On factors affecting autonomous ships operators performance in a Shore Control Center

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Abstract: The development of autonomous is driven by, among other factors, the possibility of reduction of accidents generated and/or aggravated by human error. Although autonomous ships imply less human interference in operation than regular ships, they will probably rely on human operators working onshore for supervision or remote control when necessary. The shift from onboard operation to onshore brings new factors regarding human error and human factors. Authors have discussed the factors that could influence operators' decisions and actions when working onshore; and these factors can be further analyzed and modeled as Performance Influencing Factors (PIFs) in a Human Reliability Analysis (HRA) of the system. This paper discusses the main factors pointed by authors as influential to operators' decisions and actions when working onshore. Especially four factors are repeatedly highlighted: information overload, situation awareness, skill degradation and boredom. This paper also discusses how these factors are approached in the literature on regular ships' operation, and how they can be modeled as PIFs in a HRA of autonomous ships. This paper aims to "bridge" human factors cited by different authors in autonomous ships and PIFs of a future HRA method that would consider the peculiarities of this operation.

Keywords: Autonomous ship, Human Reliability, Human Factors, Shore Control Center

1. INTRODUCTION

Autonomous ships have gained considerable attention in recent years. Different projects visualize different modes of operation of autonomous ships, especially regarding the presence of crew onboard on the different phases of the voyage. The AWWA - Advanced Autonomous Waterborne Applications Initiative, a project led by Rolls Royce to develop specifications and possible designs for autonomous ships, works with the concept of unmanned ship for all voyage. Munin - Maritime Unmanned Navigation through Intelligence in Networks, a research project co-funded by the European Commissions, considered initially the concept of having crew onboard when approaching and leaving harbor, but has changed to unmanned in all phases of the voyage. Konsberg's vessel Yara Birkeland, a fully electric autonomous container ship planned to operate in the latter half of 2018, is expected to be initially manned, shifting to unmanned in 2019 and expected to be capable of performing fully autonomous operations from 2020.

Regardless of the abovementioned different concepts regarding the crew onboard, it is safe to assume that most probably autonomous ships, for the unmanned voyage phases, would require operators working onshore. These operators' responsibilities will depend on the autonomy level of the ship operation – for a high level of autonomy, the operators' tasks can be limited to remote supervision and for a lower autonomy level their task can be remote control of the ship when needed.

The Munin project introduces the Shore Control Center (SCC), where the tasks of remote control or supervision by the operators would take place. In the SCC the operators would have access to a number of information on the status of the ship and its operation parameters, in addition to weather and environmental conditions. The SCC as envisaged by Munin would comprehend supervisor, captains, engineers and operators, and each operator could supervise six unmanned vessels in the

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workstation[1]. More information on SCC organization and available information onscreen for the operators can be seen at [2], [3] and the project website[†].

One of the motivations for the use of autonomous ships is the possibility of reduction of accidents generated and/or aggravated by human error. Dhillon [4] points out that human error contributes to 89–96% of ship collision, 79% of towing vessel groundings, and that over 80% of marine accidents are caused or influenced by human and organization factors. Although the fact that autonomous ships have less human interference in its operation than regular ships indicates a possibility of reducing these numbers, they will probably still rely on human operators for supervision or remote control when necessary. Therefore, human errors can still occur and measures must be taken to prevent this as far as possible [3].

The shift from onboard operation to a remote onshore operation (or supervision) brings new factors regarding human error and human factors. Through Human Reliability Analysis (HRA) it is possible to model, analyze and quantify human errors in these operations. HRA is a tool to develop measures to prevent these errors, and increase the safety of autonomous ships operations. This is crucial for the autonomous ships' future, since one of the keys for its use is that it is at least as safe as existing vessels [4].

Although human error is the main object of study of HRA, it should not be viewed as the product of individual shortcomings [5]. As argued by Hollnagel [6], one of the undisputed assumptions in HRA approaches is that the quality of human performance depends on the conditions under which the tasks or activities are carried out. These conditions, in turn, have generally been referred to as Performance Shaping Conditions (PSFs) or Performance Influencing Factors (PIFs). They serve to either enhance or degrade human performance relative to a baseline.

Several HRA methods use PIFs to estimate Human Error Probability; however, there is not a standard set of PIFs used among the methods [7]. The review and analysis of PIFs are essential in determining and understanding the root causes and opportunities for the manifestation of failure [8]. Indeed, in order to assess human reliability, first and most importantly, the PIFs should be identified [9].

In the current literature on autonomous ship operation authors have pointed factors that could influence operators' decisions and actions when working on a SCC. These factors can be further analyzed and modeled as PIFs in a HRA of this system. The present paper aims to review the literature on autonomous ships in order to identify and discuss the main factors that have been pointed out by the authors as influential to operators' decisions and actions. Moreover, it will also discuss how these factors are approached in the literature on regular ships' operation, and examine how these factors can be modeled as PIFs in a HRA of autonomous ships.

This paper does not intent, at this point, to provide a set of PIFs to be used in autonomous ships. A PIF set tailored for this operation should have roots on cognitive science, inputs from experts and operators, and should benefit from operational observation, in addition to the literature itself. Nevertheless, this paper initiates this discussion, and aims to bring light to the topic as well as serve as a basis for a final PIF set. This is a part of a larger project, which intends to analyze the risk and reliability of autonomous ships.

This paper is organized as follows: Section 2 presents the concept of PIFs, how they are treated in different HRA methods and the shortcomings of the current sets. Section 3 introduces the factors that can affect autonomous ships operators as discussed by different authors, and section 4 presents the final thought and conclusions.

[†] http://www.unmanned-ship.org/munin/

2. PERFORMANCE INFLUENCING FACTORS

Performance Influencing Factors, as stated in the previous section, are used to represent the situational contexts and causes that affect human performance in different systems [10]. These influencing factors are also named Performance Shaping Factors (PSFs), Error Forcing Contexts (EFCs), Common Performance Conditions (CPCs), or Error Producing Conditions, depending on the HRA method [9, 10].

The importance of the identification and assessment of PIFs relies on the acknowledgement that the operators may not be the ones to blame, at least exclusively, in case of an accident derived from operators' failure. Indeed, the human behavior is dependent on a series of factors that can influence information gathering, decisions and actions. The consideration of the PIFs when analyzing human error, then, allows identifying *why* the operator can fail, rather than only which errors they can commit. This is essential to evaluate techniques to decrease the probability of human error in any operation.

The first formal HRA method to be presented (in 1963), Technique for Human Error-Rate Prediction (THERP), already accounted for the impact of PIFs in human performance [5]. Since them, virtually all HRA methods considers influencing factors – the only exception being the HCR method, which relies upon a normalized time reliability curve (time required to perform an action divided by the time available to perform the action) for the quantification of the Human Error Probability (HEP) [12].

THERP, as all first generation HRA methods, do not account for cognitive factors as PIFs, as pointed by Hollnagel [6]. In fact, he suggests that methods should be categorized as first or second generation considering its use of cognitive factors in their PIFs sets - more modern methods explicitly consider and model cognitive PSFs [5].

In the qualitative HRA, PIFs are used to identify contributors to human performance. In quantitative HRA, PIFs are often used to derive the HEP [13]. The approach used in the quantification process is also different between methods. In some methods, such as THERP and SPAR-H, the PSFs are used as multipliers to the HEP. Others, such as Phoenix, uses Bayesian Belief Networks (BBNs) to model the influence of the PIFs in the human error.

Although the HRA methods have used PIFs in its qualitative and/or quantitative analysis since the first formal method, there is not a standard set of PIFs used among methods [6, 7, 8, 11]. For instance, THERP categorizes PSFs as: external, including work environment (e.g., equipment design, written procedures or oral instructions), and internal, including individual characteristics of operators (e.g., skills, motivations, and experience), and psychological and physiological stress. The Standardized Plant Analysis Risk-Human Reliability Analysis (SPAR-H), on the other hand, considers eight PSFs: available time, stress/stressors, complexity, experience/training, procedures, ergonomics/HMI, fitness for duty, and work process [9]. Phoenix [14] makes use of 9 main groups of PIFs: stress, mapping emotional factors, Knowledge/Abilities and Bias mapping cognitive response, and Team Effectiveness, Human System Interface (HSI), Task Load, Time Constraint, Resources, Procedures mapping physical world [7]. In order to develop a PIF set for HRA of emergency tasks, Kim & Jung [15] categorized PIFs in four main groups: i) Human (personal characteristics and working capabilities of the human operator), ii) System (MMI, plant hardware system, and physical characteristics of the plant process), iii) Task (Procedures and task characteristics required of the operator) and iv) environment (Team and organization factors, and physical working environment).

The Information, Decision and Action in a Crew Context (IDAC) methodology [16] provides a PIF set with roots in cognitive and psychological literature, in addition to operating evidence and other HRA methods. It also defines high-level interdependencies between the PIFs (Figure 1).

Boring [17] points out that, in addition to the internal / external categories usually used in HRA methods, PIFs should also be categorized as Direct or Indirect measure of human performance. As the name implies, the direct PIFs can be measured directly, while for the indirect ones the magnitude can only be determined multivariately or subjectively.

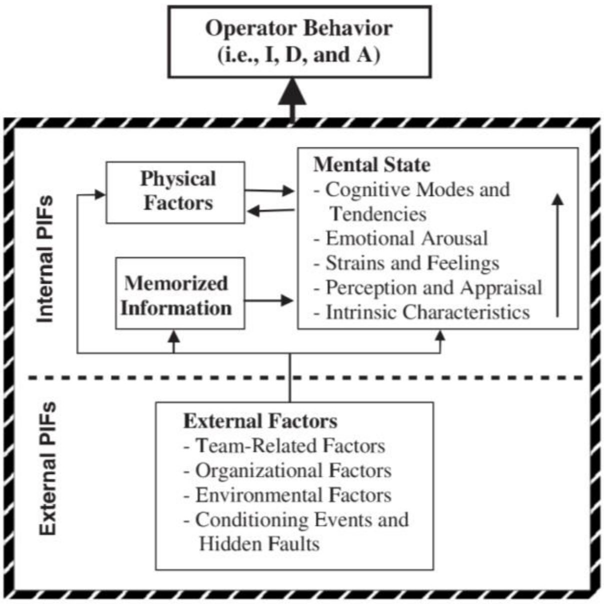

Figure 1: IDAC PIFs set [16]

Since each method has its own set of PIFs, it is expected that some factors repeat themselves between the methods, while others are uses only by few methods. Kim & Jung [15], in order to come with a taxonomy of PIFs for HRA in emergency tasks, reviewed various methods and categorized the PIFs in regard to the frequency they are used (Table 1).

Table 1: PIFs categories in regard to frequency of use in HRA methods [15]

Frequency of use in HRA methods	PIFs
Frequently used	training, experience, procedure, MMI/information, and time.
Moderately used	stress, workload, motivation, task complexity, simultaneous goals/tasks, working condition, supervision, team factors, and communication.
Used in the minority of methods	adequacy of resources, decision making criteria, response dynamics and system coupling, availability of equipment, trend and value of critical parameters, time of day, organization factors, task organization, and safety culture.

Even though some PIFs are repeatedly used in most of the HRA methods, Groth & Mosleh [10] state that, generally, they are not defined specifically enough to ensure consistent interpretation of similar PIFs across methods. Moreover, they point that there are few rules governing the creation, definition, and usage of PIF sets. Indeed, three major problems of most of the current PSFs set where identified by Liu et al [9]:

1) Overlapping and unclear definitions [18]
2) The range of PSFs covered is not appropriate for several HRA methods [18]
3) Several PSF models may cover too many PSFs, which may influence the quantitative predicting ability of HRA methods.

Groth & Mosleh [10] actually identifies the overlapping among PIFs as one of the major issues – especially when considering a model-based HRA method. They explain that, when an expert is assessing the PIFs, the expert can mentally adjust for overlapping definitions. However, in a model it is necessary to either capture this mental adjustment explicitly or to remove the overlap. They also state that some sets were not comprehensive, i.e., they contained too little information about the PIFs. Moreover, some methods include specific behaviours as PIFs (as "work conduct"), and some methods contain too many factors that cannot be measured.

In order to overcome the shortcomings mentioned above, some authors have suggested guidelines or principles to be followed for the development and/or use of adequate PIFs set, summarized below:

1) Analysis should consider only those PIFs that directly impact the individual's performance. PIFs that have affected previous events do not directly influence the actor: If a fatigued maintenance worker returns a broken pump to service, the operator's performance is affected only by the broken pump, not by the maintenance worker's fatigue [10].
2) Orthogonality: PIFs must be defined orthogonally, i.e., they must be separately defined entities [10]. Boring [9] adds that, especially in the case of multidimensional indirect constructs of a single PSF such as Fitness For Duty, the analyst should utilize measures that do not overlap, which would introduce the possibility of double-counting effects. Laumann & Rasmussen [19] support this, stating that the content of each of the PSFs should as far as possible not overlap with other PSFs and the described content should define the limits of the PSF. Overlaps in meaning between PSFs increase the risk that the same issue is double-counted.
3) PIFs should be ''value neutral'' to leave room to expand the way they are used in characterizing context. The value neutral PIFs will ensure that there is an equal opportunity for PIFs to be selected as positive or negative [10].
4) PIF sets should be supplemented with a corresponding set of behaviors and metrics that are visible indicators of invisible PIFs. [10].
5) Direct versus Indirect: pick the best available PSF, whether direct or indirect - direct PSF is not inherently preferable to an indirect PSF [9]
6) Verify the reliability of the PSF. The stability and generalizability of PSFs need to be carefully considered in an analysis of human reliability. In the case where expert judgment is used to select the appropriate level of the PSF, a PSF that does not adequately consider human decision making processes and biases could result in inconsistency in PSF assignment between analysts or even by the same analyst on a different occasion

In addition to the shortcomings above, Boring [9] remarks that a PSF that is designed for a particular domain (e.g., nuclear power plant (NPP) control room operations) may not generalize to another domain (e.g., aircraft piloting). Indeed, most of the HRA methods are developed for NPPs operations, and actions taken in a nuclear power plant control room do not in all cases generalize to the types of actions performed in other industries [18, 19]. The same applies to PIFs – the factors influencing the operators' actions working in a SCC, supervising and operating autonomous ships, may not be the same factors that influence operators working in a NPP. In this sense, it would be highly beneficial to the analysis of the possibility of human error in autonomous ships operation, having a set of PIFs that reflect the specificities of this system. Moreover, it is important that this PIF set not only benefits from the developments of PIFs sets of various HRA methods cited in this section, but also considers the shortcomings of current PIFs sets pointed by previous authors.

Next section brings an overview on the possible factors influencing human performance in autonomous ships operations pointed in the current literature on the topic, and discuss how these factors can be considered in a PIF set for this operation.

3. FACTORS INFLUENCING HUMAN PERFORMANCE IN AUTONOMOUS SHIPS OPERATION

This section reviews the possible factors influencing human performance of operators of autonomous ships as they have been discussed in the literature. Moreover, it identifies how these factors are present in regular ships operations, and how they are treated in different HRA methods. Four factors are repeatedly pointed as decisive when shifting the operation from onboard to onshore: information overload, situation awareness, skill degradation and boredom – discussed in sections 3.1 to 3.4. Other factors, including the ones that can affect negatively operators' performance onboard but are non probable (or non existent) in onshore operation, are discussed in section 3.5.

3.1 Information overload

Information overload is, simply put, the fact of receiving too much information. Eppler & Mengis [22] highlights that, up to a certain amount, the information an individual receives is actually beneficial to his/her performance. However, beyond that point, performance rapidly declines. The human performance against the amount of information received can then be illustrated by an inverted U-curve, in which the performance decreases when the information amount reaches the information overload point (Figure 2).

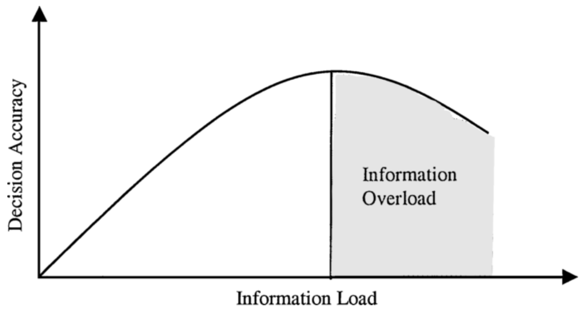

Figure 2 – Information Overload inverted U-curve [22]

Information overload played important role in accidents throughout the history. In the Mile Island NPP accident for example, the operators were overwhelmed by the number of alarms activated within a few minutes following the initiating event [16].

According to the AAWA whitepaper [23], information overload applies to autonomous ships operations particularly when an operator working in a Shore Control Center is monitoring several vessels at the same time. Information overload is also seen as a potential factor in this operation by other authors [22, 23]. At a study with master mariner program students on the different tasks and actions onboard and ashore [26], information overload was also mentioned by the interviewees as a key factor, only behind situation awareness.

In addition to the situation where information from different ships can cause information overload, it is possible that too much information from one specific ship could cause it. The onshore operation system will have to ensure the operator would be receiving all the information he/she would receive if operating onboard. Therefore, the system would have to provide the operator relevant information about the environment (e.g. available water or wave direction), navigational instruments (e.g. ECDIS or radar), and factors regarding spatial movement of the vessel (e.g. slamming, rolling, heaving or pitching), in addition to all necessary information to contribute to the operator's "ship sense" [1]. A balance between having access to all information needed while not reaching the information overload point will be crucial for a successful operation in the SCC.

The possibility of information overload is not an exclusivity of autonomous ships operation. In regular ship operation, it is also possible that the amount of information the operator receives becomes excessive. If the ship's HMI is not ergonomically designed, the information it presents may overload or confuse the operator [27]. Nonetheless, since the operator working onshore would receive the information he/she would receive if he/she was working onboard and, *in addition*, information to give a sense of the ship and replace the visual aspects not accessible from onshore, it is expected that the shift from onboard to onshore increases the possibility of information overload.

Information overload is recognized in different HRA methodologies. In SPAR-H, it is considered indirectly, as a factor that can increase the possibility of the PIF Stress – "multiple instruments and annunciators alarm unexpectedly and at the same time" would bring the PIFs Stress to "high" [28]. In IDAC, it is included in the PIF Passive Information Load into "strain and feelings", related to the mental state of the operator. It is also named Passive Information Load in Phoenix, a 2nd level PIF in the Task Load Group. It also modeled as "complexity/information load", an external PIF on THERP.

3.2 Situation Awareness

Situation Awareness (SA) can be defined as "being aware of what is happening around you and understanding what that information means to you now and in the future" [29]. In the context of a specific operation, only those pieces of information that are important for the task are considered in Situation awareness. This definition can be broken into three Levels (Figure 3):

Level 1 - *perception* of the elements in the environment
Level 2 - *comprehension* of the current situation
Level 3 - *projection* of future status

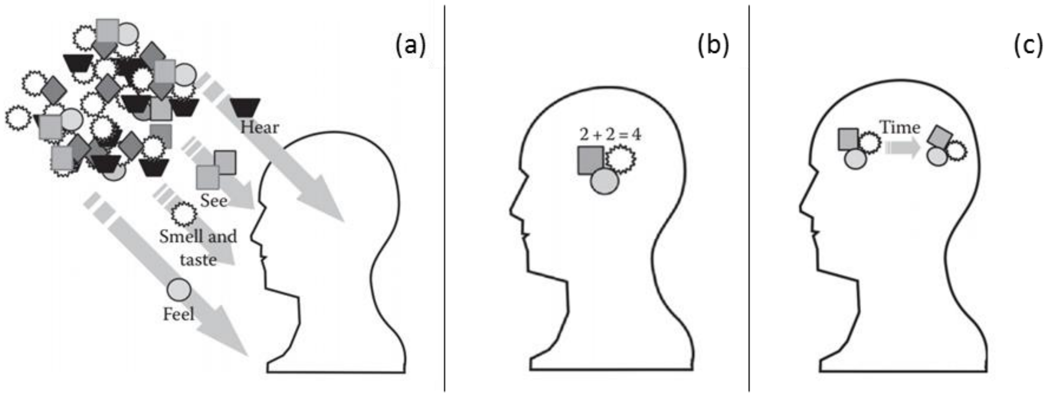

Figure 3: Levels of Situation Awareness. (a): Level 1 – perception of needed data; (b): Level 2 – Comprehension of information; (c): Level 3 – Projection of future status [29]

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In a study on human factors for the MUNIN project with master mariners and a ship engineer [1] the participants marked situation awareness as the most significant key to focus on when shifting ship handling from ship to shore.

Indeed, Parasuraman et al. [30] highlight that the possibility of situation awareness decrease is a key element in the interaction between operators and an automatized system. They argue that humans tend to be less aware of changes in environmental or system states when those changes are under the control of another agent (whether that agent is automation or another human) than when they make the changes themselves. Moreover, the system can be actively distorting the operator's mental picture by operating behind the curtains [31].

Rødseth & Tjora [32] state that situational awareness is a problem as the ships operate automatically or autonomously, since when an unexpected situation arises, the operator needs time to understand and respond to it – and the response time must be a short as possible. SA is also mentioned as an important factor for autonomous operation by other authors [22, 28, 32, 33].

Lack of situation awareness is also mentioned as "out of the loop" by some authors. The out of-the-loop syndrome will occur if parts of the system, that need more than a glance to gain sufficient understanding, suddenly require human decision-making [31].

The possibility of decrease of situation awareness in the operation of autonomous ships relates also to the lack of "feel" of the ship, as mentioned in the discussion on Information Overload. This can affect the assessment of situations as well as teleoperation of the ship, when/if needed. The fact that there is no bodily feeling of the ship and the look outside, even if communicated via camera feeds, may provide only limited understanding of the conditions to the operators [22, 23].

Lack of situation awareness – in its different levels - is also a concern in other industries. A research on situation awareness errors in aviation [35] stated that 76% of Situation Awareness errors in pilots were related to not perceiving needed information. Moreover, in some cases this was because the information was not provided to the person who needed it, or was not clear due to system limitations or shortcomings.

In the maritime industry, the effect of situation awareness in safety would not be a novelty brought by autonomous ships: it is already present in regular ships operation. A report of the U.S. Coast Guard in September in 2006 mentioned loss of situation awareness as a risk factor in seventeen of twenty-five events analysed [27]. Grech et al. [27] actually provide an illustration on how situation awareness applies to an anti-collision context on board of a ship, in terms of Endskey's model (Figure 3):

Level 1) Perception: the detection of another vessel

Level 2) and 3) Comprehension of information and projection: the assessment of the possibility of courses intersection and risk of collision

These would be followed by the execution phase – actions to avoid collision.

The operators can, then, fail in any of the levels of the SA: they may not detect another vessel, or incorrectly assess the possibility of courses intersection, or incorrectly project the possibility of collision. It is possible, therefore, to identify how the operators can fail in each of these levels of SA and, furthermore, identify PIFs that can affect the probability of these errors.

Indeed, generally SA is not analysed as a PIF itself in the HRA methods. Instead, the methods account for PIFs that can affect the SA. Experience and training, PIFs of Phoenix methodology, for example, are factors that can affect the probability of an operator to assess the probability of course intersection with another ship. Attention and fitness for duty (fatigue), in its turn, are crucial for the operator to detect another ship in the path. In autonomous ships operation some factors will be crucial for SA – perhaps even more than for regular operation. For the SA Level 1 and Level 2, for instance, it is essential that the Human Machine Interface provides all important information about the ship and its environment, since it will have to replace visual detection. Communication will be also important, for transmitting information between different shift operators.

3.3 Skill degradation

Skill degradation relates to the loss of skills – physical or cognitive – following disuse. It is analyzed in a large body of research in cognitive psychology [30]. Since disuse of skills is an outcome of more automatized systems, and thus autonomous systems, skill degradation is a recognized possible consequence of autonomy. The basic principle of skill degradation is that if the decision-making (and action functions) are consistently performed by automation, there will come a time when the human operator will not be as skilled in performing that function [30]. In that sense, automation can not only result in loss of psychomotor dexterity but also degradation of the cognitive skills required to accomplish the task successfully [36]. Moreover, that degradation of cognitive skills may be particularly important following automation failure [30].

Skill degradation is a familiar issue for aviation. As its systems are highly reliable and failures are rare, many pilot responsibilities have shifted from direct, hands-on control of the aircraft to that of a systems monitor, intervening only when the primary system fails or cannot perform a given task as well as the human operator. Without consistent use of the piloting skills developed during training, pilot skill degradation is a reality [37].

As in all autonomous systems in general, skill degradation is a possible outcome of shifting ship operation from onboard to onshore [25]. Laurinen [23] highlights that maintaining good skills in autonomous ships operation could be especially difficult if monitoring a fleet of different kinds of ships. This is due to the practical differences of each of the ships that the operator should have to learn. In particular, the operator could easily forget or fail to recognize relevant issues when switching the operation from one ship to another.

Grech et al. [27] recognizes skill degradation as a factor affecting performance of operators of regular, non-autonomous ships as well, as it becomes more automatized. In the longer term, they claim, removal of operators from the direct control of a ship may result in their skills and abilities declining. They add that, coupled to the skill fade, there may be a loss of motivation and/or status, as they may view their roles as simple monitors of equipment, rather than as skilled mariners.

In HRA methods skill degradation can be analyzed through PIFs related to cognitive and physical skill to perform a task – those could be more important in autonomous ships operation than regular ships. In Phoenix methodology, for example, this could be measured through the PIF "Knowledge / Experience / Skill". In SPAR-H, one could assess skill degradation through "Experience / Training". In IDAC, "Knowledge and experience" and "Skills" could reflect skill degradation.

3.4 Boredom

Cummings et al. [38] point that there is not a consensus on the definition of boredom. Authors have defined it as "a state of weariness caused by dullness and tedious repetition", "an unpleasant, temporary affective state resulting in a human's lack of interest for a specific current activity", or "decreased arousal state associated with feelings of repetitiveness and unpleasantness".

It has been shown that boredom produces negative effects on morale, performance and quality of work [38]. Indeed, a study on simulated radar control tasks showed that participants who viewed the task as monotonous and boring had a significant increase in their response time; while the ones viewed is as non monotonous had a decrease on their response time [39].

Boredom is cited by authors as a factor that can affect operators' performance while working on a Shore Control Center [21, 23, 32]. Laurinen [23] makes a parallel between autonomous ships and unmanned aircraft systems (UAS) operation and refers to a study that shows that 92% of UAS operators have reported "moderate" to "total" boredom. They add that boredom could results in loss of vigilance and is therefore a risk factor in autonomous ships operation. Ohlands [34] remarks that boredom and lack of attention are especially prone to happen during voyages in which no unexpected situation happens. Cunningham & Regan [40] indicate that, in boredom periods, drivers of autonomous vehicles may seek to engage in other activities (e.g., a task that is more entertaining) as opposed to monitoring and supervising the autonomous driving.

In HRA methods, boredom can be considered a factor that influences some PIFs. In Phoenix PIFs set, boredom could influence, for example, attention, morale / motivation / attitude, and stress. In SPAR-H, it relates to stress and fitness for duty. In IDAC, attention, alertness, stress, morale / motivation / attitude, fatigue.

3.5 Other factors

In addition to those discussed in the previous sections, other factors are also mentioned in the literature on autonomous ships. However, rather than being a safety concern when shifting from onboard operations to onshore operations, those are mentioned as positive outcomes of this change. They are seen as factors that have a negative impact on the crew onboard of a ship and that are not expected to occur in a shore control center: sleep deprivation, fatigue and motion sickness [2, 25, 33, 34, 41].

Sleep deprivation and fatigue are actually interrelated. Rothblum [42] points out that work schedules which do not provide the individual with regular and sufficient sleep time produce fatigue. Some vessels do not operate with multiple shift systems, occasionally leading to extended periods of crew sleep deprivation [43]. Moreover, a study on sleep deprivation [44] states that sleep loss is an important contributor to fatigue in maritime personnel. Indeed, a survey with Australia seafarers pointed that 31% of pilots had less the 4h of sleep per day and 65% had between 4-6hr of sleep per day when on duty. In contrast, 75% of pilots reported 7-8 h of sleep per day when off duty [45]. Fatigue is a complex phenomenon, and can have various causes in addition to sleep deprivation. Akhtar & Utne [46] studied the effect of human fatigue on the risk of maritime groundings, and concluded that fatigue seems to play a significant role in maritime grounding accidents - a fatigued Bridge Management Team (BMT) has about 16% higher probability of grounding than a non-fatigued team. The autonomous vessel can reduce the human errors made by fatigue by offering a more comfortable work environment and longer rest periods for the operators [34].

Although sleep deprivation and fatigue are expected to not happen with the same severity in a Shore Control Center and onboard operations, it could still happen. Seasickness, on the other hand, would occur only in onshore operation. Seasickness can lead to disorientation, lack of concentration and dehydration, which can lead to accidents in sea. Practical observation proved that the consequences of motion sickness at sea can form a danger for anyone on board of a sea going vessel, especially when this individual carries responsibility for the proper execution of certain tasks on board [47].

Fatigue, sleep deprivation and seasickness can be analysed through fitness for duty related PIFs. In Phoenix, this is indicated by the PIF "Physical Abilities and Readiness", as well as "Attention". In Spar-H, they can be analysed through the PIFs "stress" and "fitness for duty". In IDAC, those factors would affect "Alertness", "Attention to current task" and "Fatigue".

4. DISCUSSION AND CONCLUDING THOUGHTS

Autonomous ships will most probably be supervised by human operators working onshore, whose tasks may vary from monitoring to remote control of the ship. The assessment of human error, through Human Reliability Analysis, allows identifying the possible human errors in those tasks and developing measures to decrease the probability of these errors. To achieve this, however, it is necessary to identify the factors that influence human decisions and actions when working on a Shore Control Center, which can be modeled as PIFs in the HRA.

There is no agreement on a set of PIFs between HRA methods; moreover, the methods were in majority developed for Nuclear Power Plant operations. A HRA of autonomous ships should identify the PIFs that are specific of this operation, in order to reflect its particularities. Several authors have pointed to different factors that can influence the performance of an operator working in a Shore Control Center. Some of these factors are not new to the maritime industry, as they occur also in regular ships, nor to other industries, as aviation. These factors cannot, however, be directly used as PIFs in a HRA, as they may be non-observable or have overlapping definitions, among other factors. Nevertheless, a set of PIFs for autonomous ships can – and should - leverage from the discussions on these factors.

As a summary of the discussion in this paper, some considerations can be drawn on how to build a PIF set for autonomous ships: i) the set has to leverage the existing discussion on human factors for this operation; ii) the set has to be developed considering the guidelines present in the literature in order to overcome limitations of general PIF sets used in some HRA methods; iii) it should have roots on cognitive science and better understanding of the mechanisms in order to consider dependencies – *attention* for example, would be less severe in autonomous ships considering that there is no sleep deprivation, but would be increased considering that there is *boredom*. Attention, in its turn, would affect *situation awareness*.

The discussion present in this paper aims to be an initial "bridge" between human factors cited by different authors in autonomous ships and a PIF set in a future HRA method that would reflect the peculiarities of this operation and the considerations abovementioned.

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