brain is not logical [37]. Brain research has since shown that humans make decisions based on stored memories and emotions [59,60].

The case of Phineas Gage is a prime example. He suffered brain damage in an accident at a railway construction site. He suffered heavy damage, and especially to his frontal lobe. Gage, whose ventromedial prefrontal cortex (responsible for emotional processing) in the frontal lobe was damaged, showed antisocial tendencies and was unable to perform rational decision making [61]. However, he was capable of logical and mathematical operations.

In summary, memory and emotions are important for rational judgment. The newly revealed human decision-making process is depicted in Figure 2.

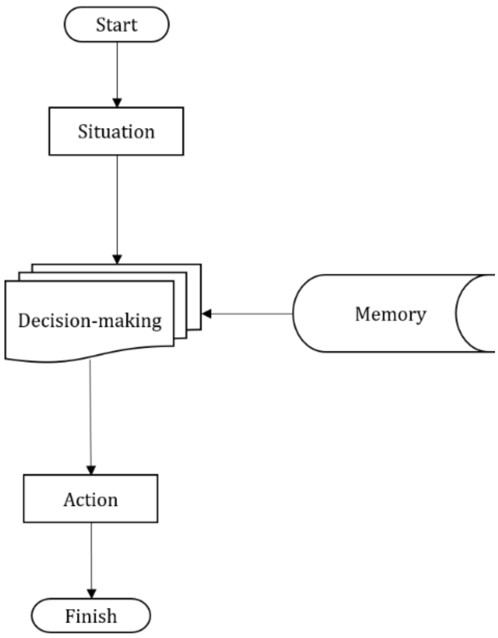

Figure 2. Human decision-making process as revealed by cognitive science.

As shown in Figure 2, human decision making is based on memories of past experiences, as well as on the emotions in these memories [59,60]. For example, when someone goes to Place A, a bad memory and emotion are stored. When he/she goes to a Place A′, which is similar to Place A, he/she does not assess the place or situation logically, but assesses the place or situation based on the bad memories he/she has of Place A.

2.1.2. Navigator Decision Making and Memory

The decision making of navigators, which was analyzed in this study, is also a part of human decision making. Human decision making has been studied through cognitive science, which has revealed the following results.

Human decision making is based on memory [59,60,62]. Memory is divided into short- and long-term memory [63]. Short-term memory is memory input through sensory organs, and it is stored only from 20 s to 30 s [64]. However, long-term memory is a memory that can be stored for a lifetime [65,66]. The long-term memory applied in this study can be classified as shown in Table 1 [48].

Table 1. Types of long-term memory.

	Long-Term Memory					
Type of Memory	**Explicit Memory**		**Implicit Memory**			
Name of memory	Semantic	Episodic	Procedural	Priming and perceptual learning	Simple classical conditioning	Nonassociative learning
Storage brain area	Medial temporal lobe		Striatum	Neocortex	Amygdala and cerebellum	Refle Xpathways

As shown in Table 1, the two types of long-term memory are implicit and explicit memory. Each memory is stored in a different part of the brain according to its type [48]. Memories that can be explained verbally are classified as explicit memories, while memories that cannot be expressed in words are classified as implicit memories. The semantic and episodic memories that were applied in this study are explained as follows. A semantic memory is a memory that is learned through studying [67,68]; through this memory, human beings are able to think of things that do not exist [69]. Episodic memory is a memory in which the time, place, and events are stored as a single experience, and only humans have this ability [69]; for example, we can remember what we did last Christmas. However, if an episodic memory is also repeatedly stored as the same experience, then the content that is meant here is stored in the form of a semantic memory [70].

In summary, we expected that the navigators would assume collision-avoidance actions with qualitative judgment after judging the risk based on quantitative information. With the two CPA values, which are the quantitative values formed by explicit memory, each navigator would perform a collision-avoidance action against the TS. Of course, there would be parts that had been stored as semantic memory by repeated episodic memory. However, because this study is the first study performed through cognitive science, it was not possible to track the conversion of episodic memory into semantic memory. Therefore, only memories from experience are considered episodic memories.

2.2. Scenario

In order to perform the experiment, it was necessary to first set up a scenario and select the test subjects. We selected 30 people as test subjects among those who possessed Officer of the Watch (OOW) certificates. Details of test subjects are presented in Appendix A. And the experimental scenario was set up as shown in Figure 3.

In Figure 3, the blue ellipse is the OS, and the red ellipse is the TS, while the details of both the OS and TS are summarized in Table 1. In the scenario, the TS was positioned at 090° to the starboard side of the OS. The OS was designated as a give-way ship, while the TS was designated as a stand-on ship. The TS, a stand-on ship, was set to maintain the speed and heading angle, and the two ships were set to sail with each other on a collision course for 10 min. Thus, the DCPA and TCPA were set to 0 nautical miles and 10 min in the simulation, respectively, and the initial distance between the two ships was 3.4 nautical miles. Moreover, the navigation area was set as a restricted area in the simulation. The meaning of the restricted area in this study is the TSS (traffic separation scheme). And Table 2 shows the test ships' details.

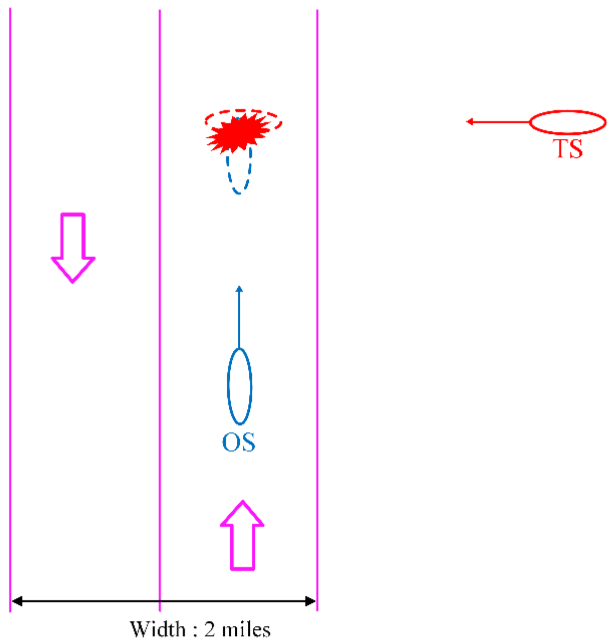

Figure 3. Graphic summary of simulated scenario.

Table 2. Simulation ships' details.

	OS	TS
Length	133 m	288 m
Width	19 m	24 m
Speed	16.00 kts	16.00 kts
Type of ship	Training ship	Bulk carrier

The reason why the TS was positioned at 090° is explained below. Theoretically, in a head-on or overtaking situation, the OS can avoid the TS without a significant change in the heading angle. However, if there is a risk of collision with the TS at 090°, or a similar position, then the OS, which is a give-way ship, needs to move out of the restricted area, or significantly change the heading angle of the OS. As a result, we tried to set up a difficult situation in which one needed to escape the restricted area as a collision-avoidance action, or otherwise significantly change the heading angle of the OS. Therefore, a situation in which the route width was limited to 2 miles was set, and only one of the mentioned situations (090°) was applied to this study (among the various crossing situations of various angle ranges). This is because this study was not a study that aimed to identify dangerous situations according to the angle range, but a study that aimed to analyze the decision-making process that is followed based on the collision-avoidance action of the navigator.

Before the undertaking of the experiment, a briefing on the situation was given to the test subjects, and in order to prevent variables due to unfamiliarity with the simulator, all the test subjects were given time to operate the simulator for 2 h. When the simulation was started in a given scenario, the test subjects were made aware that they were going to collide with the TS by the two values of the CPA. In order to avoid a collision with the TS, the test subjects were required to take action. Subsequently, the OS was set to return to original course after avoiding the TS. Figure 3 shows the conditions of the experiment and configuration of the simulator. The simulator used for the experiment was a product of Kongsberg, and the time required for the experiment was 15 min. Figure 4 shows the test subjects during the simulation.

Figure 4. Configuration of the simulator and general view of the environment in which the experiment was conducted.

3. Results

This section analyzes the results of the events that occurred during the voyage (such as the trajectory of the ship navigated independently by 30 test subjects, the timing of the use of the rudder, the angle of the rudder adopted, and the minimum distance reached between the two ships. Moreover, through an analysis of the results, a navigator-decision-making model is presented.

However, this study is characterized by limitations, as it is not a study that shows the ideal safe distance and timing for the use of the rudder. We thus attempted to analyze how many different decision-making criteria each navigator had, and why they did so.

3.1. Analysis of the OS Trajectory

Figure 5 shows the trajectories of the ship that each of the 30 test subjects followed for 10 min. The x-axis represents the longitude, while the y-axis represents the latitude. As shown in Figure 5, all the trajectories appeared in various ways. Some ships moved a lot to the starboard side in order to avoid the TS, while others avoided the TS without moving much to the starboard side.

The reason that the trajectories of all the ships were different, even in a simple scenario, can be explained by the different risk decision-making criteria adopted, the angle of the use of the rudder, and the time of the use of the rudder by the test subjects. Therefore, we analyzed the degrees of the rudder turns that the test subjects initially used (when they first used the rudder), and how much their OS headings changed.

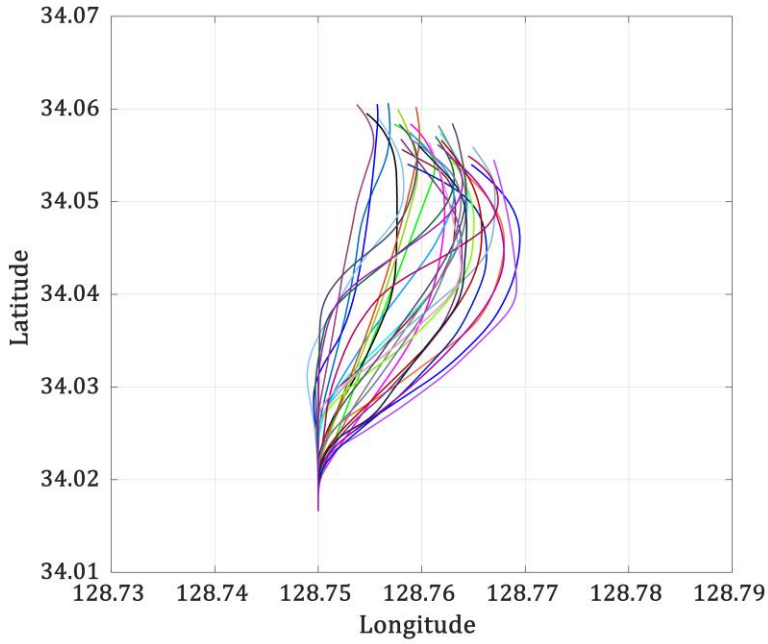

Figure 5. OS trajectories.

3.2. Analysis of Rudder Usage and OS Headings

Figure 6 shows the angles at which the test subjects turned the rudder during the experiment. The *x*-axis represents the time, while the *y*-axis represents the rudder angle. In the experiment, the maximum rudder angle adopted was ±35 degrees.

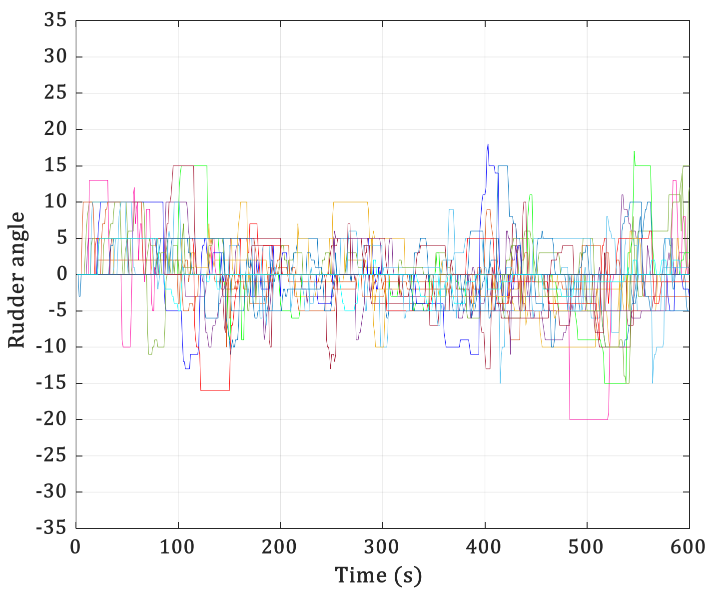

Figure 6. Test subjects' choice of turning angle at the first use of the rudder.

As shown in Figure 6, the use of the rudder differed from person to person, but most used it at intervals of approximately 5 degrees. As a result, Figure 6 looks similar to a digital signal.

The navigators used the rudder based on the memory acquired from customary experience, after evaluating the risk through quantitative information (such as the DCPA and TCPA). The CPA is a risk assessment at the current moment in time; therefore, the two values of the CPA cannot be calculated and presented for the future after the ship moves by using the rudder. Moreover, people cannot accurately predict how far the OS will move when using rudders in various sea conditions. Therefore, it is a complex task for navigators to maneuver ships by using rudders.

In other words, it is impossible to predict the transfer and advanced distance that the OS will move when a navigator quantitatively turns the rudder by several degrees. As a result, the navigator uses the rudder in the customary way. In fact, the use of the rudder on a ship depends on the type of ship, and it is customarily used. In fact, the rudder is usually turned by 5 degrees, while in bulk carriers and very large crude carriers (which are the deepest draft ships after loading), the rudder is turned by at least 15 degrees in order for them to change course.

In summary, navigators cannot precisely predict the OS trajectory after using the rudder. This is because it is difficult to estimate how the sea conditions (such as the wind, currents, and waves) will affect the course of the OS. Therefore, the ship is operated by using as much of the rudder angle as is customarily used.

Figure 7 shows the times when the test subjects first used the rudder. The x-axis is the test subject's number, while the y-axis is the time that the rudder was used for the first time (in sec). Moreover, Figure 8 shows the distance to the TS when the rudder was used for the first time. The x-axis is the test subject's number, while the y-axis is the distance from the TS at the time that the rudder was used for the first time.

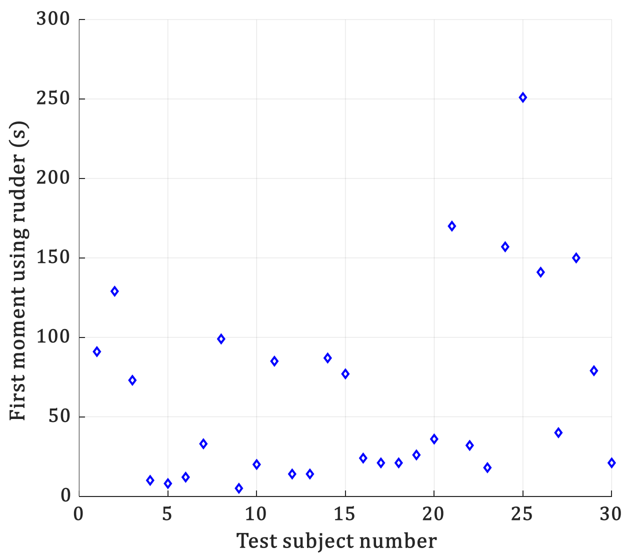

Figure 7. Moments at which navigators used the rudder for the first time.

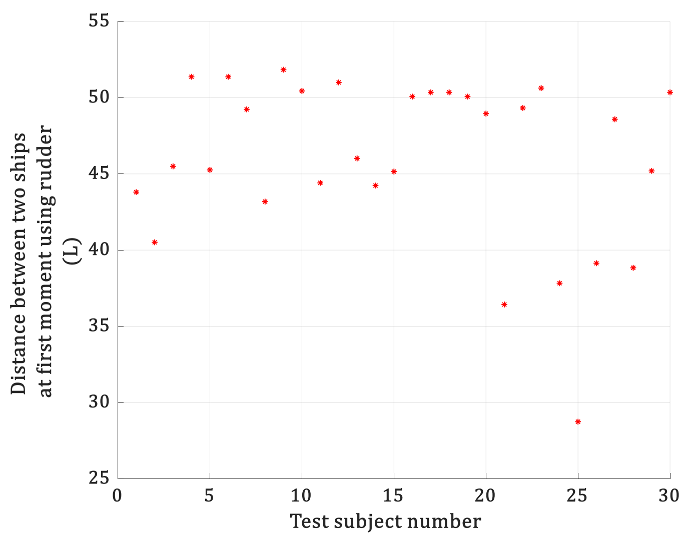

Figure 8. Distances between the OS and TS when the navigators used the rudder for the first time.

As shown in Figure 7, the maneuvering of the test subjects exhibited various trends. However, it seems that the situation was judged mainly within the first 50 s, and that the rudder was used the most. Test subject #25 used the rudder after 250 s. Overall, at the time that the rudder was used for the first time, the distance from the TS ranged, in most cases, between 40 and 52 L.

In Figures 7 and 8, even in the same simple situation, some test subjects evaluated the given situation as very dangerous, and they used the rudder quickly, while others evaluated it as somewhat risky but affordable. The angles chosen at the moments of the first use of the rudder are shown in Figure 9.

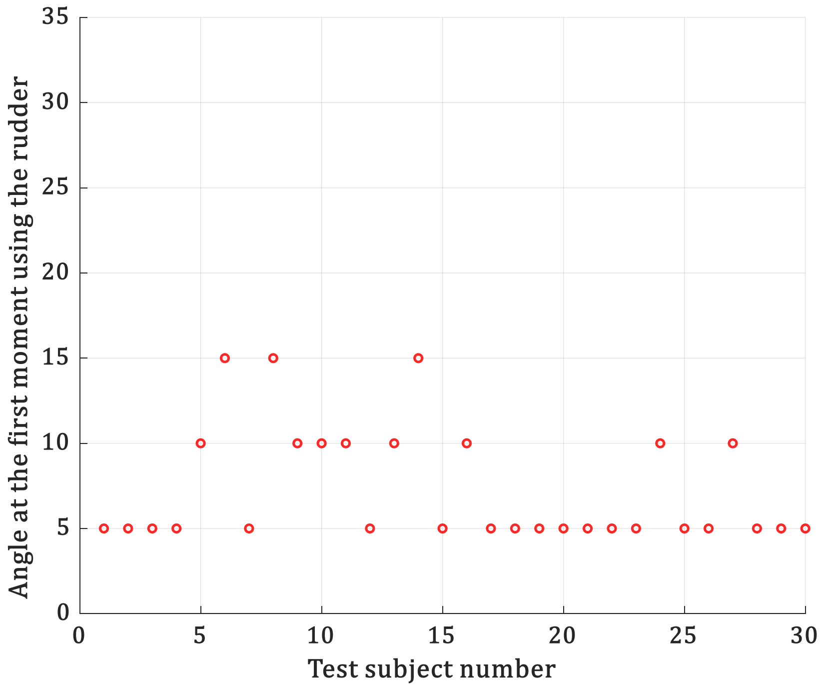

Figure 9. Angles chosen at the moments of the first use of the rudder.

In Figure 9, the x-axis represents the number of the test subject, while the y-axis represents the angle chosen when the rudder was used for the first time. Many of the test subjects only used a 5-degree turn when using the rudder for the first time. The largest rudder turn angle used was 15 degrees.

The test subjects conducted simulation tests with a ship that had never maneuvered. And we interviewed the test subjects about why they used that rudder angle. There were two reasons for deciding the rudder angles that they used. First, they used the degree of the rudder angle based on their own experience. Second, the rudder was roughly used by estimating the maneuverability of the test ship. Through this, it was confirmed that their decisions on the rudder angle to be used were based on experience.

Subsequently, we analyzed how much the OS heading changed.

Figure 10 shows the changes in the OS-heading angles and their means during the experiment. The x-axis represents the time, while the y-axis represents the amount of change in the OS heading. Moreover, the dotted lines of various colors represent the heading changes of all the OSs, while the thick black line represents the average of the heading changes. The positive value on the y-axis indicates the amount of heading change toward the starboard side, while the negative value indicates the changed heading toward the port side.

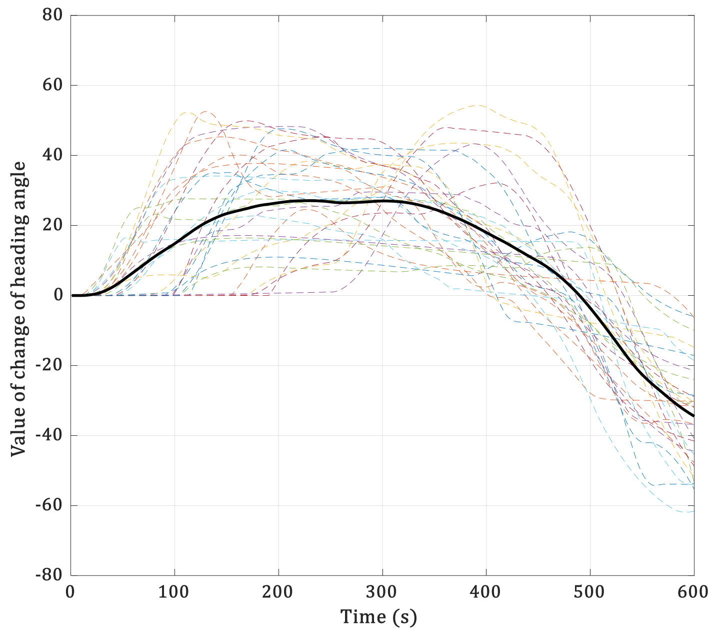

Figure 10. Amount of change in heading angles of OS.

The OS had an initial start heading of 000°. Because the rudder was used in order to avoid the TS, the heading angle was changed toward the starboard side. As a result, the heading was gradually increased to a positive value at 000°. As shown in Figure 10, the maximum heading change recorded was approximately 050°. On average, the OS heading changed toward the starboard by about 030°. Moreover, Figure 10 reveals that some of the test subjects changed the heading quickly, while others did not.

3.3. The Distance between the Two Ships

Figure 11 shows the distances between the two ships during the simulation. The x-axis represents the time, while the y-axis represents the distance between the two ships divided by the OS length (in L). The dotted lines of various colors indicate the distances between the two ships, while the thick black line indicates the average distance between the two ships.

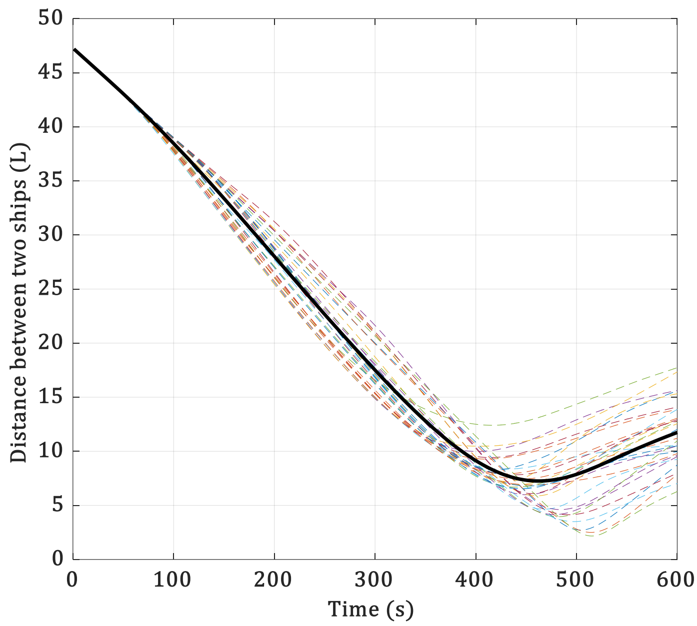

Figure 11. Distances between OS and TS.

As shown in Figure 11, the distance between the two ships became shorter as time went by, and then became farther between approximately 400 and 500 s. The shortest distance between the two ships was about 6.5 L.

On the one hand, the timing of the use of the rudder, the angle chosen when turning the rudder, and the amount of change in the heading of all the OSs exhibited large deviations, but on the other hand, the passing distance between the two ships did not reveal a large deviation (as shown in Figure 11). The timings and angles of the use of the rudder, as well as the amount of change in the heading, were different, but the passing distances between the two ships exhibited a certain tendency. Of course, because this study included only a small number of test subjects, it cannot be interpreted so as to provide an exact answer, but if the number of samples was larger, even if the rudder operation was different, then the passing distance between the two ships would show a similar trend.

Subsequently, we analyzed the closest distance between the two ships. Figure 12 shows the minimum distance recorded between the two ships. The x-axis represents the number of the test subject, while the y-axis represents the distance between the two ships, divided by the length of the OS. As shown in Figure 11, the minimum value recorded was about 3 L, and the maximum value was about 12 L. The average was 6.7 L. Due to the small sample size in this study, the minimum distance may not be very meaningful.

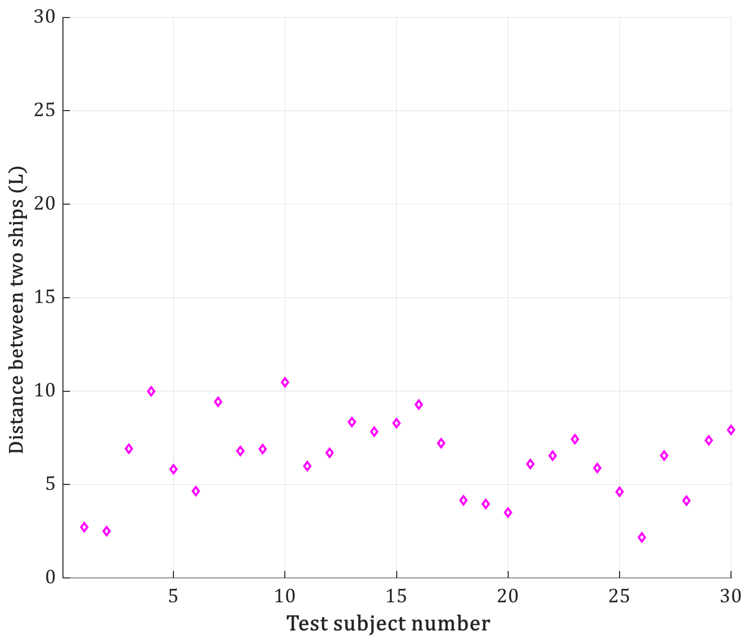

Figure 12. Minimum distances recorded between OS and TS.

The findings of this study are not intended to suggest the ideal passing distance between ships. Through this study, it was possible to confirm how different human beings with different memories operate ships with different criteria when making decisions in a given (identical) situation. As shown in Figures 6–10, they all made different decisions in the same situation. This means that they each had their own quantitative and qualitative decision-making criteria because of the differences in their memories.

3.4. Analysis of Decision Making Based on Memories

Throughout this study, the navigators judged the risk through quantitative information, and they exhibited a tendency to use the rudder by experience. However, it was not possible to confirm, in detail, how episodic and semantic memory each acted on the decision-making-criteria formation. There has been related research in the past, and we analyzed the findings of this research through cognitive science, as summarized in this study.

In a study by Lee et al. [71], 123 seafarers also had very different criteria regarding the threshold value of the safe distance. Lee et al. [71] expressed the criteria of the threshold value of the safe distance as "awareness values," and these awareness values were expressed in the form of the DCPA (in nautical miles). The awareness values of the navigators investigated in the study of Lee et al. [71] corresponded to explicit memory, as the interviewees were able to verbalize the DCPA values specifically, and in nautical miles. What was interesting is that the captains said that their awareness values were mainly formed through studying, while the navigators said that their awareness values were mainly formed through experience. On the one hand, in the case of the captains, the responsibility of being the general manager of the ship motivated them to study for their OS safety. On the other hand, the navigators directed the ship a long distance away from the TS due to the fear associated with a lack of experience, but after experiencing sailing, their awareness values decreased.

A further analysis of the results of Lee et al. [71] revealed that the captain does not operate the ship every day. On ordinary days, the sails of ships are more often operated mainly by navigators. Except for specific areas where the captain must be on the bridge, such as the Singapore Strait, Gibraltar Straight, and so on, the captain's ship-operation time is shorter than that of the navigator. Therefore, because the new memories gained through studying are stored, semantic memory can have a greater influence on the formation of the awareness values of captains.

Conversely, it can be assumed that the awareness values are mainly formed by episodic memory in the case of navigators, who accumulate sailing experience for 8 h every day. Of course, more research is needed in order to elucidate this aspect. However, when analyzing the interview results of Lee et al. [71], one can conclude that the main reasons for the formation of the awareness values of the captain and navigator are obviously different.

3.5. Presenting Decision-Making Modeling for the Navigator

The experiment in this study focused only on the navigator. It is difficult to model how the storage of the semantic memory of the captain influences the formation of the decision-making criteria. This is because more research is still required in order to figure out what kind of study specifically affects the awareness values. Thus, we wanted to model the decision making of navigators. Through simulation, we can see in Figure 6 that the test subjects' use of the rudder was a choice that was based on the experience of convention. Moreover, through the results of the study by Lee et al. [71], it was found that the formation of the awareness values of navigators is based on experience. Consequently, this study only focused on the decision-making process of navigators.

Figure 13 shows the storage of memory and the decision-making procedure of the navigators. In Figure 13, c_1 denotes the situation faced by the navigators; $\mu(c_1)$ denotes the decision making for c_1; λ denotes the semantic memory; ϵ denotes the episodic memory; M_n denotes the stored memory for the situation (c_n). As shown in Figure 13, when the first situation occurs, there will be no memory of the experience of sailing the ship, and only semantic memory. As a result, in c_1, the decision making should be performed only with λ. After the first experience, the ϵ is stored, and ϵ_1 is used for the $\mu(c_2)$.

Herein, we assume that semantic memory represents only the memory stored by studying, which, according to Lee et al. [71], is defined as the classified parameter. summarizes the parameters related to semantic memory, supplements the parameters set by Lee et al. [71].

The theoretical knowledge for the ship's navigation presented in Table 3 was defined in this study as semantic memory. κ_C represents the COLREGS knowledge, κ_M is the boarding ship's maneuverability, and κ_P is the knowledge of the ship's physical phenomena during sailing. κ_A is the knowledge through an analysis of a collision-accident case. κ_N is the navigation-area information, such as winds, waves, currents, etc.

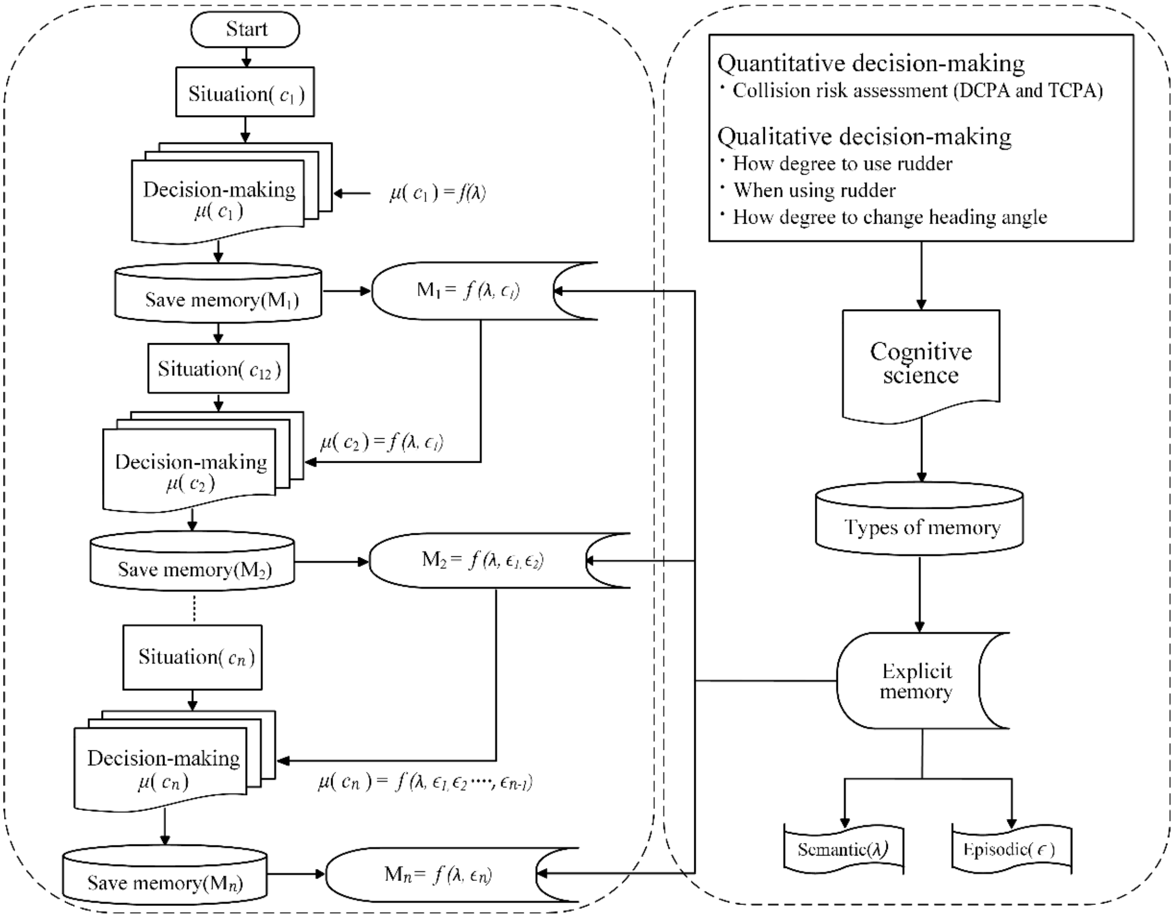

Figure 13. Decision-making process of navigator.

Table 3. Parameters used in semantic memory.

Factors	Parameters	Definitions
Knowledge (κ)	κ_C	COLREGs
	κ_M	Ship's maneuverability
	κ_P	Phenomena occurring during sailing
	κ_A	Analysis through collision-accident case
	κ_N	Navigation-area information (currents, waves, etc.)

The parameters of this knowledge are not experiences, but they can be stored through learning, and they are regarded as semantic memory. Because this differs for each individual, it is difficult to trace the process of storing individual semantic memories in this study. Equation 1 presents the algorithm procedure that is presented in Figure 13 as follows:

$$\left.\begin{array}{c} C_1 \rightarrow \mu(c_1):\ \mu(c_1) = f(\lambda) \\ C_2 \rightarrow \mu(c_2):\ \mu(c_2) = f(\lambda,\ \epsilon_1) \\ C_3 \rightarrow \mu(c_3):\ \mu(c_3) = f(\lambda,\ \epsilon_1,\ \epsilon_2) \\ C_4 \rightarrow \mu(c_4):\ \mu(c_4) = f(\lambda,\ \epsilon_1,\ \epsilon_2, \epsilon_3) \\ \vdots \\ \vdots \\ C_n \rightarrow \mu(c_n):\ \mu(c_n) = \lambda \cdot \sum_{n=1}^{\infty} f(\epsilon_{n-1}) \end{array}\right\} \quad (1)$$

where $\mu(c_n)$ is determined by λ ϵ, except for the first act of decision making. Because it is difficult to track the storage of semantic memory, the latter is treated as a constant in Equation (1). Moreover, as episodic memory can be stored close to infinity, it can be stored continuously. Therefore, the decision making for the situation is briefly expressed as Equation (2) below:

$$\mu(c_n) = \lambda \cdot \sum_{n=1}^{\infty} f(\epsilon_{n-1}) \tag{2}$$

If we express the elements that constitute semantic and episodic memory in an equation, then it would be as follows:

$$\left.\begin{array}{c} \lambda = f(\kappa_C, \kappa_M, \kappa_P, \kappa_A, \kappa_N) \\ \epsilon = f\left(\epsilon_\delta, \epsilon_\psi, \epsilon_r, \epsilon_s,\ M\right) \end{array}\right\} \tag{3}$$

where κ_n is the parameter involved in semantic memory, descried in Table 3; ϵ_δ is the experience of using rudders; ϵ_ψ is the experience of maneuvering ships according to a change in the ship heading; ϵ_r is the experience of maneuvering ships according to the rate of the ship heading; ϵ_s is the experience of the ship operating in various sea conditions; M is the experience of the decision making in a given situation.

As shown in Equation (2), decision-making depends on memory, and λ and ϵ are involved in the formation of the decision-making criteria. λ is achieved by studying in Table 3, and ϵ is the memory of the used rudder, the memory of the heading change, and the stored past experience memory.

4. Discussion

We have, herein, analyzed the decision-making procedure of navigators and the formation of the decision-making-criteria values. In this study, the navigator's decision-making-criteria values were the DCPA and TCPA. Both values are based on explicit memory, which can be described in words. When the two CPA values were formed through the study of the COLREGs and accident reports, they were regarded as semantic memories, while, when they were formed through sailing experience, they were regarded as episodic memories. Although experiences can be accumulated and converted into semantic memories [69], this study considered them to be experiential memories. Because the two memories are stored in the same brain area, further research is needed in order to further subdivide and discriminate these two memories.

There are some things that must be overcome in order to be able to apply AI to MASSs. First, the research reported by Lee et al. [71] has shown that the awareness values between the captain (the most experienced member of the ship's crew) and navigator of the safe distance are significantly different. Their study suggested that the captain's awareness value was formed mainly through studying, while the navigator's awareness value was formed mainly through experience.

Second, it is necessary to consider which values are more important so as to set the AI's decision-making-criteria values. In other words, it is necessary to consider whether to give more importance to the theoretical value, or whether to give more importance to the empirical value. This is a complex dilemma. When relying more on theoretical values, the problem is that the values based on theory make it so that the ship domain is somewhat larger. Although this is traditionally considered good for safety, it may cause some problems in passing through restricted areas [25]. For example, if it is assumed that the safe-distance-criterion value is 6 L in restricted areas, then, depending on the theoretical value, there may be cases where 2–3 TSs are sailing side by side with the OS in restricted areas. However, sometimes within 6 L, the TS that is sailing on the same course attempts to sail with the OS while maintaining a 4.5 L distance due to the surrounding traffic environment. In this case, when the TS invades the ship domain of the OS, a problem arises as to whether the MASS needs to change. If several ships are navigating side by side in a restricted area and the MASS suddenly changes course rapidly, then this can cause a dangerous situation. In these restricted areas (and contrary to common sense), it may be necessary to reduce the size of the domain even though there are many TSs around the OS, and the passage width is narrow. Consequently, the domain to be applied to the MASS should depend more on the experience value of the navigator, rather than on the theoretical value of the captain. However, the theoretical value cannot be ignored either. This is because many ship-collision-accident reports state that the accident occurred due to a violation of the safe distance [72]. If so, it may be necessary to give more importance to the captain's theoretical experience.

Of course, it has not yet been verified which values should be given more importance so as to suggest a safe distance, and therefore, further research is required. If a future AI model has the ability to predict the OS trajectory according to the angle of the use of the rudder, and to evaluate the risk of colliding with the TS based on the predicted OS trajectory, then it is expected that this will compensate for the human limitations.

5. Conclusions

This study scientifically analyzed the decision-making procedure of navigators, and it modeled it in an engineering way. It also analyzed the characteristics of the navigators' decision-making processes in the collision-avoidance action, and how the decision-making criteria were formed. In other words, we created a scenario and investigated how 30 test subjects operated the ship in the same collision situation through a simulation. When the navigators evaluated the risk of the TS, they made quantitative judgments based on the DCPA and TCPA values for their collision-avoidance actions, and they used the rudder as a qualitative judgment based on experience. Subsequently, we analyzed why they adopted such decision-making-criteria values through cognitive science.

It turns out that human decision making is based on past memories and not on logical calculations [34], and we expected that the navigators would also make decisions based on memory. Therefore, it was found that explicit memory had an effect when the test subjects evaluated the risk of colliding with the TS. Their decision-making-criteria values were determined through semantic and episodic memory. As a result of analyzing the existing research through cognitive science, we were able to identify that the formation of the captain's awareness values depends more on semantic memory, while that of the navigator's awareness values depends more on episodic memory.

This study is the first attempt to analyze the decision making of navigators through cognitive science. However, there are limitations of this study; for example, due to the lack of a sufficient number of samples in this study, studies suggesting a safe distance could not be conducted. More results could have been obtained if experiments were conducted through various scenarios, and if more test subjects were recruited. Moreover, only the episodic memory involved in the decision making was herein modeled, while the modeling of the semantic memory related to the decision making was not possible. Future studies should enroll a larger number of test subjects, and attempt to model the role of semantic memory in similar decision-making scenarios.

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Appendix A

Career	Experience	Age	Gender
36M	CHEMICAL	27	Male
12M	TRAINING SHIP	25	Male
13M	VLCC	23	Male
12M	TRAINING SHIP	23	Male
12M	LPG CARRIER	23	Male
10M	PURE CAR and TRUCK CARRIER	23	Male
7M	OIL and CHEMICAL	23	Male
7M	LNG CARRIER	23	Male
7M	LPG CARRIER	23	Male
6M	LNG CARRIER	23	Male
6M	LNG CARRIER	23	Male
6M	LNG CARRIER	23	Male
6M	CONTAINER	23	Male
6M	LNG CARRIER	23	Male
6M	LNG CARRIER	23	Male
6M	CONTAINER	23	Male
6M	LNG CARRIER	23	Male
6M	CONTAINER	23	Male
6M	TANKER	23	Male
6M	CONTAINER	23	Male
6M	CHEMICAL	23	Male
6M	CONTAINER	23	Male
6M	LNG CARRIER	23	Male
6M	LNG CARRIER	23	Male
6M	BULK CARRIER	23	Male
6M	LNG CARRIER	23	Male
6M	PURE CAR and TRUCK CARRIER	23	Male
5M	LPG CARRIER	23	Male
5M	BULK CARRIER	23	Male
5M	BULK CARRIER	23	Male

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