BEYOND TECHNOLOGY READINESS:

APPLYING HUMAN READINESS LEVELS IN MARITIME SYSTEMS

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Beyond Technology Readiness: **Applying Human Readiness Levels in Maritime Systems**

Introduction to Human Readiness in Maritime Technology

Increasingly complex digital technologies are reshaping the maritime industry. Tools such as autonomous and remote-control systems, artificial intelligence (AI), predictive maintenance systems, alternative-fuel control architectures, digital twins and augmented reality (AR) are among a wide range of technologies moving from concept to deployment across the industry. These tools are designed to reduce demands on the crew and improve operational efficiency, but in many cases their adoption is outpacing human readiness.

Accident investigations across the transportation sector have demonstrated that human-system interaction (HSI) failures, rather than component malfunctions alone, remain the dominant contributors to incidents [Papadimitriou et al., 2020; Hasanspahić et al., 2021]. Recent research on maritime autonomous surface ships (MASS) has highlighted emerging risks associated with supervisory control, automation trust, alarm overload and degraded situational awareness [Poornikoo et al, 2025; Kim et al, 2026]. Assessing product maturity, implementation viability and system-level effects is essential, but ignoring the human element can undermine successful implementation and adoption.

To manage the risk introduced by the adoption of emerging technologies, organizations have long relied on the technology readiness level (TRL) framework. Established in the 1970s by National Aeronautics and Space Administration (NASA), TRL provides a nine-point scale that evaluates technical maturity from basic scientific principles (TRL 1) through proven operational use (TRL 9). Complementary frameworks such as design readiness levels, integration readiness levels and system readiness levels have further expanded how organizations assess technical and engineering progress. While human factors analysis often occurs during the design review process, they are typically not incorporated into maturity frameworks such as the TRL.

This paper explores the value of human readiness levels (HRLs) as a structured framework for guiding the design and operations of maritime technologies. Human readiness levels help operators clearly understand system modes and limitations, support interfaces that enable rapid diagnosis and intervention, align procedures and training to the maturity of the technology and prepare organizations to adopt new operational concepts.

The remainder of this paper introduces the HRL framework, examines existing gaps in maritime human-system integration and demonstrates how HRLs can be integrated into current maritime qualification processes.

Defining Human Readiness Levels

While existing maturity frameworks offer valuable insight into technical maturity, they do not account for the human element that ultimately interacts with, operates, maintains and makes decisions with the technology. History repeatedly shows that human-system mismatches can compromise even highly mature technical systems. Incidents such as the Three Mile Island nuclear accident and the loss of NASA's Mars Climate Orbiter demonstrate how design assumptions, interface limitations, unit mismatches and cognitive workload can cascade into safety-critical failures. These examples highlight a consistent theme: technical maturity alone is not sufficient to achieve operational safety, effectiveness or mission success.

To address this gap, the HRL framework, which was formalized in ANSI/HFES 400 Human Readiness Level Scale in the System Development Process, introduces a structured approach to evaluating how prepared technology is for safer, more effective and reliable human use. Human readiness level complements TRL by incorporating human performance considerations, user requirements, interface design maturity, training implications and broader HSI factors. By assessing human-centered readiness in parallel with technical maturity, organizations can identify risks earlier, reduce integration issues, support better design decisions and increase the likelihood of successful fielding and operational performance. High risk organizations such as the United States Army have adopted the ANSI/HFES 400 HRL standard, while the Federal Aviation Administration and NASA are actively looking into incorporating HRLs in existing processes.

Technology readiness levels focus on hardware and software performance while HRLs evaluate:

- ☑ Operator roles and responsibilities
- ☑ Cognitive workload and decision authority
- ☑ Interface usability and interpretability
- ☑ Alarm strategy effectiveness
- ☑ Training effectiveness
- ☑ Procedural completeness
- ☑ Organizational readiness

To support consistent evaluation with TRLs, HRLs use a nine-level scale, with each level defining the expected maturity of HSI evidence. To operationalize these concepts, HRLs define explicit expectations for HSI at each stage of system maturity. This structured progression allows organizations to assess human readiness in parallel with technical maturity, identify risks earlier and promote safer and more effective system integration.

HR Level	Description	Suggested Measurements
HRL 1	Understanding basic human capabilities, limits and potential errors.	Basic task analysis; early workload estimates; identify failure points.
HRL 2	Defining early human requirements and interaction needs.	Initial human use guidelines; early performance goals; draft requirements.
HRL 3	Human requirements are clear and detailed for system and user needs.	Detailed task requirements; defined cognitive and physical demands.
HRL 4	Early testing with simple mockups or low fidelity models.	Human-in-the-loop tests; early usability tests; preliminary workload measures; hazard ID.
HRL 5	Testing more realistic prototypes in mission-like scenarios.	Prototype testing in realistic part-task simulations; representative user feedback.
HRL 6	High-fidelity testing of near-final system with full metrics.	Simulation data; situational awareness assessments; error rates; timing; reliability estimates.
HRL 7	Full system tested with real users in an operational environment.	Full mission human performance data; design meets human-centered requirements.
HRL 8	System verified and approved with finalized procedures before rollout.	Real-world human performance and safety checks; finalized training and procedures.
HRL 9	System fully used in real operations with ongoing monitoring.	Field performance monitoring; error/incident analysis; continuous improvements.

Table 1: HRL from ANSI 400 and suggested measurements of HRL at every level.

Together, these levels show how human readiness can be assessed in parallel with technical maturity, rather than deferred until deployment.

Despite the interest in HRLs as a complement to TRLs, there is currently no empirically unified or standardized method for measuring HRLs across the TRL scale. While there are existing methods, they are largely fragmented across disciplines such as workload assessments, usability analysis, human reliability analysis and situational awareness measurements. An empirically unified HRL method for measuring human readiness at every stage is needed to better evaluate HSI as technology matures. Additionally, ownership for HRL activities should be further explored to determine who is best responsible for integrating HRLs at each stage before a technology is ready for implementation in an operational setting.

Advancements in technologies such as AI, autonomy, digitalization and remote inspection systems have significant potential to reshape the maritime industry. In the marine and offshore industries, these innovations enable systems to perform functions such as collision-avoidance maneuvers, predictive maintenance and detection of workers in restricted zones. However, the introduction of such capabilities also brings new human element risks. For example, during an autonomous avoidance maneuver, the system may have limited ability to anticipate how its actions will influence nearby traffic, requiring human oversight to maintain safety-critical operations. This highlights the need for autonomous technologies to be robust, transparent and highly reliable across a broad range of operational scenarios.

Regulatory frameworks such as the European Union (EU) AI Act and the International Maritime Organization (IMO) MASS Code both emphasize the importance of meaningful human control and human oversight during high-risk situations. Effective oversight, however, requires that operators be able to understand the system's status, interpret its outputs and recognize when intervention is necessary. If autonomous or AI-enabled systems function as opaque black boxes and fail to provide operators with sufficient, interpretable information, situational awareness can be severely degraded. To maintain effective human oversight, that black box needs to be translated into understandable, actionable and meaningful information for the human-in-the-loop [Loyola-Gonzalez, 2019; Gunning, 2016; ISO, 2022; National Academy of Sciences, Engineering and Medicine, 2022] to allow for crew to respond appropriately. This lack of structured human-readiness assessment reduces the maritime industry's ability to anticipate and mitigate HSI risks. For more details on the development of autonomous systems for marine and offshore applications, see the ABS *Advisory on Autonomous Functionality*.

Current Gaps in Maritime Human-System Integration

A key gap in the maritime industry is the lack of a formalized HRL framework that evaluates operator preparedness, HSI and training effectiveness before new technologies or procedures are deployed. As technology evolves quickly, systems, rules and guidance often lag. Regulations and guidance around the human element in the marine and offshore industry have similarly been slow to respond. Although many organizations recognize the need for change, adoption of human element interventions often does not occur until an incident forces it. While standardization bodies such as ANSI and IMO have acknowledged the importance of integrating human factors across industries, few rules or regulations currently require the implementation of detailed HSI guidance.

Research has shown that HSI should be considered when introducing new technology, particularly automation and AI, to mitigate any unintended risks that may be introduced to the system [Xu et al, 2023]. Notable human element contributing factors which have been reported across the marine and offshore industry include:

1. ***Bourbon Dolphin*** **capsized (2007):** Contributing factors included human-factors failures during planning, risk management, crew familiarization and operational decision-making when safe stability limits were exceeded.
2. ***Viking Sky*** **cruise ship blackout (2019):** Alarm overload and poor alarm management overwhelmed the bridge crew, reducing their ability to respond effectively during the event.
3. **Passenger ferry *Alfred* grounding (2022):** Contributing factors included fatigue-related loss of situational awareness and incomplete execution of critical safety procedures.

Across these incidents, the common failure mode was not immature technology, but insufficient validation of how humans interact with increasingly complex systems. This gap is what the HRL framework is intended to address.

Integrating HRLs into Maritime Qualification Processes

Novel concepts increasingly rely on structured frameworks for qualifying systems, such as the ABS New technology Qualification (NTQ) program, SMART notations and the *Verification and Validation* Guide. These documents outline goal-based requirements for technologies involving AI, automation, digital twins and other advanced or visualization technologies systems. Beyond defining hardware and system requirements, it is essential to understand how these technologies integrate into maritime and offshore operations. Research and recent industry incidents underscore the need to consider the human-in-the-loop not only during early design phases but throughout the entire system life cycle.

Studies on certification of autonomous maritime systems emphasize the importance of explicitly defining operator roles, fallback modes and remote supervision strategies [Corsi et al., 2025]. Similarly, Song et al. [2024] highlights that emerging operational concepts fundamentally reshape crew tasks, skill demands and responsibility distribution. Recent industry incidents reinforce the need to account for human involvement at every stage of system qualification and operation.

In 2019, the cruise ship *Viking Sky* experienced a blackout event during a severe storm, losing propulsion and steering capabilities with 1,374 people on board. The ship drifted dangerously close to the shore and nearly grounded. An investigation indicated that the blackout was caused by insufficient oil in the generators, which led to a shutdown of systems during pitching and rolling. Additional contributing factors included gaps in crew preparedness for full-blackout recovery and an alarm system that generated an overwhelming volume of alerts, hindering effective situational response.

This incident highlights the importance of incorporating a systematic HRL perspective throughout a system's life cycle. Although the alarm system was not designed to overwhelm crew members, incremental changes over time, paired with declining training and insufficient procedural reinforcement, shifted the burden of adaptation onto operators rather than addressing underlying system shortcomings. Integrating HRL practices can help the HSI requirements remain visible, validated and supported as systems evolve.

Integrating HRLs into qualification processes allows organizations to identify human-system risks early, when design changes are still feasible and cost-effective. Integrating HRLs into these existing qualification processes can strengthen human-system readiness by:

- Mapping HRL milestones to NTQ phases
- Requiring human-factors evidence packages at approval gates
- Linking autonomy classes to operator-role maturity
- Verifying training and procedural readiness prior to deployment

Although many organizations acknowledge human factors and operational readiness as priorities, these elements are still often assumed to be naturally incorporated into design and operational processes. However, research has long shown that classification activities benefit significantly from structured HSI [Card et al., 2005]. With the fast development and adoption of new technologies, consideration of the human-in-the-loop and human-machine interactions is even more relevant. Human readiness levels offer a formal mechanism to embed this integration systematically and consistently.

Human Readiness Level Milestones for New Technology Systems

Human readiness level evaluates readiness across five core human-system domains that collectively determine whether a technology can be used safely and is operationally viable. Some examples include but are not limited to:

1

Operator Role Definition

- Monitoring responsibilities
- Intervention authority
- Handover protocols
- Degraded-mode control authority

2

Human-machine Interface (HMI) Maturity

- Presenting automation intent
- Displaying confidence or uncertainty
- Supporting fault diagnosis
- Minimizing mode confusion

3

Alarm Strategy

- Alarm prioritization strategies
- Alarm suppression logic
- Integrated alarm displays
- Alarm response procedures

4

Training and Procedures

- Validated training syllabi
- Simulator-based training scenarios
- Emergency response drills
- Certification criteria

5

Organizational Readiness

- Staffing models
- Watch standing policies
- Maintenance coordination
- Shore-based support structures

Methods for Assessing Human Readiness

Humans have a limited number of cognitive resources available at any moment and many of these resources cannot be used simultaneously. This is known as Multiple Resource Theory and researchers have extensively examined how attentional resources influence cognitive performance, workload and situational awareness [Wickens, 2008; Endsley, 1995]. The study concluded that human information processing relies on working memory, long-term memory and selective attention. When task demands exceed these capacities, performance can be degraded. Dividing attention between competing tasks becomes especially taxing in dynamic environments common to autonomous, remote and technologically complex systems [Wickens, 2008; Parasuraman et al, 2000].

Technological advancements, especially those incorporating AI and machine learning, have transitioned many of the controls and functions into a black box from which the operator no longer sees direct readouts of data or information. As long as the system is reliable, there is no issue. However, once human intervention is required, issues may arise as the human intervening will need sufficient knowledge to maintain situational awareness of the system and environment: what is the system doing, why is it doing it and what needs to be done next [Endsley, 2017]. To provide this information to an operator, it is imperative that HMIs provide relevant information and feedback to humans to support situational awareness for appropriate actions to be taken [Norman, 1988].

Human readiness levels assessments should rely on established and evidence-based human factors methods for evaluating human performance. These methods range from early qualitative analyses to high-fidelity quantitative modeling, increasing in rigor as HRL maturity advances.

Human Performance Modeling

Various methods and tools available to quantify human behavior, processes and cognition requirements and load. These include:

- **Task Analysis:** Task flow models that highlight critical points where human error is more likely (e.g., during data interpretation or when making judgment calls under stress).
- **Cognitive Task Analysis:** Cognitive models for tasks that require high mental effort and risk. This could include mental steps for decision-making in emergencies, like diagnosing engine problems or evaluating weather-related risks [Clark et al, 2008].
- **CogTool:** Generate simulation results that can identify potential inefficiencies in interface design, such as confusing menu options or redundant steps, leading to delays in task completion [Bellamy et al, 2010].
- **Goals, Operators, Methods, Selection Rules (GOMS):** A detailed process flow showing the most efficient way to accomplish tasks, highlighting areas where operator behavior can be optimized [Jonassen et al, 1998].
- **Cognitive Perceptual Model of Goals, Operators, Methods and Selection Rules (CPM-GOMS):** A model of operator actions that considers both cognitive factors (e.g., reasoning, decision-making) and perceptual tasks (e.g., identifying targets on radar, interpreting visual cues) [John & Grey, 1995].
- **Keystroke-Level Model (KLM):** Task performance time estimates for routine operational tasks (e.g., setting navigation waypoints, changing course), providing insights into how much time operators are spending on interactions with technology and where delays may arise [Kieras, 2001].
- **Natural GOMS Language (NGOMSL):** A task model in natural language that illustrates the sequences of actions required for critical operations, such as emergency procedures or safety checks [Kieras, 1997].
- **Cogulator:** A cognitive performance model that predicts time-to-completion and identifies potential bottlenecks or high cognitive load areas during operations [Estes, 2021].
- **EPIC (Executive-Process Interactive Control):** Workload and performance maps that identify when and where crew members are most likely to experience delays or errors due to competing task demands [Kieras & Meyer, 1994].
- **QN-MHP (Queueing Network Model of Human Performance):** Workload and performance maps that identify when and where crew members are most likely to experience delays or errors due to competing task demands [Feyen & Liu, 2001].

Situation Awareness Measurement

Endsley's [1995] framework remains foundational for evaluating perception, comprehension and projection in supervisory roles.

- **GDTA (Goal-Directed Task Analysis):** Used to identify what the operator needs at each stage and whether the technology effectively provides it and identifies where mismatches cause loss of awareness.
- **Eye-tracking and Visual Attention Mapping:** Identifies interface design deficiencies that enhance attention tunneling, scanning inefficiencies and over-reliance on automation.

Simulation and Sea Trials

High-fidelity simulators enable mode-transition testing, failure injection and training evaluation.

Usability and Interface Testing

Objective metrics may include task success, time-to-diagnosis, error rates and workload ratings. Methods mentioned above, such as GOMS, NGOMSL, KLM and CogTool also provide insights on testing of usability and digital interfaces.

Human Reliability Analysis

HFACS-based and probabilistic approaches quantify human contribution to risk [Adumene et al., 2022].

Providing explicit criteria, such as HRLs, when validating human factors in safety-critical systems gives project teams a clear structure and shared vision. Human readiness level offers a consistent framework that helps designers assess how prepared a technology is for integration and safe operation with human users. By incorporating HRLs early in development, teams can better account for operator cognitive load, reduce the likelihood of HSI risks and minimize the need for costly redesigns caused by overlooking human considerations from the beginning.

Some may argue that emerging technologies aim to remove humans from the operational loop entirely. However, reality is more complex. Even highly automated systems cannot eliminate the need for human involvement, particularly when equipment malfunctions, require maintenance or encounter a scenario it cannot resolve autonomously. In these critical moments, control inevitably shifts back to the human operator. The key question is whether the human has been adequately considered and prepared for these interactions. Human readiness level confirms that human roles, responsibilities and information needs are intentionally designed into the system, supporting safe and effective human intervention when it matters most.

Application Examples

Remote Operations in Marine and Offshore Environments

Human readiness level provides a clear measure of how operationally ready for a remote or autonomous system is for rapid and effective adoption by human operators. Remote operational tools are actively being explored and deployed in the marine and offshore industry for capabilities ranging from managing auxiliary and industrial processes, cargo handling and ballast and trim machinery functions. Remote operations centers can provide real-time monitoring and system oversight, which supports autonomous and remote-control applications. Technical requirements for remote and autonomous functions for the marine and offshore industries are outlined in the ABS *Requirements for Autonomous and Remote-Control Functions.*

Additionally, capabilities to conduct remote inspections using live-streaming video and remote inspection tools such as drones and robotic platforms are actively being used in the marine and offshore industry. These technologies support a range of use cases including surveys, difficult-to-access inspection areas and hazardous area checks. Remote inspection technology helps address challenges like reduced crew availability while also enabling faster turnaround times. Remote tools reduce risk to personnel by minimizing the need to enter confined spaces or other high-risk environments.

Technical guidance for remote inspections in class and non-class inspections in the marine and offshore industries is supported in the ABS *Guidance Notes on the Use of Remote Inspection Technologies.*

Understanding the human-system interactions involved in remote inspection technologies is essential. By assessing how effectively crew members and remote operators can use these tools, HRLs help determine how ready these technologies are for real-world adoption. A high HRL reduces the risk that remote inspection systems not only meet technical requirements but can be made more usable, intuitive for safer operational integration.

AI Decision Support Tools in Marine and Offshore Environments

Artificial intelligence can generate large amounts of information. Human readiness levels assess whether operators can process and act on this information without cognitive overload or distraction. It can decrease the load on crew members by taking in large amounts of data and running predictive analytics to predict an issue before it happens. It can predict trends, detect anomalies, monitor the health of machinery and support navigational tasks. Research has also explored the balancing act required for AI and humans to work in tandem. It's important that humans are provided with enough information and understand what the system is doing and why it is doing it to better respond in a timely

manner during critical-safety events. Technical guidance for smart functions in the marine and offshore industry is supported in the ABS *Guide for Smart Functions for Marine Vessels and Offshore Units.*

Understanding the HSIs involved in AI decision-support tools is essential for safe operations. Over-reliance on automation can reduce operator vigilance, weaken critical thinking and impair the ability to respond effectively during manual interventions [Parasuraman & Riley, 1997]. Likewise, operators engaged in continuous monitoring tasks face the risk of cognitive underload, which can lead to boredom, reduced vigilance and slower reaction times; ultimately increasing the likelihood of missing critical environmental cues [Young & Stanton, 2002]. These risks highlight the importance of regular drills, situational awareness training and workflow designs that keep operators meaningfully engaged.

A high HRL reduces the likelihood of misuse or disuse and supports safer, more intuitive and more effective operational integration.

AR in Simulated Marine Environment

Human readiness level helps evaluate how well humans can safely and effectively use technology in real operational conditions. ABS and Texas A&M University are evaluating the limitations of AR headsets in a simulated marine environment. The study examines three different AR features to determine whether they introduce any safety or performance impacts related to navigation, memory, manual interactions or visual information processing.

The findings from this work help define requirements for head-mounted AR devices used in marine operations and, through experimentation and modeling, identify which tasks AR is best suited to support. In addition, the project provides guidance on how AR systems can be designed to enhance situational awareness rather than distract or overload the wearer.

By understanding these HSIs, the project directly informs the HRL of AR technologies. The results from this research strengthen HRL assessments

by providing evidence-based insight into user limitations, performance impacts and operational suitability supporting AR solutions that are not just technically capable, but truly ready for human use in the marine environment.

Guidance for Owners and Vendors

Emerging maritime technologies require qualification processes that extend beyond technical maturity to evaluate whether they can be operated safely and effectively throughout their entire life cycle. Incorporating considerations on the human element is essential and the HRL framework provides owners, operators and developers with a structured approach that supports safer operations while reducing unnecessary cost and rework. This guidance can be integrated into existing Safety Management Systems as outlined in ABS *Guide for Marine Health, Safety, Quality, Environmental and Energy Management.* As technology advances, new systems should enhance crew performance and include appropriate mitigations that support the level of situational awareness required for human intervention when necessary. To effectively operationalize HRLs, organizations should:

- **Conduct human-factors analyses early in the design process**
- **Embed HSI requirements into procurement specifications**
- **Require HRL documentation from vendors**
- **Perform integrated simulation testing**
- **Avoid late-stage interface retrofits**

Integrating HRLs can help reduce late-stage redesign, enhance operational safety and support responsible deployment of emerging maritime technologies. The HRL framework is a valuable complement to existing hardware and technology-readiness assessments and together these tools offer a structured and efficient pathway for bringing new technologies into industry. By addressing human-system risks early, HRLs help assess whether a given technology is prepared for safe and effective human operation.

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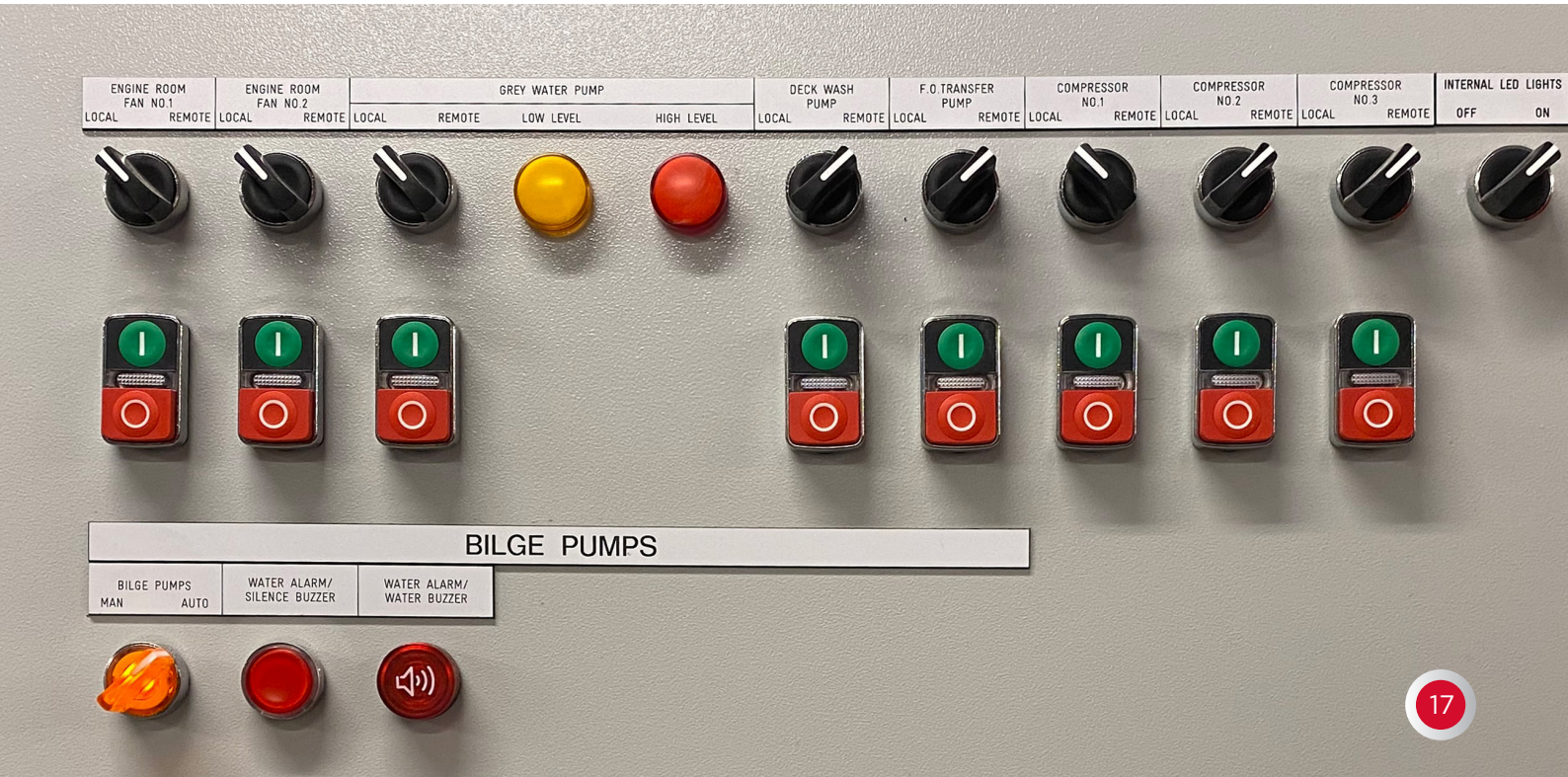

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