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RESEARCH ARTICLE

Social-material aspect of navigation technology: using structural topic models to identify the causes of ship accidents (1973–2018)

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Abstract
What are the major factors contributing to ship accidents, and how do these factors evolve in the long term? This study addresses these two questions by leveraging an unsupervised machine learning method named structural topic modelling to identify the causes of ship accidents. The study analysed 2,341 task errors manually collected from 441 reports issued by four government agencies covering a 45-year time span. The results show that the structure of causes of ship accidents remained essentially the same during this period. This highlights the social-material aspect of navigation technology, indicating that the use of advanced technology may not necessarily lead to safer navigation practices, and the interaction between the technology and human agency must be focused on in the bridge management context. Additionally, the computer-assisted textual data analysis highlights pilot-related factors, which might be rooted in the unsupervised and difficult-to-verify handover procedures between pilots and captains, thereby underlining the importance of appropriate piloting regulations.

1. Introduction

Maritime navigation has been recognised as one of the most challenging activities in which human beings have ever engaged, involving tragic memories of hundreds of millions of casualties and substantial property loss. The famous RMS *Titanic*, the flagship of White Star Line, sank on her maiden voyage to New York in 1912, taking with her more than 1,500 lives two hours and 40 minutes after the collision[1]; Exxon Valdez struck a reef in Alaska's spectacular Prince William Sound on 24 March 1989. A total of 11,000,000 gallons of crude oil leaked from the ruptured hull of the super-tanker, resulting in one of the most devastating human-caused environmental disasters in history, with the initial clean-up of the spill costing \$2·1 billion.[2] Various prescriptions have been developed both institutionally and technically to tame the 'beast'. In 1914, two years after the *Titanic* disaster of 1912, maritime nations gathered in London and adopted the International Convention for the Safety of Life at Sea (SOLAS Convention), taking into account lessons learned from the sinking of the ship that was commonly named 'the ship of dreams'. The Exxon Valdez crisis led to the creation of the Oil Pollution Act 1990, which called for the introduction of double hulls, among other things. Ships are now also compulsorily equipped with high-tech navigation-assisted appliances, as required by the International Maritime Organisation (IMO) to facilitate safety at sea. These systems include the global maritime distress and safety system (GMDSS),

[1]https://www.titanicinquiry.org
[2]http://www.explorenorth.com/articles/exxon_valdez_oil_spill.html

automatic radar plotting aids (ARPA), electronic chart display and information system (ECDIS) and automatic identification system (AIS).

Although the notable efforts of the maritime community have helped significantly to reduce the uncertainties associated with ocean shipping, the number of reported shipping casualties or incidents actually increased by 5% to 2,815 in 2019 year-on-year (Allianz, 2020). Why does well-regulated and high-tech-equipped maritime navigation still create enormous losses for society? The massive international trade associated with increasingly heavy seaborne transportation logically appears to contribute to the growth in the number of ship accidents worldwide. Another disturbing fact is that the social-material aspect of technology (Orlikowski and Barley, 2001) might hinder it from achieving its complete effectiveness. As Orlikowski and Barley (2001) suggested, 'treat[ing] it deterministically (often as a material cause)' might eventually detach the technology from its embedded context by ignoring the social factors involved, such as the interaction between the technology and various adopters, as well as the user preferences. To illustrate, in 2019, the US Navy announced that it aimed to replace touch screens with manual controls in 2020 after an investigation of an incident involving one of its vessels in 2017 that resulted in fatalities (Allianz, 2020).

Eventually, this study is interested in whether deliberately crafted regulations and advanced shipping technologies significantly influenced the causes of ship accidents relative to their causes at the end of 20th century. This theoretical study is aimed at addressing the research question: *how have ship accident causes evolved with the continual advancement in shipping regulations and technology?* Empirically, this study adopts a data-driven approach by using a natural language processing technique to analyse more than 2,300 task errors manually collected from the UK Marine Accident Investigation Branch (MAIB), the National Transportation Safety Board of the USA (NTSB), the Transportation Safety Board of Canada (TSB) and the Australian Transport Safety Bureau (ATSB), among other databases. The results from structural topic modelling (STM) using these data provide insightful supplements to extant theories in the domain of maritime safety.

2. Literature review

Given that the global shipping industry is responsible for transporting as many as 90% of the items traded worldwide, the safety of its vessels is critical. Unfortunately, the number of ship accidents has increased in recent years, despite significant enhancements in industry regulation and navigation technologies. Statistics reported by the European Maritime Safety Agency indicate that 535 vessels were involved in 505 accidents in and around EU waters in 2006 (EMSA, 2007). In the following 13 years, this figure increased more than five-fold relative to the figure in 2006, with 2,904 accidents in 2019 (EMSA, 2020). In maritime safety research, one of the most popular topics is to identify the factors that have led to actual ship accidents or factors that might lead to ship accidents, based on the statistical significance. The remaining section briefly discusses these two research streams.

The first stream of ship accident research adopts a theory-driven approach, aiming to identify factors that have led to ship accidents by using accident reports from maritime authorities as inputs. In most cases, research in this stream is based on qualitative data from textual materials issued by maritime safety authorities, such as the MAIB, NTSB and TSB, and the conduct of content analysis (Kum and Sahin, 2015) or mixed-method analysis (Qiao et al., 2020) by using existing theoretical frameworks as coding protocols, including the Swiss cheese model and human factors and classification system (HFACS). For example, Chauvin et al. (2013) adopted the HFACS framework to identify human and organisational factors in 27 collision cases reported by the MAIB and TSB from 1998 to 2012. Graziano et al. (2016) focused on the cognitive dimension of the seafarers' behaviour. Using the technique for the retrospective and predictive analysis of cognitive error (TRACEr), the authors coded 52 grounding and collision accidents in the period 2004–2013. Navigation, supervision and traffic monitoring were identified as the top three categories for task errors in bridges (Graziano et al., 2016). Schröder-Hinrichs et al. (2011) conducted a content analysis of 41 accident reports related to machinery space fires and explosions, adopting the HFACS as a protocol to code the contributing factors. Instead of accepting the

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assessment of the IMO that organisational factors are the foremost safety factors that contribute to ship accidents, the authors noted that 'contributing factors at the lower end of organizational echelons are over-represented' (Schröder-Hinrichs et al., 2011). In several cases, the conventional framework and method are regarded as insufficient for risk analysis due to their drawbacks of having a static nature that cannot address uncertainties. Scholars have also contributed to theory development by introducing new analytic frameworks. Qiao et al. (2020) developed a new human factor analysis framework known as the multidimensional analysis model of accident causes (MAMAC) and empirically tested it using a dynamic fuzzy Bayesian network associated with data extracted from reports of 58 accidents that occurred in China in 2018. Compared with the data-driven approach in the second stream of research, which was based on statistical significance, the abovementioned content analysis of accident reports provided scholars with solid grounds to infer the causality of accidents. In contrast, the results of the first stream of research depended largely on the theoretical framework through which the qualitative data were processed or coded. Hence, findings from the first stream of research were largely determined by how they were derived. This aspect may explain why external factors, such as weather and waves, were largely ignored in this stream of research.

The second stream of ship accident research adopts a data-driven approach to identify the factors that are statistically likely to lead to ship accidents. This stream is also known as risk evaluation (Heij and Knapp, 2015) or safety level analysis (Eliopoulou et al., 2016). Compared with the first stream of research that adopts a theory-driven approach, the second stream exhibits a notable advantage in terms of the amount of data that can be processed (Chen et al., 2019). By relaxing the need for accident reports that contain accident details as an essential input in the model, the second stream of research can leverage a large amount of data to facilitate the analysis, including AIS data and information regarding the oceanographic conditions, locations and particular ships (Roberts et al., 2013). For example, by incorporating data from multiple sources, including the HIS-Maritime, IMO, Lloyd's Maritime Intelligence Unit and the International Comprehensive Ocean Atmosphere Data Set (ICOADS), Heij and Knapp (2015) processed more than five million data entries with a binary regression model, including the wind speed, wave height, ship type, etc. The results showed that the effect of the wind speed and wave height on the ship incident risk varied by ship type, region, season and period (Heij and Knapp, 2015). Eliopoulou et al. (2016) focused on critical accidents associated with merchant passengers and cargo ships built after 1980. The researchers used 4,572 serious accident data points extracted from the HIS Sea web and indicated that the safety level of various ship types remained, on average, at approximately the same level in the last decade (Eliopoulou et al., 2016). Bye and Aalberg (2018) employed a multivariate logistic regression model to process a combined dataset of 1,414 ship accident entries extracted from historical AIS records and ship accident records from the Norwegian Maritime Directorate. Vessel type, vessel length, low visibility conditions and flag of convenience were identified as major predictors of navigation-related accidents (Bye and Aalberg, 2018). The results of these data-driven analyses were based on probability; therefore, the solid causality rooted in the conclusion section of the accident reports was likely sacrificed. Additionally, the second stream of research largely focuses on external environmental factors (Wu et al., 2009) and vessel-specific factors (Li et al., 2014) rather than operating, communication and mechanical failures, as in the first stream of research (Awal and Hasegawa, 2015; Uğurlu et al., 2015), and these aspects can be observed only in the accident reports.

In summary, theoretically, the extant research on ship accidents provides a comprehensive understanding of the factors that have caused or might lead to ship accidents. The major contributing factors that have been identified in the existing literature include the specifics of vessels, environmental factors and human factors such as communication and navigation. The literature review further supports the idea that the two streams of research have struggled to balance the availability of data and the reliability of the predictors; notably, the first stream of research is highly restricted by the availability of accident reports. Therefore, although this stream prevails in terms of the reliability of predictors, the results associated with the limited numbers of accident reports are largely dependent on the theoretical framework used to analyse the accident reports. Moreover, although the second stream of research can leverage a large amount of data, the reliability is dependent on the level of effectiveness of the statistical model or algorithms used. Additionally, most of the existing research pertains to static analyses rather than dynamic evolutionary research, focusing on the factors contributing to the accident. The evolution of the causes over a prolonged period is largely ignored. Therefore, by examining the causal dynamics, this study aims to complement the extant maritime safety research, providing insights for both academics and practitioners from an evolutionary perspective.

3. Research design and methods

This study theoretically addresses the research question of how ship accident causes have evolved since the 1970s. This investigation is more valuable if the significant improvements in the industrial regulations and technologies are considered. Thus, this study attempts to contribute to the theoretical development by filling the gap in the literature pertaining to the causal dynamics from an evolutionary perspective. Empirically, this study decomposes the research question into two logically connected sub-questions: 1. Historically, what are the major factors contributing to ship accidents? 2. How have these factors evolved in the long term? Methodologically, although the extant literature has laid a solid foundation for understanding maritime safety contributors, this research adopts a natural language processing method to analyse accident reports. The data-driven approach enables this study to extract results from unstructured qualitative datasets, thereby minimising the influence of the existing theoretical framework on the outcome. In this manner, this study can enhance the understanding of the contributors to maritime safety. The remaining section introduces the data collection and data analysis techniques adopted in this study.

3.1. Data collection

The accident reports issued by government agencies provide an ideal and reliable source to investigate the causes of ship accidents over a long time span (Ellis, 2011; Mazaheri et al., 2015). This study selects only reports written in English from the databases of four representative government agencies: MAIB, ATSB, NTSB and TSB. Although countries such as China are playing an increasingly vital role in the international shipping industry, considering the language comparability of textual data from different nations, this study does not incorporate those data into a dataset. Furthermore, this study filtered out the accident reports in which none of the involved vessels was a cargo ship. The authors propose that, by virtue of their use in ocean transportation, cargo ships exhibit operational patterns that are significantly different from those of non-cargo ships, such as barges, fishing vessels and powerboats, in terms of their manoeuvring habits, mechanical systems, communication and coordination. Therefore, focusing on this particular type of ship could benefit the results by preventing counterfactuals arising from endogenous factors associated with different types of ships. Moreover, given that cargo ships account for a large proportion of world fleets, this sampling strategy involves benefits in terms of the research data availability and representativeness of the conclusion. This study further narrows the sampled cases to three major types of accidents: collision, grounding and allision. Finally, the study extracts task errors from the conclusion section of each report (Graziano et al., 2016), and the dataset consists of 2,341 task errors from 441 cases in a 45-year time span. Details regarding the samples are shown in Table 1.

3.2. Data analysis

Statistical topic models have emerged as effective computational textual analytical tools to derive implications from unstructured qualitative data such as open-ended surveys and online comments (Roberts et al., 2014). As a computer-aided, probabilistic-based text mining technique, a statistical topic model enables researchers to discover latent semantic structures in large collections of texts rather than implement assumptions that correspond to theoretical expectations. As an unsupervised machine learning method, a statistical topic model defines topics or messages as distributions of a vocabulary

Table 1. *Sample details.*

Accident type	MAIB	ATSB	NTSB	TSB	Total
Collision	65	52	30	29	176
Grounding	50	73	8	64	195
Allision	20	7	22	21	70
Total	135	132	60	114	441

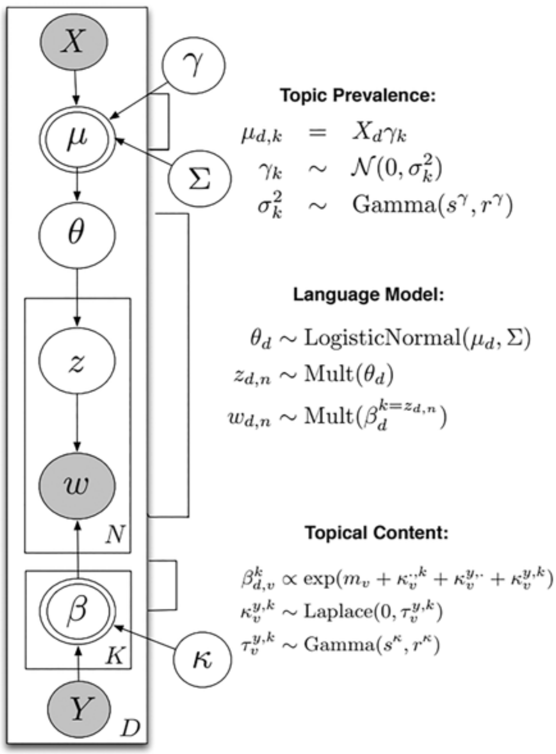

Figure 1. *Structural topic model in plate notation (by Roberts et al., 2013).*

of words that are semantically interpretable ‘themes’ (Roberts et al., 2014). One key advantage of these statistical topic models is their ability to capture how meanings emerge from relations among words, considering the contexts in which the words appear. Two of the most commonly used topic models are latent Dirichlet allocation (LDA, Blei, 2012) and STM (Roberts et al., 2013). Roberts et al. (2013) proposed that, compared with the LDA model, STM can accommodate a corpus structure through document-level covariates affecting the topical prevalence and/or topical content (see Figure 1). Therefore, such modelling involves three crucial differences: (1) the topics can be correlated, (2) each document has its own prior distribution over topics, and (3) word use within a topic can vary (Roberts et al., 2014). Thus, STM can serve as an ideal tool to identify multiple causes among task errors in accident reports. To the best of the authors’ knowledge, STM is commonly used in social science, such as tourism research, assisting scholars in processing textual data more effectively than human coders (Hu et al., 2019; Vu et al., 2019). However, in the transportation safety domain, except in a few pilot studies (Kuhn, 2018), the advantages of STM have not been fully recognised.

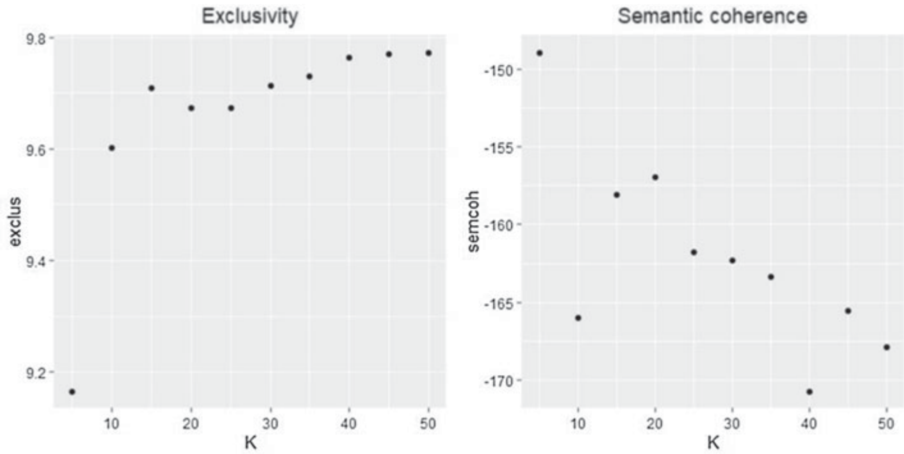

Figure 2. *Statistics used to identify the number of topics.*

This study used the R package 'quanteda' to process the dataset, generating topics for further interpretation. For an analyst, STM can alleviate the burden of developing a categorisation scheme from scratch (Grimmer and King, 2011). Thus, analysts can focus on topic interpretation, associating documents with those categories (Roberts et al., 2014). In terms of operational details, this study adopts the most popular two-step data-processing procedure, described as follows:

(1) *Selecting the number of topics*: As Kuhn (2018) noted, no single correct approach exists to select the number of topics. Researchers must carefully balance the semantic coherence and exclusivity (Airoldi and Bischof, 2016). The former index is designed to measure how frequently individual words occur and pairs of distinct words co-occur, which generally decreases as the number of topics increases (Mimno et al., 2011). The latter index is designed to indicate the exclusiveness of words that have a high probability of appearing conditional on that topic having low probabilities conditional on other topics (Kuhn, 2018). This study analysed the semantic coherence and exclusivity given different numbers of topics ranging from five to 50 in intervals of five, as shown in Figure 2. All three authors carefully reviewed the list of the highest-probability terms for each topic and independently returned to the representative 'task error' for a given topic. Finally, the authors performed a collective discussion and reached a consensus that 25 is the most appropriate number of topics in the particular research context.

(2) *Identifying the topic labels*: Instead of automatically generating intuitive meanings of a topic, this study interpreted each topic based on the highest-probability words associated with the frequency and exclusivity (FREX) that STM provides. Although the former technique is intuitive, balancing the FREX of terms can effectively characterise the topical content, thereby rendering the content more interpretable than the frequency (Airoldi and Bischof, 2016). The labelling was performed based on a group discussion. In general, this process entails strong requirements for the interpreter to have an industry background. Most of the authors have systematic education backgrounds in the international shipping industry. The first author and corresponding author are experts in their own research field. To interpret a given topic more effectively, the authors additionally engaged in a deeper reading of task errors with the five highest proportions assigned to each topic. The decision to identify each topic's intuitive meanings was made collectively. Finally, this study aggregated similar topics into three topic groups to render the analysis clearer and more comparable. The results of the interpretation of the STM outcomes are presented in Table 2.

To address the second sub-question empirically, this study considered the temporal evolution of ship accident causes and distribution of topic groups from 1973 to 2018, as shown in Figure 3.

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Table 2. *Topic details.*

Topic details			Percentage	Explanation (task error)	Topic label	Topic group
Topic 1	Highest Prob	provid, safeti, inform, system, pilotag, plan, guidanc	4·35%	The SMS on board *Shoreway* was a computer based fleet-wide generic safety management system that was of little benefit to the ship's crew as it contained no vessel-specific information, guidance or instructions.	Defects in safety management system on board	Technical failure
	FREX	provid, safeti, guidanc, contain, manag, medic, regard				
Topic 2	Highest Prob	requir, maintain, collis, regul, board, compani, intern	3·79%	A proper lookout, in accordance with the International Regulations for Preventing Collisions at Sea (COLREGs), was not maintained on board Total Response. No one, including the deckhand acting as watchkeeper, saw *Jag Arnav* or was aware of its approach.	Violation of international regulation	Human-related factor
	FREX	requir, regul, maintain, craft, intern, compani, contrari				
Topic 3	Highest Prob	radar, light, visual, detect, keep, collis, either	5·26%	It is probable that visual detection of the light on *Chester* was affected by the reflection of moonlight from the water.	External environment/Natural	External factor
	FREX	visual, light, sight, presenc, bear, detect, observ				

Continued.

Table 2. *Continued.*

Topic details			Percentage	Explanation (task error)	Topic label	Topic group
Topic 4	Highest Prob	monitor, avail, resourc, pilot, team, master, progress	5·09%	Bridge resource management (BRM) was not effectively implemented on board *Maersk Garonne*. The ship's passage plan for the pilotage was inadequate, its bridge team members were not actively engaged in the pilotage and they did not effectively monitor the ship's passage	Communication and coordination between crews and pilot	Human-related factor
	FREX	resourc, progress, avail, monitor, share, principl, member				
Topic 5	Highest Prob	fatigu, master, work, minut, sleep, affect, hour	3·00%	The skipper of *Ocean Odyssey* was fatigued after two days of poor quality sleep and day of prolonged physical activity. The time of day combined with the wheelhouse environment was also conducive to sleep.	Adverse mental state/Fatigue	Human-related Factor
	FREX	fatigu, sleep, work, minut, day, rest, schedul				
Topic 6	Highest Prob	speed, visibl, reduc, restrict, becam, cabl, master	3·35%	The masters of *Washington Senator*, *Lykes Voyager* and *Notori Dake* did not consider it necessary to reduce speed below their required passage speeds, when both restricted visibility and large concentrations of fishing vessels were encountered. In the experience of the MAIB, their decisions with regard to speed would have been made by many masters in similar situations.	Decision error/speed reduction	Human-related Factor
	FREX	visibl, cabl, becam, restrict, appar, speed, proceed				

Continued.

Table 2. *Continued.*

Topic details			Percentage	Explanation (task error)	Topic label	Topic group
Topic 7	Highest Prob	appreci, situat, engin, develop, vessel, ahead, movement	2·68%	The mate made a reasonable and prudent decision to give *Gibson Rock* a wider berth, however having done so he did not appreciate the rapidly developing new situation and that his vessel was standing into danger. He endangered the vessel unnecessarily by failing to call the master and by attempting to regain the track laid down, when the vessel was already to the south of the track and clear water lay in that direction.	Decision error/Appreciate	Human-related factor
	FREX	appreci, rapid, ahead, accept, develop, slow, situat				
Topic 8	Highest Prob	team, pilot, communic, master, plan, situat, awar	5·79%	The pilot did not proactively communicate with *Sea Express 1* and VTS at an early stage to ensure that all parties were aware of the hazard that *Alaska Rainbow* presented to other traffic, resulting unnecessarily in the development of a close quarters situation	Communication error/Pilot	Human-related Factor
	FREX	team, communic, exchang, discuss, intent, act, fulli				

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Table 2. *Continued.*

Topic details			Percentage	Explanation (task error)	Topic label	Topic group
Topic 9	Highest Prob	time, action, avoid, collis, taken, prevent, late	4·65%	The action taken by *Petunia Seaways'* master was insufficient and too late to avoid a collision.	Decision error	Human-related Factor
	FREX	time, late, action, taken, avoid, unawar, rate				
Topic 10	Highest Prob	vessel, fish, signal, advis, collid, assess, servic	4·67%	The skipper of the *Ocean Warrior* did not maintain a proper lookout, nor did he use sound signals to alert the fishing vessel.	Violation	Human-related Factor
	FREX	advis, fish, signal, collid, vessel, locat, meet				
Topic 11	Highest Prob	offic, watch, second, watchkeep, master, mate, asleep	4·72%	The officer of the watch had fallen asleep shortly after taking over the watch at midnight	Adverse mental state/ Asleep	Human-related Factor
	FREX	watch, offic, alon, asleep, charg, watchkeep, second				
Topic 12	Highest Prob	control, steer, oper, system, failur, emerg, result	5·00%	The bridge crew was not adequately familiarised with the characteristics of the *Halit Bey*'s steering control system and did not know how to regain steering control after the autopilot override alarm activated.	Insufficient training	Human-related Factor
	FREX	steer, control, autopilot, gear, familiar, emerg, switch				

Continued.

Table 2. *Continued.*

Topic details			Percentage	Explanation (task error)	Topic label	Topic group
Topic 13	Highest Prob	radar, oper, display, system, inform, electron, general	3·29%	The majority of radar reflectors have inherent problems in practicality and in producing a consistent echo on a radar screen from all angles.	Defects in radar	Technical Failure
	FREX	reflector, general, display, electron, radar, fit, focus				
Topic 14	Highest Prob	direct, master, collis, might, vhf, radio, pass	2·97%	The use of VHF radio for collision avoidance was an unhelpful distraction. In particular, the conversation with *Spread Eagle* wasted time and distracted *King Arthur's* chief officer from his primary role of assisting the master with collision avoidance advice.	Communication error	Human-related Factor
	FREX	vhf, direct, radio, might, pass, sidelight, vigil				
Topic 15	Highest Prob	due, bow, caus, generat, starboard, vessel, shallow	2·82%	There was no appropriate means of determining the amount of diesel oil in the generator service tank from inside the engine-room. The engine-room staff were not aware that the internal arrangement of the generator service tank was such that the last 1·8 tonnes were unpumpable.	Decision error	Human-related Factor
	FREX	due, generat, bow, shallow, tank, clean, engine-room				

Continued.

Table 2. *Continued.*

Topic details			Percentage	Explanation (task error)	Topic label	Topic group
Topic 16	Highest Prob	anchor, drag, master, difficult, ship, vessel, hold	3·57%	The master's early and unwise decision to remain at anchor unless the anchor dragged was based on his assumption that the ship's anchor would hold in the prevailing conditions and his expectation that Newcastle port would, if required, issue instructions for ships in the anchorage to put to sea. Most other ships remaining at anchor, and his expectations, predisposed him to confirmation bias and probably reinforced, in his mind, the decision to stay at anchor.	Decision error	Human-related Factor
	FREX	anchor, deploy, drag, slip, difficult, hold, brake				
Topic 17	Highest Prob	engin, fuel, power, room, experienc, failur, system	4·10%	The blockage of the sea-water cooling system, which resulted in a total power failure, was caused by mud, sand and shells churned up from the sea bed and drawn into the system while the engine was being run astern off the berth at Gove.	Defects in power system	Technical Failure
	FREX	room, fuel, experienc, intermedi, engin, electr, power				

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Table 2. *Continued.*

Topic details			Percentage	Explanation (task error)	Topic label	Topic group
Topic 18	Highest Prob	posit, chart, ship, master, cours, monitor, track	4·54%	Using an outdated electronic chart, which no longer displayed the channel or buoy positions accurately, to verify the wheel-over position likely led the master to initiate the turn later than intended.	Defect in chart	Technical Failure
	FREX	chart, posit, scale, plot, fix, mark, 2nd				
Topic 19	Highest Prob	pilot, manoeuvr, tug, vessel, master, assist, conduct	6·72%	The navigation personnel neither asked for nor were they given a full explanation by the pilot concerning the exact manoeuvres to be performed while docking.	Communication and coordination between crews and pilot	Human-related Factor
	FREX	manoeuvr, conduct, tug, assist, pilot, problem, concern				
Topic 20	Highest Prob	duti, carri, increas, risk, train, lack, pilotag	2·48%	The pilot was affected by a measurable degree of fatigue. The volume of shipping at that time put an extra demand on pilotage services, resulting in shorter than normal breaks between duty periods. The pilot was at the end of his rostered-on period.	Adverse mental state/Fatigue/Pilot	Human-related Factor
	FREX	carri, duti, down-riv, regular, licenc, assign, increas				
Topic 21	Highest Prob	strong, wind, forc, drift, allow, track, vessel	2·32%	Strong winds and the downstream current contributed to the vessel drifting towards the shoal.	External environment/Natural	External Factor
	FREX	forc, wind, hydrodynam, south-west, strong, drift, fender				

Continued.

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Table 2. *Continued.*

Topic details			Percentage	Explanation (task error)	Topic label	Topic group
Topic 22	Highest Prob	condit, weather, prevail, master, advers, circumst, sail	2·99%	In the prevailing weather conditions, *Sea Wasp's* white topsides would have made its visual detection more difficult.	External environment/Natural	External Factor
	FREX	forecast, prevail, adjust, weather, condit, advers, cross				
Topic 23	Highest Prob	cours, proper, alter, collis, fail, risk, rule	6·24%	The master failed to properly ascertain the situation with respect to the *Blue Goose of Arne* and whether it was safe to alter course to 180 degrees.	Decision error/Appreciate	Human-related Factor
	FREX	alter, fail, rule, proper, cours, consid, risk				
Topic 24	Highest Prob	ground, effect, order, tidal, ship, reduc, pilot	4·45%	Shortly after 2000 on 29 October 2013, the pilot issued a series of port helm orders to the helmsman. However, on each occasion he applied starboard helm. The ship's heading and rate of turn increased to starboard and resulted in the ship grounding.	Decision errors/Pilot	Human-related Factor
	FREX	ground, tidal, error, propel, helm, judgment, head				
Topic 25	Highest Prob	master, vessel, command, lack, execut, awar, ship	1·15%	The lack of proper monitoring of the helmsman by the pilot, whilst he was giving commands and they were being executed, contributed to the contact with beacon E5.	Decision errors/Pilot	Human-related Factor
	FREX	command, execut, master, narrow, awar, lack, contact				

The italics of texts are the names of ships involved in accidents.

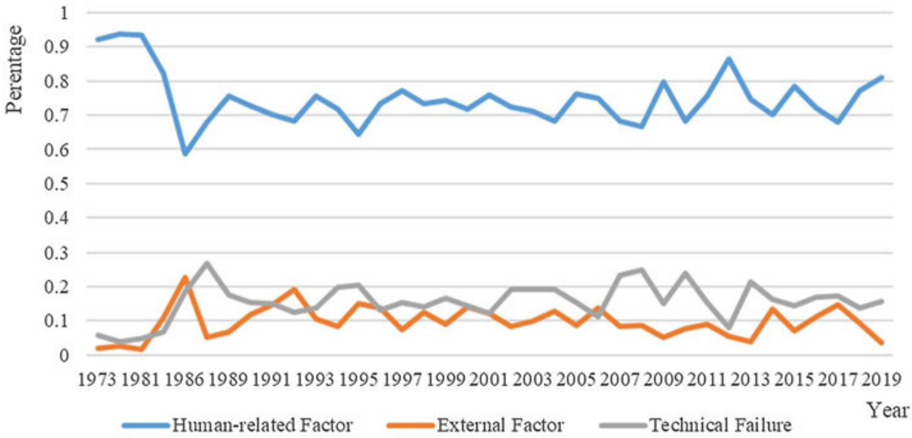

Figure 3. *Evolution of ship accident causes (1973–2018).*

4. Findings and discussion

By analysing task errors collected from accident reports, this study determined the major ship accident causes during the observation period by labelling topics and aggregating similar topic labels into topic groups. In addition, this study demonstrated how these major accident causes evolved from 1973 to 2018. Furthermore, this study identified possible reasons behind the evolution pattern by leveraging the knowledge of the extant literature as well as operational practices.

4.1. Major factors contributing to ship accidents

This paper grouped 25 topic labels into three topic groups based on the derived meanings: technical failure, external and human-related factors. This general categorisation of the contributing factors is consistent with the existing knowledge related to the landscape of ship accidents (Rothblum, 2000; Baalisampang et al., 2018). In addition, the distribution of contributing factors echoes the IMO's statement that human factors are the leading factors in ship accidents and account for 80% of the accidents occurring worldwide (MAIIF, 2014).

4.1.1. Human-related factors

The literature regarding maritime safety suggests that human-related factors can be classified into four categories based on management procedures: organisational influences, unsafe supervision, preconditions for unsafe acts and unsafe acts (Reason, 2000). The research indicates that human-related factors are the foremost contributing factors in ship accidents, accounting for 73·14% of all accidents. Eighteen topic labels are included in human-related factors, which can be generalised into five sub-topic groups: violation regulations (topics 2 and 10; 8·46% of the total), communication error (topics 4, 8, 14 and 19; 20·57% of the total), adverse mental state (topics 5, 11 and 20; 10·2% of the total), decision error (topics 6, 7, 9, 15, 16, 23, 24 and 25; 28·916% of the total) and insufficient training (topic 12; 5% of the total). Interestingly, this paper noted that pilots are frequently involved in task errors, especially in sub-groups such as communication errors and decision errors. As an illustration, in the case of the collision between *Sea Express 1* and *Alaska Rainbow*, the MAIB's report highlights the defect in communication between the crew members and pilot, as follows: 'The pilot did not proactively communicate with Sea Express 1 and VTS at an early stage to ensure that all parties were aware of the hazard that Alaska Rainbow presented to other traffic, resulting unnecessarily in the development of a close quarters situation' (topic 8). Therefore, human-related factors can also be classified into two groups depending on whether pilots are involved in the accident. The pilot-related in human-related factor includes topics 4, 8, 19, 20, 24 and

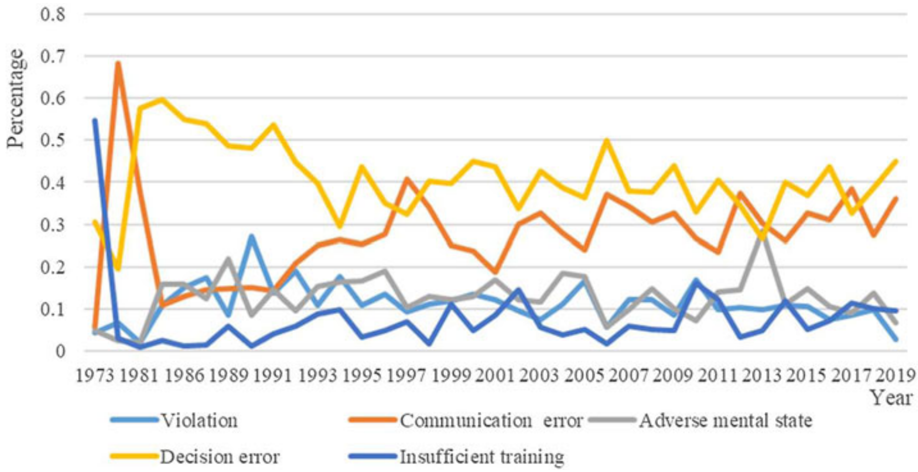

Figure 4. *Evolution of five sub-causes among the human-related factors (1973–2018).*

25, representing 25·68% of the total. This finding complements the previously reported observations that the pilotage is of significance to maritime safety (Debnath and Chin, 2009).

4.1.2. Technical failure

A technical failure is usually considered a total or temporary loss of the ability to operate or manoeuvre a ship; a failure in electric power or failure to contain onboard cargo; or damage to the equipment, system or ship (MAIB, 2012). This study identified four accident labels, accounting for 16·28% of the total: defects in safety management systems onboard (topic 1, 4·35%), radar (topic 13, 3·29%), power systems (topic 17, 4·1%) and charts (topic 18, 4·54%). These technical failures are triggered either by an inherent problem of the material equipment or by negligence/inappropriate crew behaviour, eventually becoming the main factors contributing to the accident. As an illustration, in the case of the collision between the UK registered fishing vessel *Beverley Ann II* and Liberian-registered ro-ro/vehicle carrier *Cypress Pass*, the MAIB concluded that 'most radar reflectors have inherent problems in practice and produce a consistent echo on a radar from all angles' (topic 13). Similarly, the TSB attributed the grounding of the self-discharging bulk carrier *Atlantic Erie* to the negligence of crew as follows: 'Using an outdated electronic chart, which no longer displayed the channel or buoy positions accurately, to verify the wheel-over position likely led the master to initiate the turn later than intended' (topic 18).

4.1.3. External factors

External factors are identified among the three types of factors leading to ship accidents. External factors mainly include strong winds (topic 21) and weather/visibility (topics 3 and 22). Most of these external factors have been identified in the previous literature; thus, the study's results enhance the extant knowledge regarding maritime safety. For example, Heij and Knapp (2015) suggested that oceanographic conditions, including the wind strength and wave height, affect the risk of shipping incidents. Similarly, Wu et al. (2009) clarified that in general, the shipping risk increases as weather conditions become more unfavourable, while the concentration of ice exerts the largest influence on the magnitude of incident rates for a given level of traffic exposure.

4.2. Evolution of ship accident factors

To uncover patterns in the evolution of contributing factors, this study aggregated the task errors by topic group at the year level, as shown in Figure 3. The figure shows a constant and stable pattern in which human-related factors have been the dominant ship accident factors, contributing approximately 75% of

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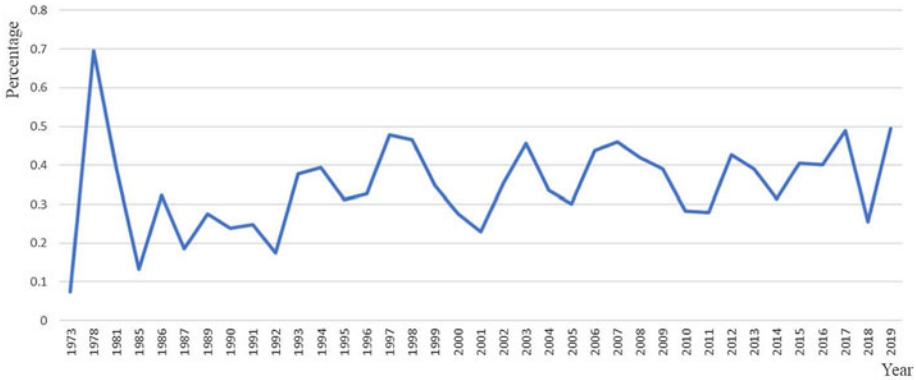

Figure 5. *Evolution of pilot-related factors (1973–2018).*

the total. This finding echoes the statement of Uğurlu et al. (2015) that 'the main factor in the occurrence of collision and grounding accidents is human error. Seventy-seven per cent of the basic reasons causing occurrence of collision accidents, and 81% of the basic reasons causing occurrence of grounding accidents arise from human error.' Furthermore, external factors and technical failures account for approximately 15% of the cases throughout the period. Counterintuitively, given the considerable advancements in navigating technologies and shipping regulations, the percentage contributions of both technical failures and external factors to ship accidents have not decreased significantly over time.

Therefore, this study more deeply investigated the evolution of five sub-topic groups aggregated into human errors at the year level. The dynamic of percentage of each sub-topic groups during the observation period is shown in Figure 4. The decision errors exhibited a slight downward trend with a slope of −0·0017, while the communication errors presented an upward trend with a slope of 0·0025. The remaining three sub-topic groups in human error remained stable with slight fluctuations of approximately 10%. Additionally, this study conducted a similar analysis on the evolution of pilot-related factors, as shown in Figure 5. Throughout most of the observation period, the percentage of pilot-related factors fluctuated between 20% and 50%, with an average of approximately 35%.

4.3. Discussion of the evolution patterns

Practitioners have endeavoured to enhance the navigation safety through rule amendment and technology development. However, the present analysis shows that the structure of ship accident causes remained essentially the same as it was in the 1970s, with human error acting as the dominant factor, accounting for almost 75% of the total, followed by technical failures and external factors, which exhibit comparable weights. Therefore, explaining the conflict between the abovementioned significant advancements in the technical and institutional environment and the stabilised structure of the ship accident causes is an interesting and challenging research opportunity. In the following sections, instead of focusing on whether navigation has become safer, the evolution patterns are briefly discussed:

4.3.1. Social-material aspect of navigation technology

In the past decades, in most cases, theorists and practitioners have been naturally restricted by the materialist perspective, conceptualising technology abstractly and deterministically (as a material cause) and largely ignoring the human agency in shaping the use of technology. Considering the materialism orientation, Orlikowski and Barley (2001) noted that 'technologies are simultaneously social and physical artefacts. Similar technologies can thus be embedded into different social systems in different ways, occasioning different social outcomes.' The authors highlighted the social-material aspect of technologies, proposing that 'technology' should be investigated in association with its embedded social system rather than being construed as a material determinant of its designed purpose (Orlikowski and Barley,

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2001). The social-material aspect of navigation technology has already been discussed in certain existing studies pertaining to the maritime safety domain, highlighting the importance of human-technology interaction in a specified context and its outcomes. For instance, Sauer et al. (2002) compared three types of interface designs of radar and electronic chart information presented to operators: integrated displays, functionally separate displays and spatially separate displays. The results indicated slight navigational advantages of the integrated display, which was assumed to facilitate information collection, over the two alternative display types; however, this advantage came at the cost of increased workload, reduced situation awareness and increased fatigue, which have led to significant negative effects in tests related to navigation safety (Akhtar and Bouwer Utne, 2015).

Therefore, considering the rapid development of navigation technologies over the last four decades from a materialist perspective, it is challenging to rationalise a stable structure for the causes of ship accidents, as shown in Figure 3. The central issue is to address the question of why advanced computer-assisted technologies have effectively failed to reduce human errors, as expected. The social-material perspective of navigation technology has provided an appropriate explanation that the interaction between technology and human agency, rather than the technology alone, leads to safer navigation practices. Accordingly, researchers should devote more attention to how crews use advanced technologies and how these technologies shape the organisation and coordination in the bridge, both of which have been largely under-explored in the previous research.

4.3.2. Inside the human-related factors: does tech help?

Figure 4 shows the evolution of sub-causes among the human-related factors over time. Figure 3 provides an overall landscape of the evolution of major contributing factors, indicating that the structure of the causes of ship accidents has generally remained the same in the past four decades. In contrast, Figure 4 presents an interesting pattern of evolution among the human-related factors: although the communication factors exhibit a steady rise, the decision errors present a gradual decline, and the remaining three factors fluctuate slightly at approximately 10%.

This study proposes that the dual-attribute theory of technology (Orlikowski and Barley, 2001) can explain the pattern of evolution presented in Figure 4. First, as physical artefacts, advanced technologies can help crew members on the bridge to implement more effective decisions. For example, with the help of an AIS associated with an ECDIS, crew members can be better prepared in multi-ship encounters because they are provided with the predicted areas of danger for target ships and a route that can simultaneously enable avoidance of multi-ship encounter collisions and of geographical obstacles (Tsou, 2016). ARPA can provide images of passing vessels, banks, buoys and channel structures, and thus represents a key piece of equipment to perceive the environment and avoid collisions for vessels underway (Ma et al., 2015). For similar reasons, this study observes that the decision error in Figure 4 is reduced with a slope of $-0{\cdot}0017$, which might be partially explained by the abovementioned evidence associated with rapidly developing navigation technologies, such as ARPA, ECDIS and AIS. Second, as social artefacts, advanced technologies influence navigation practice through their interaction with human agency and may thus lead to unexpected side-effects. For example, communication technologies enable crews on different ships to engage in conversations easily, although such conversations are unnecessary in certain cases and may distract crew from their primary role onboard. As an illustration, in the collision between the container vessel *ANL Wyong* and the gas carrier *King Arthur*, the report highlighted that ‘the use of VHF radio for collision avoidance was an unhelpful distraction. In particular, the conversation with Spread Eagle wasted time and distracted King Arthur’s chief officer from his primary role of assisting the master with collision avoidance advice.’ In addition, technology provides comprehensive and sufficient navigation information to bridge members, which may cause them to ignore the importance of communication with external stakeholders, such as the VTS and ships with potential collision risks. For instance, in the case of the collision between *Sea Express 1* and *Alaska Rainbow*, the accident is attributed to the fact that ‘the pilot did not proactively communicate with Sea Express 1 and VTS at an early stage to ensure that all parties were aware of the hazard that Alaska Rainbow presented to other traffic, resulting unnecessarily in the development of a close quarters situation’.

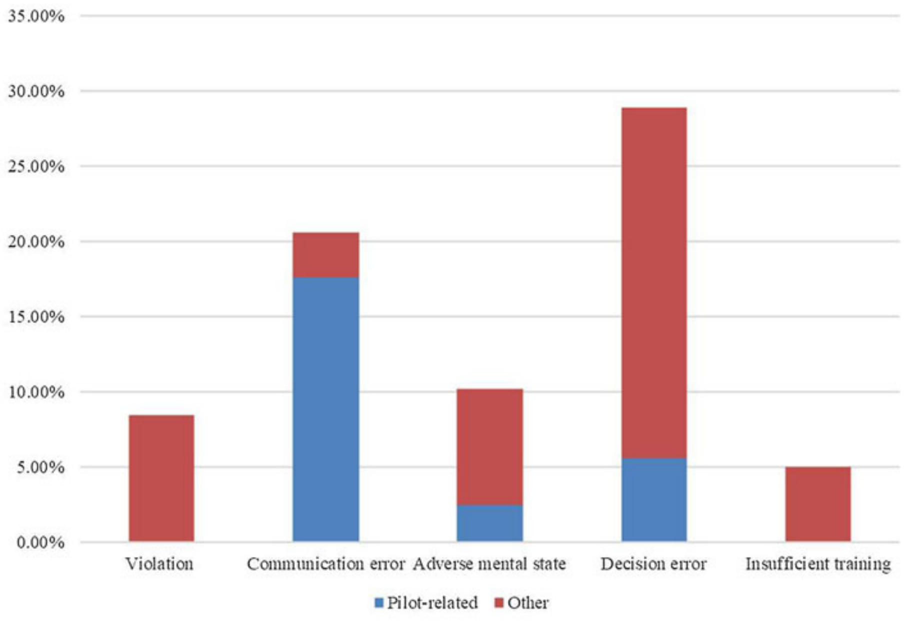

Figure 6. *Pilot-related factors in the sub-causes among human-related factors.*

Advanced technologies associated with the complex and diversified physical system on the bridge also entail higher requirements for the operators' capability, especially regarding pilotage when a pilot is not always familiar with the system onboard the vessel, foreshadowing a communication failure between the pilot and crew members. In the case of the grounding of the Canadian tanker *Diamond Star*, 'the navigation personnel neither asked for nor were provided a full explanation by the pilot concerning the exact manoeuvres to be performed while docking', leading to the tragedy. The evolution of sub-topics among the human-related factors again demonstrates the dual-attribute nature of navigation technology by confirming the positive effect of technologies in assisting decision making and highlighting the importance of the interaction between the technology and human agency.

4.3.3. Why does the pilot matter?

The results indicate that the pilot-related sub-topic accounts for approximately 35% of the total task errors, most of which pertain to communication and discussion errors, as indicated in Figure 6. This finding is also consistent with the suggestion in the extant literature that pilots should be considered at least one of the major triggers of ship accidents (Debnath and Chin, 2009). Furthermore, after returning to task errors and engaging in a deeper reading of representative documents, this study found that most of these errors are rooted in the pilots' unfamiliarity with either the technology environment or organisation onboard. To illustrate, the grounding of the general cargo vessel *Vaasaborg* was attributed to the fact that 'the pilot had not acquired the proficiency and familiarity with the autopilot that was necessary to safely operate it in an emergency situation'. To further investigate the reason underlying this finding, this study conducted a follow-up interview with several Maritime Safety Administration of the People's Republic of China officers in a major port in China. In addition to supporting the findings, the officers provided valuable comments highlighting the defects in unsupervised and difficult-to-verify handover procedures between the pilots and captains. Unlike the standard procedure formulated by the IMO to be enforced on all ships, no mandatory regulation exists to standardise the handover procedures after a pilot boards the ship, and no standardised, traceable documentation exists to record the whole procedure in a logbook for navigation. Based on his practical experience, one of the interviewees stated, 'In our port, we provide guidance regarding the handover procedure; however, this process is not mandatory; in most cases, when the vessel is finally docked on the berth after a long journey along the approach channel, the captain is quite tired. Therefore, the handover procedure, which is required to be conducted through face-to-face communication based on guidance, is merely a ritual, actually implemented as paperwork.'

5. Conclusion

This study supports Luo and Shin's (2019) conclusion that ship accident research has shifted towards a human error-focused paradigm, becoming more inter- and multi-disciplinary with multiple data sources. Empirically, this study extracts three major factors contributing to ship accidents associated with 25 sub-factors out of 2,341 task errors manually collected from 441 reports issued by four government agencies over a 45-year time span. The theoretical contribution can be summarised as follows. First, this study confirms and complements the existing understanding of the maritime safety theory. As discussed in the literature review section, most of the existing literature on maritime safety is based on a presuppositional theoretical framework that restricts the expansion of the existing knowledge of the factors and mechanisms that lead to ship accidents. The analytic tool used in the present research enables us to extract meaning from massive textual data with fewer preconditions. Thus, although the results basically confirm this study's understanding of maritime safety contributors, they can be considered to complement the extant literature. Second, from a dynamic perspective, the results depict the landscape of evolution of the causes of ship accidents over a 45-year time span, indicating that the structure of causes remains nearly the same, dominated by human-related factors. Curiosity about how and why the causes essentially remain the same despite the significant advancements in industrial regulations and navigation technologies led the authors to reflect deeply on the nature of technology from a practitioner's perspective. Thus, this study's third theoretical contribution is based on the social-material aspect of technology, proposed by Orlikowski and Barley (2001), which highlights the interaction between the technology and human agency in a bridge management context. Finally, the results call for attention to the pilot-related risk rooted in the unsupervised and difficult-to-verify handover procedures between pilots and captains. In addition, this study highlights three promising avenues for future research. First, methodology-wise, this research encourages scholars to leverage natural language processing as an innovative and effective method, which can enhance the understanding of the underlying mechanism of various phenomena in the navigation context. Second, this study reminds scholars of the importance of the interaction between the technology and human agency onboard the ship. Even if the shipping community is approaching fully unmanned navigation, it is the human, not machine, that actually controls ships. The authors would like to remind the readers of the subjectiveness of the obtained conclusion, which is rooted in the labelling process. The third avenue for future works is to reduce the subjectiveness either by enhancing the algorithm or using big data.

Furthermore, this study provides the following insight for practitioners. First, the social-material aspect of navigation technology, such as the VHF in the case of the collision between *ACX Hibiscus* and *Hyundai Discovery*, indicates that technology may not necessarily lead to safer navigation practices. Practitioners should focus on how technologies are used and whether seafarers can and do interact appropriately with these advanced technologies. Second, practitioners and policymakers should be aware of the importance of appropriate pilotage in terms of maritime safety.

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