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# Autonomy aweigh: Evaluation metrics and supporting seafarers' basic psychological needs in energy-efficient route planning DSS

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A B S T R A C T

To achieve necessary $CO_2$e emission reductions in the maritime industry, decision support systems (DSS) can assist seafarers in energy-efficient operations. However, adequate evaluation measures beyond classical human–machine interaction (HCI) metrics are required to ensure these systems are human-centered and align with Industry 5.0 goals, including human–machine cooperation and basic psychological needs, especially autonomy. Objectives of this research were (1) to understand how different metrics evaluate route-planning DSS and a route adaptation feature, and (2) to explore autonomy support in DSS usage. Simulator ($N$ = 48) and online ($N$ = 20) studies with experienced seafarers showed HCI metrics alone did not quantify the adaptation feature's potential. Thematic analysis of interviews highlighted algorithm comprehensiveness, usability, user empowerment, and collaborative workflows as key autonomy aspects. Furthermore, seafarers preferred automated information acquisition and analysis but human decision-making for route planning. We discuss design guidelines to improve autonomy satisfaction for energy-efficient route planning.

## 1. Introduction

The maritime industry, especially commercial shipping, is a key working context, in which individual and organizational decision-making plays a significant role in reducing global $CO_2$e emissions (International Maritime Organization, 2021). Recognizing this, the International Maritime Organization (IMO) aims to reduce $CO_2$e emissions per transport work by at least 40% by 2030 and has mandated measures such as the Ship Energy Efficiency Management Plan to facilitate energy-efficient operations onboard (International Maritime Organization, 2011). In particular, fuel consumption for propulsion accounts for roughly 70% of a ship's operating costs, and reducing it is a priority for both environmental and economic reasons (Rehmatulla and Smith, 2015). Nevertheless, the maritime industry faces an 'energy efficiency gap', where the technical potential for consumption and emission reductions is not fully realized in practice (Jaffe and Stavins, 1994; Johnson and Andersson, 2011; Acciaro et al., 2013). This gap presents an ongoing challenge that requires the attention of experts in human factors and ergonomics to support the United Nations Sustainability Goals 13 (Climate Action) and 8 (Decent Work and Economic Growth) (United Nations, 2015).

Energy efficient route planning (EERP) is a key abatement measure to bridge the energy efficiency gap, showing reduction potential of up to 48% of $CO_2$e (Bouman et al., 2017). However, seafarers feel hindered by high workload, fatigue, and pressures exerted by shipping companies, charterers, and regulations (Zoubir et al., 2023; Poulsen and Sampson, 2019; Poulsen et al., 2022). These factors contribute to a demanding work environment, complicating seafarers' ability to perform operational abatement measures efficiently (von Knorring, 2019). One approach is implementing Decision Support Systems (DSS)—interactive, computer-based systems that assist users in balancing occupational demands with efficient, data-driven decision-making, particularly in complex and dynamic environments (Shim et al., 2002).

DSS have demonstrated effectiveness in optimizing energy-efficient transportation by integrating diverse data sources. In public transportation, DSS incorporating geographical and traffic flow data have facilitated environmentally sustainable route planning (Arampatzis et al., 2004). Similarly, DSS applications in urban logistics have reduced driving distances and emissions by optimizing vehicle routing based on multiple constraints (Leyerer et al., 2019). In the maritime sector, DSS leveraging Artificial Neural Networks have been developed to optimize fuel consumption by analyzing operational parameters such as ship speed, engine RPM, draft, and environmental conditions

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(Beşikçi et al., 2016). By automating complex calculations and providing actionable recommendations, DSS can ease cognitive workload and support decision-making under operational pressures, making energy-efficient route planning more feasible for seafarers (Beşikçi et al., 2016; Viktorelius et al., 2021). However, for DSS to be effective in high-demand environments, they must align with user needs and workflow constraints.

Onboard, technical systems risk abandonment if they do not support operational realities (Viktorelius, 2017). To ensure human-centered (focused on users' requirements) rather than technology-driven design, which can cause usability and adoption issues (cf. Grech et al., 2008), comprehensive assessment questionnaires can quantify how well user requirements are met. Classical *human–machine interaction* metrics, such as usability and user experience, are crucial for optimizing individuals' interaction with a system. Simultaneously, in dynamic working environments where humans and systems collaborate, *human–machine cooperation* metrics, such as trust and perceived cooperativity, can assess a system's role in achieving mutual goals (Hoc, 2000). Even so, these approaches are strongly focused on the human and machine aspects of interaction and may neglect other work aspects, such as intrinsic motivation and well-being. This latter metric may be crucial for Industry 5.0, which aims to place employees at the center of production processes, as emphasized, e.g., by the European Commission's report highlighting the necessity of addressing workers' needs (European Commission et al., 2021).

One example to illustrate need frustration onboard is that seafarers, despite the requirement to operate energy efficiently, have limited control over their actions due to regulations or charterer contracts (Poulsen and Sampson, 2019), reducing their scope of action and introducing a goal conflict. Additionally, seafarers experience reduced control beyond these limitations (Zoubir et al., 2023), leading to decreased motivation to apply available abatement measures. To quantify this subjective experience, Basic Psychological Needs (BPN) can be applied. According to Self-Determination Theory (Ryan and Deci, 2000), BPN includes three needs that, when satisfied, enable intrinsic motivation: *Competence*, feeling effective in one's interactions with the environment; *Relatedness*, feeling connected to others; and *Autonomy*, feeling in control of one's actions and goals. Previous studies indicated that seafarers experience reduced autonomy need satisfaction at work compared to competence or relatedness (Zoubir et al., 2025a), suggesting greater motivational potential for sustainable behavior if this need is fulfilled. While BPN can inform system design to increase need satisfaction (Hassenzahl et al., 2010; Moradbakhti et al., 2024), further research on integrating these needs into DSS design is warranted. This includes an understanding of how (1) interaction, (2) cooperation and (3) BPN metrics can detect changes in system design.

First empirical research with BPN metrics in maritime systems found that seafarers utilizing a DSS providing route suggestions rated the DSS positively on usability and user experience but lower on autonomy need satisfaction compared to a digital map charting tool (Zoubir et al., 2025b). In this study, seafarers most often requested an adaption feature, i.e. the ability to adjust route plan details. However, it is unclear to what extent more adaptability indeed leads to more autonomy fulfillment. For one, while adaptability can increase feelings of control, in other contexts it has increased system complexity and users' time on task (e.g. Nurkka, 2013; Mackay, 1991). Furthermore, previous research with seafarers identified a negative correlation between autonomy satisfaction at work and preferences for automated decision-making in route planning, i.e. those experiencing less freedom at work preferred more automation in their DSS (Zoubir et al., 2025a). Further research is therefore necessary to understand the relationship between DSS features and autonomy satisfaction.

One further important avenue to explore autonomy is to differentiate facets of autonomy, especially in the context of human–machine interaction. Savolainen and Ruckenstein (2022), based on a review of human-algorithm interaction studies, identifies four specific aspects of autonomy: *algorithmic competence* (understanding algorithms), *situational mastery* (overcoming challenges and seizing opportunities), *breathing space* (freedom to make decisions), and *co-evolution* (collaborating with technology for mutual growth). Examining these facets during system development can provide a deeper understanding of emerging requirements for energy efficiency DSS.

### 1.1. Research objectives

The present research had two main objectives (RQ1-2) and one secondary objective (Table 1). First, we examined how a suggestion adaptation feature in a decision support system (DSS) affected evaluation metrics. **RQ1** investigated and compared seafarers' ratings of Human–Machine Interaction, Human–Machine Cooperation, and Basic Psychological Need Satisfaction measures during route planning with an EERP DSS. Second, we explored factors supporting autonomy during this DSS usage. **RQ2** examined seafarers' descriptions of autonomy with a DSS featuring suggestion adaptation, focusing on the facets algorithmic competence, breathing space, situational mastery, and co-evolution. Finally, we investigated preferences for automation types and their relation to autonomy need satisfaction, seeking to replicate the findings of Zoubir et al. (2025a). **RQ3** assessed seafarers' preferences for automation in route planning and whether a preference for automated decision selection correlated with low autonomy need satisfaction. Due to recruitment challenges, we conducted two empirical studies: a professional ship-bridge simulator study ($N$ = 20) with quantitative data and interviews, and an online study ($N$ = 48) to substantiate findings with a larger sample.

## 2. Method

The presented studies received ethical approval from the University of Luebeck ethics commission (Approval Number 2023–406). The online study was pre-registered at https://doi.org/10.17605/OSF.IO/RTN7Q.

### 2.1. Participants

For the **Simulator study**, we recruited experienced seafarers ($N$ = 20) by approaching pilots and channel controllers during training exercises, in cooperation with the University of Applied Sciences in Flensburg, Germany. Participants, compensated €60, were familiar with the ship simulator. Due to technical errors in the survey tool, two surveys were excluded from the quantitative analysis ($n$ = 18), but included in qualitative analyses ($N$ = 20).

For the **Online study**, we recruited seafarers ($N$ = 48) through mailing lists of international maritime training facilities, shipping companies, and crewing agencies. Participants were compensated with €20 via bank transfer. Data sets were inspected for plausibility, focusing on response timing and consistency (e.g., schematic response behavior) to ensure validity. Additionally, responses to an attention check at the beginning of the survey ("Please select 'Somewhat disagree' for this question".) were evaluated. No participants had to be removed.

Both populations included experienced nautical officers (Simulator: $M_{\text{years}}$ = 7.5, SD = 7.4, Online = $M_{\text{years}}$ = 4.5, $SD$ = 8.1), who had planned numerous routes (Simulator: $M_{\text{routes}}$ = 44 $SD$ = 45.2; Online: $M_{\text{routes}}$ = 48, SD = 255.8). Regarding Affinity for Technology Interaction ATI, which evaluates a person's tendency to engage actively in technology interaction (Franke et al., 2019), were above-average (score range: 1–6, Simulator: $M$ = 4.0, $SD$ = 0.7; Online: $M$ = 4.1, $SD$ = 0.7), being higher than the distribution of a quota sample assumed to represent the general population in Germany (3.61 as described in Franke et al., 2019). This aligns with the technical nature of the seafaring profession. Furthermore, participants rated their familiarity with other route planning software on a scale of 0 (not familiar at all) to 10 (extremely familiar). Participants were somewhat familiar

**Table 1**
Research Questions, Hypotheses, and Samples.

| Research Question | Hypotheses/Comparisons | Samples |
|---|---|---|
| **RQ1:** How do seafarers rate Human–Machine Interaction, Human–Machine Cooperation, and Need Satisfaction when using route planning tools for EERP? | **Ha:** DSS leads to higher ratings than map charting. | |
| | **Hb:** DSS with suggestion adaptation leads to higher ratings than standard DSS. | Simulator; Online |
| **RQ2:** How do seafarers describe autonomy with a DSS featuring suggestion adaptation in terms of competence, breathing space, mastery, and co-evolution? | Descriptive; no hypothesis. | Simulator only |
| **RQ3:** How do seafarers rate automation preferences in route planning, and does preference for decision selection correlate with low autonomy need satisfaction? | **Hc:** Preference for decision selection correlates negatively with autonomy need satisfaction. | Simulator; Online |

with third-party commercial software such as BonVoyage or Octopus (Simulator: $M = 2.8$, $SD = (2.9)$; Online: $M = 5.5$, $SD = (3.6)$), and somewhat less familiar with websites such as OpenSeaMaps (Simulator: $M = 1.6$, $SD = 1.6$; Online: $M = 4.0$, $SD = 3.0$). Therefore, participants were neither unfamiliar nor overly familiar with systems used or similar to those used in this study.

### 2.2. Procedure

In both studies, participants were tasked with planning three routes with the least fuel consumption possible between two positions in either the Alaskan, Mediterranean or Andaman Sea, with a duration between 2 and 5 day. The routes were created together with subject-matter experts to ensure practical relevance and realism. In a within-subject design, participants used one of each route-planning tool once: (1) OpenSeaMaps (OSM; a digital charting tool), (2) an energy efficiency DSS (see Section 2.3) without an adaption feature, and (3) the DSS with an adaption feature. Order of tool and geographical location were counter-balanced across participants.

In the simulator, participants conducted planning in a professional ship bridge simulator (Wärtsila, 2023). They received comprehensive route planning information (e.g. vessel specifications, oceanographic and meteorological data). Participants performed watch duties during planning, including monitoring surroundings and avoiding collisions. After each planning session of max. 20 min ($M_{\text{sec}} = 696.6$, $SD = 671.8$), they completed questionnaires in LimeSurvey v3.28 (Limesurvey GmbH, 2015). Online, participants only conducted route-planning with the web-based route-planning tools on their computers. They received comprehensive route planning information via text in the survey tool and each session lasted for max. 20 min ($M_{\text{sec}} = 413.8$, $SD = 334.9$). Since the online study did not include a watch task, which could influence ratings of task-relevant metrics, we analyzed each sample separately for RQ1. For RQ3, which examined setting-independent constructs, we combined the samples.

### 2.3. Decision support system

The DSS utilized in this study was developed through a user-centered design process as described in Schwarz et al. (2023). The interface (Fig. 1) was presented on a tablet (simulator) or a responsive web interface (online). The DSS included a nautical chart with optional overlays for e.g. atmospheric pressure isobars, current direction arrows, wind vanes, and significant wave height heat maps (A). The ship's current position, past track, and suggested routes were also visualized (B). A timeline control simulated virtual ships' progress along different routes while considering forecasted weather conditions (C). A fly-out module provided comparisons of routing options based on key performance indicators (KPIs) such as fuel-oil consumption, travel duration, ETA, and weather warnings (D). In the "DSS with added adaption feature" condition, participants could access a dedicated screen for editing route suggestions (E). This screen displayed pre-defined waypoints, which could be moved via drag-and-drop, or points between waypoints, allowing the addition of new waypoints. Participants could undo/redo changes. Saving the route updated the KPIs to reflect these changes, showing, for example, increases in time or reductions in fuel consumption.

### 2.4. Measures

A range of validated scales was used to assess Human–Machine Interaction, Human–Machine Cooperation, and Basic Psychological Need Satisfaction. Interaction measures included usability and user experience assessments, while cooperation measures focused on trust and perceived cooperativity. Psychological need satisfaction was evaluated in both technology use and workplace contexts, with subscales for autonomy, competence, and relatedness. Table 2 provides an overview of all measures, including their constructs, scale ranges, and citations.

Furthermore, we included the Preference for Automation Types scale (PATS; see Table A.1 in Appendix A), which assesses users' preferences for either human or automated control of different levels of functions based on Parasuraman et al. (2000)'s framework. The scale includes four dimensions: information acquisition (e.g., "Gather data from multiple sources or sensors"), information analysis (e.g., "Perform calculations with current data"), decision selection (e.g., "Make a decision on which action(s) to carry out based on current data"), and action implementation (e.g., "Put a decision into action"). The development and validation of the scale is described in Zoubir et al. (2024b).

### 2.5. Statistical analysis

Power analyses with G*Power (Faul et al., 2007) assumed a medium effect size ($d = 0.5$ or $r = 0.3$), $\alpha = .05$ and $\beta = .8$. The minimum sample size for Ha and Hb (one-sided, dependent $t$-Tests) was 27. Therefore, the simulator sample ($n = 18$) lacked sufficient power to detect medium or small effects, so non-significant results may reflect false negatives. The online sample ($N = 48$) was sufficiently powered. The minimum sample size for Hc (one-sided, Pearson's product-moment correlation) was 64, which was achieved by pooling both samples ($N = 66$). Pooling was justified as autonomy need satisfaction at work was a construct independent of DSS interaction and the PATS was administered before tool use. Additionally, Walter et al. (2019) found that online panel data has comparable psychometric properties and validity to conventional data, further supporting the pooling of samples here. We utilized parametric tests despite partially non-normal distributions to maintain greater statistical power and sensitivity to detecting actual differences, while outliers were included to preserve the variability present in the sample. Effect sizes were interpreted in accordance with (Cohen, 2013).

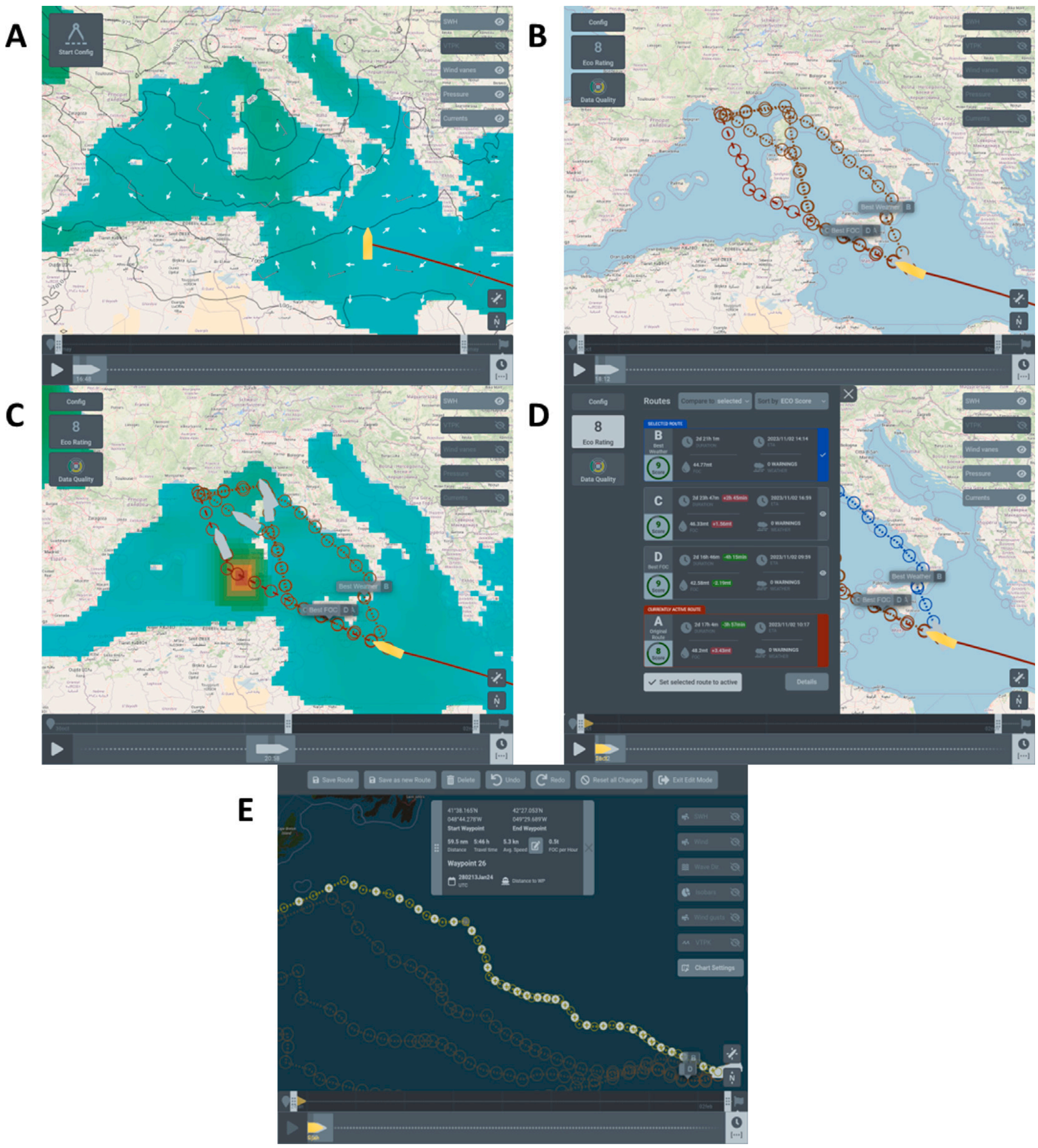


**Fig. 1.** Route-planning DSS. Displayed are weather overlays (A), route suggestions (B), dynamic timeline control (C), and route KPI comparisons (D). The route suggestion adaptation feature is displaying in E.

### *2.6. Qualitative analysis*

Conducted interviews followed the proposed framework of autonomy in human–algorithm relations by Savolainen and Ruckenstein (2022). Following a semi-structured guideline, each of the four dimension was introduced and participants questioned about to what extent they felt the system fulfilled or did not fulfill that facet, and which system features contributed to this. An R-based offline tool for WhisperTranscribe (Radford et al., 2022; Wijffels et al., 2023) was used to transcribe the interviews verbatim, followed by verifying the accuracy of the transcripts. Thematic analysis was applied consistent with Braun and Clarke (2006). MZ and MG first familiarized themselves with the data and subsequently created initial codes. The coders then discussed observed patterns and develop initial themes in a workshop. Next, coders independently assigned participants' responses to a theme. For each dimension, individuals' responses were classified as pertaining to a theme or not. In this manner, we examined how many participants addressed a theme, without counting e.g. repeated mentions of a theme by an individual. Results of this initial coding cycle showed a strong inter-coder reliability ($\kappa$ = .89). In a subsequent workshop, categorizations were discussed until coders obtained a consensus. See Appendix B for all themes and definitions.

## 3. Results

### *3.1. RQ1 - Evaluation metrics*

#### *3.1.1. Ha comparison of DSS with conventional charting tool*

Ha predicted that DSS usage would lead to higher ratings of Human–Machine Interaction, Cooperation, and BPN metrics compared to conventional map charting tools. One-sided dependent t-tests showed a significant increase in all metrics except trust and autonomy need satisfaction in both samples (Table 3). Effect sizes ranged from small to large, with particularly strong improvements observed in Hedonic Quality ($d$ = 1.69, 0.98), Cooperativity ($d$ = 0.77, 0.63), and Relatedness with Technology ($d$ = 0.82, 0.56).

The pattern of results was largely consistent across both samples, though effect sizes were generally smaller in the online study, suggesting that direct interaction with the DSS in a simulator setting may have

**Table 2**
Summary of Measures.

| Category | Scale Name | Construct Measured | Range | Citation |
|---|---|---|---|---|
| Interaction | System Usability Scale (SUS) | System effectiveness, efficiency, and satisfaction | 0–100 | (Brooke, 1996) |
| | User Experience Questionnaire Short Scale (UEQ-S) | | −3–3 | (Schrepp et al., 2017) |
| | Hedonic quality | Emotional response and engagement | | |
| | Pragmatic quality | Perceived usefulness and functionality | | |
| Cooperation | Checklist for Trust between People and Automation | Perceived trust in automation (reliability, predictability, dependability) | 1–7 | (Jian et al., 2000) |
| | Perceived Cooperativity Scale | Perceived cooperativity of agents in joint activities | 1–6 | (Attig et al., 2024) |
| Needs | Basic Psychological Need in Technology Use (BPN-TU) | | 1–6 | (Moradbakhti et al., 2024) |
| | Autonomy | Self-regulate one's experiences and actions | | |
| | Competence | Effectance and mastery | | |
| | Relatedness to Others | Socially connected to others through usage | | |
| | Relatedness to Technology | Socially connected to technology | | |
| Other | Basic Psychological Need Satisfaction at Work Scale (BPNSWS) | Satisfaction of autonomy, competence, and relatedness needs at work | 1–6 | (Chen et al., 2015) |
| | Preference for Automation Types Scale (PATS) | Preference for automation in information acquisition, analysis, decision selection, and action implementation | 1–6 | (Parasuraman et al., 2000) |

**Table 3**
Ha: Comparison of Human–Machine Interaction, Human–Machine Cooperation and BPN measures between conventional digital charting and Decision Support Systems.

| Measure | Simulator ($n$ = 18) | | | | Online ($N$ = 48) | | | |
|---|---|---|---|---|---|---|---|---|
| | Chart $M(SD)$ | DSS $M(SD)$ | $t$ ($p$) | $d$ | Chart $M(SD)$ | DSS $M(SD)$ | $t$ ($p$) | $d$ |
| Usability | 41.7 (20.4) | 59.8 (16.0) | 2.91 (.005)** | 0.69 | 44.4 (15.5) | 55.1 (13.8) | 3.62 (<.001)*** | 0.52 |
| Hedonic Quality | −1.1 (1.1) | 1.1 (1.1) | 7.15 (<.001)*** | 1.69 | −0.5 (1.5) | 1.0 (0.9) | 6.79 (<.001)*** | 0.98 |
| Pragmatic Quality | −0.4 (1.7) | 1.3 (1.2) | 3.27 (.002)** | .0.77 | 0.0 (1.4) | 1.2 (1.0) | 5.62 (<.001)*** | 0.81 |
| Trust | 3.9 (1.4) | 4.0 (0.6) | 0.29 (.387) | 0.07 | 3.9 (1.0) | 4.1 (0.6) | 1.09 (.141) | −0.16 |
| Cooperativity | 2.8 (0.7) | 3.7 (0.9) | 3.27 (.002)** | 0.77 | 3.0 (0.9) | 3.8 (0.7) | 4.37 (<.001)*** | 0.63 |
| Autonomy | 3.5 (1.5) | 4.1 (1.2) | 1.20 (.124) | 0.28 | 4.2 (1.2) | 4.0 (1.1) | −0.69 (.753) | −0.10 |
| Competence | 3.1 (1.2) | 4.0 (1.1) | 2.07 (.027)* | 0.49 | 3.5 (1.1) | 4.0 (1.1) | 2.36 (.011)* | 0.34 |
| Relatedness (Others) | 2.4 (0.9) | 3.3 (1.2) | 2.69 (.008)** | 0.63 | 2.8 (1.2) | 3.4 (1.2) | −2.98 (.002)** | −0.43 |
| Relatedness (Tech) | 2.3 (1.1) | 3.6 (1.3) | 3.47 (<.001)*** | 0.82 | 2.7 (1.4) | 3.6 (1.3) | 3.91 (<.001)*** | 0.56 |

amplified the perceived benefits. Notably, trust and autonomy need satisfaction showed no significant differences in either sample. This suggests that while the DSS improved perceived usability, cooperation, and competence, it may not have sufficiently addressed factors influencing trust or autonomy perception, such as system transparency or user control.

Thus, Ha was only partially supported: Interaction metrics consistently improved with large effect sizes, but trust and autonomy showed no significant differences.

### 3.1.2. Hb: Comparison of DSS with and without adaption feature

Hb: Comparison of DSS with and without Adaptation Feature

Hb predicted that DSS usage with a suggestion adaptation feature would lead to higher ratings of Human–Machine Interaction, Cooperation, and BPN metrics compared to a DSS without this feature. One-sided dependent t-tests showed a significant increase in trust, autonomy need satisfaction, usability, and hedonic quality in the online sample, with small effect sizes (Table 4). No significant improvements were found for cooperativity, competence, or relatedness with technology.

Effect sizes for trust ($d$ = 0.42), autonomy ($d$ = 0.41), usability ($d$ = 0.29), and hedonic quality ($d$ = 0.42) were small, suggesting that while the adaptation feature improved user experience, its impact on overall perception remained modest. The simulator sample showed similar trends but with slightly stronger effects for usability ($d$ = 0.52) and especially trust ($d$ = 0.95). However, cooperativity and competence did not significantly improve in either sample, indicating that while the adaptation feature enhanced usability, trust and a feeling of being autonomous, it may not have strengthened perceptions of collaboration or user skill.

Thus, Hb was only partially supported: The adaptation feature improved ratings on selected scales, particularly trust, usability, and autonomy satisfaction, but did not lead to broader improvements across all measured metrics.

## 3.2. RQ2: Qualitative analysis of dimensions of autonomy

Interviews explored the four dimensions of human-algorithm interaction postulated by Savolainen and Ruckenstein (2022), and extracted factors supporting perceived autonomy during DSS usage. The results of the thematic analysis of seafarer interviews were summarized in an Ishikawa fishbone diagram (Ishikawa and Loftus, 1990, ; Fig. 2). Due

**Table 4**
Hb: Comparison of Human–Machine Interaction, Human–Machine Cooperation, and BPN measures between DSS- (without adaption feature) and DSS+ (with adaption feature).

| Measure | Simulator ($n$ = 18) | | | | Online ($N$ = 48) | | | |
|---|---|---|---|---|---|---|---|---|
| | DSS- $M(SD)$ | DSS+ $M(SD)$ | $t$ ($p$) | $d$ | DSS- $M(SD)$ | DSS+ $M(SD)$ | $t$ ($p$) | $d$ |
| Usability | 59.8 (15.97) | 64.2 (15.84) | 2.20 (.021)* | 0.52 | 55.1 (13.78) | 57.4 (12.50) | 1.99 (.026)* | 0.29 |
| Hedonic Quality | 1.1 (1.11) | 1.2 (1.22) | 0.53 (.303) | 0.12 | 1.0 (0.94) | 1.3 (1.00) | 2.90 (.003)** | 0.42 |
| Pragmatic Quality | 1.3 (1.17) | 1.5 (1.19) | 1.22 (.121) | 0.29 | 1.2 (0.97) | 1.1 (1.15) | −0.72 (.764) | −0.11 |
| Trust | 3.97 (0.61) | 5.00 (1.25) | 4.01 (<.001)*** | 0.95 | 4.05 (0.65) | 4.40 (1.14) | 2.91 (.003)** | 0.42 |
| Cooperativity | 3.69 (0.87) | 3.87 (0.88) | 1.29 (.108) | 0.30 | 3.75 (0.69) | 3.84 (0.84) | 1.07 (.146) | 0.15 |
| Autonomy | 4.13 (1.23) | 4.68 (1.13) | 2.35 (.016)* | 0.55 | 4.03 (1.09) | 4.35 (0.88) | 2.86 (.003)** | 0.41 |
| Competence | 3.98 (1.14) | 4.13 (1.32) | 0.54 (.299) | 0.13 | 4.01 (1.08) | 4.14 (1.00) | 1.18 (.122) | 0.17 |
| Relatedness (Others) | 3.28 (1.25) | 3.61 (1.37) | 2.92 (.005)** | 0.69 | 3.38 (1.16) | 3.51 (1.15) | 1.13 (.132) | 0.16 |
| Relatedness (Tech) | 3.65 (1.28) | 4.06 (1.15) | 1.59 (.065) | 0.37 | 3.56 (1.26) | 3.76 (1.30) | 1.50 (.070) | 0.22 |

to space constraints, the following section summarizes only the major results and examples; please refer to Appendix B for full definitions, quotations and theme distribution across participants.

*Algorithmic competence.* Regarding factors increasing their ability to interact with the algorithm, seafarers frequently mentioned features supporting *Algorithm Comprehensiveness* ($n$ = 17), including explicit explanations of the DSS or implicit assumptions by users. The latter often involved *Data Transparency* ($n$ = 16), such as correlating unabridged wave height data with DSS route suggestions to reconstruct the tools' planning process. Affordances supported *Algorithm Recognition* ($n$ = 17), often regarding assumptions about how input data (e.g., Requested Time of Arrival) influenced outputs (e.g., Estimated Time of Arrival). *Perceived Limitations* ($n$ = 10) included scepticism about the certainty of suggestions, with seafarers suggesting e.g., traffic light systems to indicate system confidence in a result.

*Situational mastery.* To overcome challenges and make the most of opportunities, seafarers most often specified support via *System Usability* ($n$ = 14), particularly ease of use, which increased task speed, e.g. compared to traditional, manual route planning. Furthermore, seafarers pointed out support through *Data Integration* ($n$ = 11), such as combining weather data typically displayed on different systems on the bridge onto one screen, and *Data Visualization* ($n$ = 7) of information usually not displayed spatially or digitally (e.g. tide tables). Furthermore, seafarers mentioned *Increased Decision Accuracy* ($n$ = 11) and *Increased Confidence* ($n$ = 8), e.g., through features comparing route KPIs, or simply confirming that a human-created route would also be suggested by the DSS. A key *Perceived limitation* ($n$ = 11) was insufficient data transparency (e.g. unclear how recent weather data was), which itself hindered seafarers' need for safety.

*Breathing space.* Supporting the feeling of freedom to make autonomous decisions, seafarers responses were coded for *User Empowerment* ($n$ = 18), e.g. system considering additional calculations for which users do not have the capacity to consider, and *Decision Flexibility* ($n$ = 18), the availability of an adaption feature. Furthermore, *Increased Work Efficiency* ($n$ = 13) would reportedly give seafarers the capacity to multitask other duties on the bridge. Additionally, seafarers mentioned the *Moderating Effect of Work Experience* ($n$ = 11), suggesting that seafaring experience (e.g. familiarity with a geographical region) increases task efficiency more strongly than less experience. Regarding negative effects on breathing space, some seafarers warned of *System Intrusiveness* ($n$ = 12), i.e. suggestions of routes seafarers would not travel; potentially dangerous with less experienced seafarers. At the same time, the *User Retains Responsibility* ($n$ = 12) for EERP and safety, and seafarers often mentioned that they could simply ignore the DSS if they disagreed with recommendations.

*Co-evolution.* Mutual growth of user and system was influenced by the possibility of *Collaborative Workflows* ($n$ = 16), with seafarers often referring to DSS suggestions as "brainstorming" new routes. Similarly, *Co-Learning* ($n$ = 15) was experienced by seafarers receiving route suggestions they had never considered, and suggested the DSS incorporate historical routing data to adapt to personal preferences. Work experience was again relevant, with seafarers highlighting the need to *Balance System & Human Knowledge* ($n$ = 10). For example, one route suggestion through the Strait of Messina did not consider that this route requires taking on a pilot, which is non-digitalized experience knowledge. A *Perceived Limitation* ($n$ = 11) was a lack of trust, with some seafarers declaring necessary double-checking of DSS suggestions an impediment and suggesting that manual edits to routes be remembered and incorporated into future route suggestions.

*General feedback.* After discussing autonomy-related aspects, participants provided general feedback on their DSS experience, highlighting additional needs. Weather-related features were the most frequently mentioned ($n$ = 7), followed by data representation and system transparency concerns, including raw data access, quality indicators, and symbol clarity ($n$ = 4). Requests for more route proposals ($n$ = 3), trust-related concerns citing uncertainty or mistrust ($n$ = 3), and map features such as legends, overlays, and scaling ($n$ = 3) were also noted. Other aspects mentioned once included position tracking, ship data, waypoints, safety corridor displays, increased intuitiveness, system onboarding, pilot requirement indicators at ports, and fishery data. Some feedback was in response to issues raised while exploring autonomy facets, such as raw data access (Algorithmic Competence), weather integration (Situational Mastery), and intuitiveness (Breathing Space). However, aspects like safety corridor displays, pilot requirement indicators, and fishery data point to broader usability and information needs beyond the autonomy framework, while participants issues regarding trust point to aspects more strongly associated with system trust.

### 3.3. RQ3: Correlation of autonomy need satisfaction at work and preferences for decision selection

After pooling samples from both studies ($N$ = 66), preliminary explorations compared the subscales of the PATS to a neutral scale

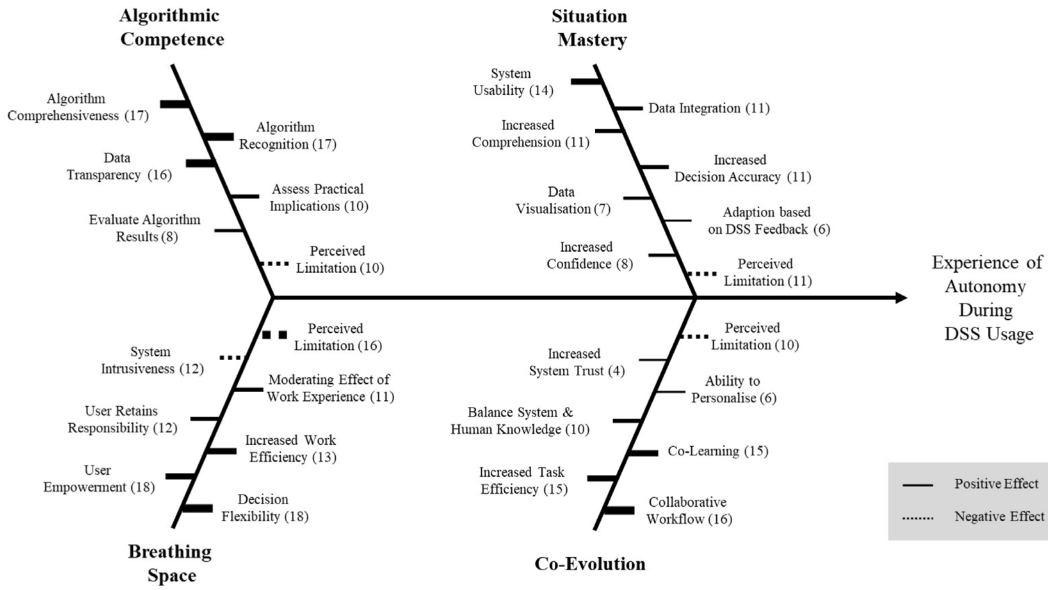


**Fig. 2.** Fishbone diagram showing themes for Dimension of Autonomy in Human-Algorithm Interaction, with the number of participants coded as addressing each theme in parentheses.

mean of 3.5 via one-sample $t$-Tests. For Information Acquisition ($M$ = 3.9, $SD$ = 0.9, $t(65)$ = 4.07, $p$ < .001, $d$ = 0.50, moderate effect) and Information Analysis ($M$ = 4.0, $SD$ = 0.9, $t(65)$ = 4.17, $p$ < .001, $d$ = 0.51, moderate effect), results deviated significantly from the neutral mean, suggesting seafarers prefer these functions be carried out by automated systems. For Decision Selection ($M$ = 2.8, $SD$ = 0.8, $t(65)$ = −7.04, $p$ < .001, $d$ = −0.87, large effect) and Action Selection ($M$ = 3.0, $SD$ = 1.0, $t(65)$ = −4.43, $p$ < .001, $d$ = −0.55, moderate effect), there was a significant difference in the opposite direction, indicating a preference for human control.

Previous research (Zoubir et al., 2025a) reported a negative correlation between autonomy need satisfaction and preference for decision selection, suggesting that seafarers who experienced greater frustration with autonomy tended to report a greater preference for automated decision-making. This finding appeared counterintuitive, as one might expect lower autonomy satisfaction to correspond with a stronger preference for retaining decision control.

To replicate this, Hc predicted a negative correlation between autonomy need satisfaction at work (BPNSWS, $M$ = 3.5, $SD$ = 0.8) and the Decision Selection subscale of the PATS. However, Pearson's product-moment correlation ($r(63)$ = −0.078, $p$ = .269) indicated only a weak negative relationship that was not statistically significant. Thus, Hc was not supported.

While the direction of the correlation aligned with previous findings, the lack of statistical significance suggests that autonomy need satisfaction may not be a strong predictor of decision selection preferences in this sample, that additional factors influence this relationship, or that the sample size had limited statistical power to detect a small effect, if one existed.

## 4. Discussion

### 4.1. Summary

The objective of the current study was twofold: with experienced seafarers (1) examine the effect of a DSS suggestion adaption feature on Human–Machine-Interaction, Human–Machine-Cooperation, and Basic Psychological Need Satisfaction metrics with AB-testing, and (2) explore facets of autonomy in DSS usage with qualitative data analysis. For the first, results showed significant improvements in most metrics except trust and autonomy need satisfaction when comparing the DSS to a digital charting tool. Comparing DSS versions, an adaption feature showed significant increases in autonomy satisfaction, trust, usability, and hedonic quality. Thus, Ha and Hb were partially supported, showing improvements in selected Human–Machine Interaction, Cooperation, and BPN metrics. For the second objective, qualitative analyses underlined the role of Algorithm Comprehensiveness, System Usability, User Empowerment, and Collaborative Workflows in supporting the experience of autonomy. In further analyses exploring preferences for automation types, seafarers indicated preferring automated Information Acquisition and Information Analysis for EERP but preferred human Decision Selection and Action Implementation. Finally, a correlation analysis could not replicate a significant relationship between autonomy satisfaction at work and automated decision selection, meaning Hc was not supported.

### 4.2. Theoretical and methodological implications

*Diversity of evaluation metrics.* Some user experience research has modeled BPN fulfillment using ratings of positive affect and hedonic quality (Hassenzahl et al., 2015, 2010), or with acceptance, intention to use, and hedonic quality (Stiegemeier et al., 2024). However, the present research demonstrated two findings: (1) Ha showed that hedonic quality increased in parallel with competency and relatedness, but not autonomy, need fulfillment, and (2) Hb showed that increases in autonomy need fulfillment coincided with increases in hedonic quality, while competency and relatedness did not change significantly. This supports the conclusion of Stiegemeier et al. (2024) that generally fulfilling needs enhances enjoyment of tool usage. However, it also underlines the necessity of using a comprehensive set of evaluation metrics during system development. Focusing only on hedonic quality in comparisons between the DSS and the control condition would have overlooked the lack of features supporting trust and autonomy needs. This emphasizes the need for metrics tailored to the usage context. For example, the collaborative nature of EERP and challenges to experienced autonomy onboard indicated a need for Human–Machine Cooperation and BPN metrics.

*Deeper understanding of seafarers.* Our results indicate differences between seafarers and other user groups. Seafarers frequently requested access to large amounts of raw data to verify system reliability, emphasizing data transparency. Typically, trust research (cf. Hoff and

Bashir, 2015, for a key review) recommends automation transparency, including explicit system reliability information, but seafarers preferred manual checks, which increases friction (i.e., making a task more difficult to complete). This contrasts with "ease of use" design guidelines, where usability can lead to higher trust and performance (Brauner et al., 2019, e.g.,). Qualitative responses indicate that seafarers' trust in DSS was contingent on their ability to cross-check system outputs rather than relying on system-provided reliability scores. Given their high safety requirements and experience in processing meteorological and oceanographic data, manual verification may serve as a trust-enhancing mechanism rather than a usability barrier, as seafarers see this as part of their professional role (Danielsen et al., 2021). In other words, seafarers preferred friction, which has been shown to be an effective nudge to calibrate trust in automated systems (Naiseh et al., 2021).

However, when seafarers rated preferences for automation types, they indicated a preference for automated information acquisition and analysis. This suggests that while manual reliability checks should remain possible, automated route calculation – especially the processing of aforementioned extensive meteorological and oceanographic data – is preferred. Given their rigorous training (International Maritime Organization, 2018), technical systems should support existing workflows (e.g., route safety checks) and complement areas where this training may be lacking, such as energy efficiency (Dewan and Godina, 2024). Furthermore, seafarers' PATS ratings here highlight the need for systems to focus on human decision selection and action implementation. This can be achieved through the generation of new routing ideas or rationales for energy-efficient routing, respecting seafarers' expertise and preference for control over decision making and execution.

### 4.3. Practical implications

#### 4.3.1. Designing for autonomy

Fulfilling basic psychological needs at work is essential for fostering greater intrinsic motivation and well-being among employees (Deci and Ryan, 2008). Our qualitative analysis suggests concrete design guidelines to enhance the fulfillment of a key need that is particularly constrained on board: autonomy.

Regarding *algorithm competence*, explainable AI (XAI) can support users' algorithm comprehension and recognition, e.g. by highlighting raw spatial data and captioning the influence on a suggestion (cf., e.g. Mohamed et al., 2022; Schrills and Franke, 2020). However, a systematic review of XAI research has underlined that explanations are often data-driven and not goal-driven, i.e. they do not explain the agency available to artificial and human agents (Anjomshoae et al., 2019). To support XAI and autonomy needs, a DSS should therefore also visualize the proportion of systems' processing to users' input (e.g. data, conditions, or customization) on a suggestion.

Another key finding was how the integration and visualization of multiple data sources improved *situation mastery* through increased task efficiency, a principal advantage of Industry 4.0 applications (Zhang et al., 2021). To further enhance decision accuracy, spatial mapping should incorporate meta-information (e.g., data source and recency), which can positively impact confidence without reducing performance (Riveiro et al., 2014). Additionally, incorporating spatial–temporal visualizations (i.e., time as a fourth dimension) enhances the comprehensibility of DSS suggestions and empowers users to generate situational explanations (Ltifi et al., 2016). However, reviews of DSS in clinical settings have identified increased visualization complexity as a significant challenge (Wang et al., 2021), highlighting the necessity of human-centered design, including performance testing, to ensure users are not overwhelmed.

Other reported advantages of increased efficiency were seafarers' ability to multitask bridge duties (facilitated by the DSS being on a tablet), contributing to *Breathing space*. At the same time, seafarers perceived a possible intrusiveness of suggestions and a moderating effect of work experience on performance. Adaptable automation, where task allocation is decided by the operator (Parasuraman and Wickens, 2008), could allow seafarers to customize the DSS level of automation to their preferences (e.g., suggest entire routes vs. suggest only improvements to manual routes), to find a balance between efficiency and system influence. While this could encourage seafarers to set automation to their level of experience, previous research with adaptable automation has shown that users often select constant high levels of automation, even under low system reliability (e.g. Sauer et al., 2011; Chavaillaz et al., 2016). However, BPN could be used to motivate the selection of lower levels of automation by appealing to seafarers' increased autonomy and competence.

Feelings of growth in the sense of *Co-Evolution* were often linked with inspiration for routing alternatives, possibly indicating that some seafarers had a usual or prototypical route in mind before route suggestions were created. DSS could increase learning effects by highlighting path similarities and differences between a prototypical route (e.g. based off historical data) and energy-efficient alternatives, and quantify KPI changes. Additionally, the maritime industry often involves collaborative work between different officers on board and between onboard and offshore personnel (Zoubir et al., 2023, 2025a). DSS systems should include features that support workflows with third users, such as reporting rationales (e.g., projected trade-offs between time and consumption) for routing decisions, possibly in the form of data visualizations like Pareto curves (Garcia-Gonzalo et al., 2013), to empower users' decision-making in multi-stakeholder teams.

#### 4.3.2. Integrating motivation

The present research contributes to the growing body of motivation research in human factors, which has traditionally emphasized cognition (Szalma, 2014). By demonstrating how specific DSS features can enhance autonomy – a key driver of intrinsic motivation – this study offers a structured approach to integrating motivation into human-centered design. Motivation is not only essential for technology adoption (Peters et al., 2018) but also helps mitigate mental fatigue (Herlambang et al., 2019), a known challenge in maritime operations. Moreover, it plays a crucial role in fostering long-term sustainability cultures (Hanson, 2013).

Prior research has shown that onboard fuel consumption trackers can reduce fuel use by up to 10%, particularly when combined with collaborative workshops that enhance knowledge and awareness (Jensen et al., 2018). However, such improvements depend on users' willingness to engage with new systems and processes, which is shaped by intrinsic motivation. The satisfaction of BPN has been found to strongly predict individuals' preference for learning new things (Rowicka and Postek, 2023), aligning with broader behavioral change models in energy efficiency that emphasize intrinsic motivation as a key factor (e.g., Barr and Gilg, 2007).

By identifying design elements that enhance autonomy, this research underscores the role of motivation in effective DSS implementation. Ensuring that systems align with users' psychological needs can drive long-term engagement and facilitate sustainable behavioral change, reinforcing the key role of human factors in technological solutions for energy efficiency.

### 4.4. Limitations and future research

One of the primary limitations of this study is the diversity of the study sample. The population for the simulator study mainly consisted of seafarers operating in northern European waters. Although the sample for the online study was recruited internationally, we did not collect data on seafarers' place of training or their shipping company. Consequently, our results cannot account for influences by shipping type (e.g., tramp or line shipping) or company culture (cf. Hammander et al., 2015). While the Standards of Training, Certification, and Watchkeeping for Seafarers (International Maritime Organization, 2018) ensure similar training content internationally, it is unclear to what extent other aspects of education (e.g., available time for simulator training) may influence seafarers' personal requirements for a DSS or EERP, or even differences in BPN experience. These differences should be evaluated in future studies.

Furthermore, the PATS described a system with a static level of automation, where functions were either entirely human-operated or fully automated. This limits our understanding of how preferences might shift under dynamic automation conditions, an approach which could positively impact autonomy satisfaction (see Section 4.3). Future research should therefore examine preferences for adaptable or adaptive automation types, i.e., where task allocation is adjusted by the operator or the system (Parasuraman and Wickens, 2008), and evolve the PATS to better quantify dynamic conditions.

This study examined subjective assessments in DSS usage, providing insights into user interactions but not capturing performance outcomes like fuel efficiency. Subjective perceptions shape technology adoption (cf. Granić, 2024, for an overview of models), trust (Hoff and Bashir, 2015), and decision-making (Bader and Kaiser, 2019). However, the absence of objective metrics limits direct evaluation of how DSS features impact operational efficiency, decision accuracy, or task effectiveness in real-world settings. Without performance-based data, it remains unclear to what extent increased motivation and perceived improvements translate into tangible benefits, such as reduced fuel consumption or faster response times. Future research should incorporate measures like fuel efficiency and task completion times to complement subjective evaluations and provide a more comprehensive assessment of DSS effectiveness.

## 5. Conclusion

Our findings emphasize the critical role of Human-Centered Design in developing sustainability applications for the maritime industry, particularly to support workers' needs during energy-efficient operations. We demonstrated that classical Human–Machine Interaction metrics were insufficient to identify requirements for trust or autonomy needs. Additionally, we showed that suggestion adaptation features significantly enhanced autonomy fulfillment. Furthermore, by probing experienced seafarers, we provided design guidelines to support autonomy in complex working environments like maritime navigation, including the integration and visualization of (meta-)data to support XAI and collaborative workflows onboard and onshore. Finally, our study offers insights into seafarers as a unique user group who preferred manual checks over automation transparency, which increases task friction but enhances trust. We highlighted avenues for future research, which should explore diverse shipping cultures and evaluations of adaptable automation. By focusing on human-centered, adaptable DSS, we can significantly improve operational efficiency and sustainability while enhancing employee well-being and intrinsic motivation. Seafarers could thus better manage energy-efficient workflows while feeling more autonomous and supported, instead of being caught up in conflicting goals. This approach fulfills current industry needs, whilst establishing a solid foundation for the collaborative and innovative advancements envisioned in Industry 5.0, ultimately fostering a more sustainable and efficient maritime industry.

## 6. Key points

- Basic psychological need metrics can enhance human-centered DSS for industry 5.0
- Seafarers' autonomy satisfaction may motivate energy-efficient route-planing
- Thematic analysis of seafarers' autonomy experiences suggested key design guidelines
- Route adaptation features enhance autonomy and trust
- HCI metrics alone are insufficient for DSS evaluation

## CRediT authorship contribution statement

**Mourad Zoubir:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **Marthe Gruner:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization. **Jan Heidinger:** Writing – review & editing, Software, Methodology. **Benjamin Schwarz:** Writing – review & editing, Software, Investigation. **Hans-Christian Jetter:** Writing – review & editing, Supervision, Project administration, Conceptualization. **Thomas Franke:** Writing – review & editing, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization.

## Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT in order to improve the readability of the manuscript and enhance the English language. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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## Appendix A. Preference for automation types scale

Imagine that an automated system could support the task of planning energy-efficient routes. This task includes steps such as gathering data on the ship and environment, calculating metrics such as fuel consumption, selecting an optimal route, and creating a voyage plan based on this route.

This automated system would work to complete steps that could have been (either partially or completely) performed by humans.

Please indicate the degree to which you would prefer the following steps to be carried out either solely by a human or solely by an automated system

## Appendix B. Thematic analysis - Theme definitions and codings

See Table B.1 and Fig. B.1.

**Table A.1**
Preferences for Automation Types Scale.

| Task | Preference | | | | | |
|---|---|---|---|---|---|---|
| | Completely Prefer Human | Mostly Prefer Human | Somewhat Prefer Human | Somewhat Prefer Automated | Mostly Prefer Automated | Completely Prefer Automated |
| Obtain data from relevant sources | | | | | | |
| Organize data based on criteria | | | | | | |
| Highlight which data might be important | | | | | | |
| Filter out irrelevant data | | | | | | |
| Predict task progression using current info | | | | | | |
| Process data to get new information | | | | | | |
| Fill gaps in the data using available info | | | | | | |
| Combine data from different sources to make deductions | | | | | | |
| Present options based on available information | | | | | | |
| Make a decision weighing costs and benefits | | | | | | |
| Use reasoning to make a decision | | | | | | |
| Make a decision based on conditions | | | | | | |
| Do the decided upon actions | | | | | | |
| Use tools or hardware to complete actions | | | | | | |
| Combine different actions to perform tasks | | | | | | |
| Ensure the chosen task gets done | | | | | | |


**Fig. B.1.** Codings. *Note:* Due to time constraints, participants 203 and 212 did not answer interview questions regarding Co-Evolution.

**Table B.1**
Algorithm Interaction Overview.

| Topic | Code | Definition | Example Quote | ID |
|---|---|---|---|---|
| Algorithmic Competence | Algorithm Comprehensiveness | Statements reflecting users' grasp of how the algorithm processes data or make decisions, and what features support this. | "[...] the algorithm knows that if the weather is not so nice, then maybe we had better not go that way." | 201 |
| | Algorithm Recognition | Statements identifying and acknowledging the presence of algorithms in the system, and the context used to identify them. | "It then loaded various parameters, processed them and issued route suggestions." | 208 |
| | Result Evaluation | Statements reflecting users' ability to critically evaluate the decisions made by algorithms, their outcomes and what features support this. | "[...] then I take the route suggestions and compare it with my own ideas.[...]" | 211 |
| | Transparency & Trust | Statements reflecting the extent to which users can see the data and operations used by algorithms, their perceived reliability and what features support this. | "So it was just no longer clear to me why this program displayed this exactly." | 215 |
| | Practical Implications | Statements reflecting the impact of algorithms on users' decision-making processes and their practical applications | "[...]if you had to calculate it manually, it would really take longer. [...]" | 209 |
| | Perceived Limitations | Statements identifying limitations of the system and suggestions for improvement. | "Sometimes it just showed me information and I did not know where it came from." | 219 |
| Situational Mastery | Increased Comprehension | Statements that emphasize the increased understanding of a situation or decision through system interaction. | "[...]it took a second to load all the weather conditions for the simulation. But once they were loaded, it was very practical for me to compare." | 218 |
| | Decision Accuracy | Statements that highlight the system's role in supporting the accuracy of decisions. | "[...]it supports comparing fuel consumption and travel duration, which are crucial in shipping. Time is money, and so is fuel consumption. Ultimately, one must prioritize which factor takes precedence." | 204 |
| | Usability | Statements that discuss the system's support in the effectiveness, efficiency, and satisfaction of decision-making in general, or specific features. | "[...]makes it easier, clearer and faster" | 202 |
| | Visualization | Statements related to the visual representation of data. | "[...]I could already see which factors were influencing it." | 201 |
| | Data Integration | Statements that highlight the integration and combination of different data types. | "And in terms of energy efficiency, it is of course much easier because everything flows together." | 211 |
| | Adaption | Statements focusing on users adapting their decision-making based on system feedback. | "[...]there were suggestions that I might not have considered, resulting in an 'aha' moment, realizing that we can do it that way too." | 212 |
| | Confidence | Statements that reflect the users' feeling of control and confidence in their decisions facilitated by the system. | "And that is a great thing if you can avoid collisions and solve a second task at the same time." | 218 |
| | Perceived Limitations | Statements identifying limitations of the system and suggestions for improvement. | "[...]in the end the decision is of course always dependent on the quality of the data that is utilized, but also on what the navigator or the decision-maker ultimately trusts in himself, the crew and the ship." | 220 |
| Breathing Space | Decision Flexibility | Statements emphasizing the freedom to choose or modify routes. | "[...]I had a complete choice between the suggested routes, I could just as easily edit each individual route." | 201 |
| | Work Efficiency | Statements discussing how the system affects work efficiency and time management. | "So the system creates a space for me in which I gain time." | 204 |
| | Users' Empowerment | Statements emphasizing how the system empowers users or respects their autonomy. | "Travelling [...]near Corsica, I would not have realized that you travel through there quickly and all that. It is easier, of course." | 205 |
| | Users' Retain Responsibility | Statements focusing on who makes the final decisions and the responsibility associated with them. | "This means that the system does not interfere with my decision-making process or my intention to decide as I see fit." | 208 |
| | System Intrusiveness | Statements expressing negative feelings about the system's intrusiveness or perceived control. | "[...] is also a danger, to offer simple solutions." | 214 |
| | Work Experience | Statements reflecting how experience and skill level affect the use of the system. | "[...]the more experienced the navigators are, the more cautious or situationally aware they are in choosing their data and making decisions based on it. | 214 |
| | Perceived Limitations | Statements identifying limitations of the system and suggestions for improvement. | "[route editing] was a bit time-consuming." | 206 |

(*continued on next page*)

**Table B.1** (*continued*).

| Topic | Code | Definition | Example Quote | ID |
|---|---|---|---|---|
| | Collaborative Workflow | Statements highlighting the collaborative aspect of working with the algorithm to achieve a common goal. | "It provided me with a basic route, giving me the opportunity to work on making improvements." | 209 |
| Co-Evolution | Increased Task Efficiency | Statements referencing the efficiency and precision of decision-making when working with the system. | "[...] the system is just better suited to implementing this than you could do manually." | 202 |
| | Personalization | Statements mentioning how the system offers customization based on user input. | "[...] but the system is currently limited and cannot, for example, account for distances to obstacles that are personally important to me." | 207 |
| | Co-learning | Statements discussing the learning process between the user and the system. | "To validate its decision, I really considered all the possibilities. Just as a final check, brainstorming or just to confirm it myself." | 214 |
| | Trust | Statements expressing trust in the algorithm's recommendations and its reliability in various conditions. | "[...] I trust that the person who programmed this knew what they were doing." | 206 |
| | Balancing System/Human Knowledge | Statements referencing the need for a trade-off between algorithmic suggestions and human experience/knowledge. | "[...]allows the watch officer to incorporate their experience into the simulation. If I know there is a low-pressure area somewhere, I can roughly estimate how the wind and waves will come from." | 220 |
| | Perceived Limitations | Statements identifying limitations of the system and suggestions for improvement. | "But the system is already so limited that it cannot yet, for example, suggest distances to obstacles that are important to me individually, it will always suggest the same thing." | 207 |

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