Towards a data-driven naval maintenance organisation: the importance of a social roadmap

Tiddens, Wieger[1,*]; Ten Zeldam, Sophie[1]; Curvers, Dennis[1]; Zegers, Jan[2]; Pollmann, Bart[1]

[1]Directorate of Materiel Sustainment, Royal Netherlands Navy, Den Helder, the Netherlands
[2]CIO Office, Royal Netherlands Navy, Den Helder, the Netherlands
[*]Corresponding Author, E-mail: WW.Tiddens@mindef.nl

Synopsis

The Royal Netherlands Navy (RNLN) aims to bring new platforms into service across its force structure, including a combat support ship (CSS), anti-submarine warfare frigates (ASWF), air defenders, submarines, and various auxiliary vessels. Constant pressure to reduce ships' crews and the increasing complexity of systems aboard naval ships create challenges for the maintenance of these future vessels. This necessitates the development of improved shore support, provided by the Directorate of Materiel Sustainment (DMI). The rise in the number of sensors on board and the emergence of learning algorithms is essential to facilitate this. It offers an opportunity to identify failures at an earlier stage, better plan maintenance, and reduce (corrective) workload aboard ships through data analysis. Consequently, the RNLN is actively transitioning from its traditional approach of planned periodic maintenance with a high corrective workload towards embracing data-driven maintenance. This shift encompasses the increase of condition-based maintenance (CBM) and the adoption of predictive maintenance (PdM) based on advanced condition monitoring and data analysis techniques.

This paper adopts a design science research approach, beginning with the identification and motivation of the problem. We then delve into an examination of the organizational challenges associated with the introduction of data-driven maintenance and explore solutions outlined in existing literature. Within this study, we employ four lenses as guiding design principles for the development of the social roadmap: maturity models, work system approaches, technology acceptance models, and change management models. We then proceed to outline the initial steps towards designing a social roadmap based on six guiding design principles from the four lenses. Furthermore, this paper presents practical examples of developments and challenges encountered in the implementation of data-driven maintenance, shedding light on the social dynamics involved in implementing data-driven maintenance within the RNLN's maintenance organization. By sharing these examples, we aim to provide insights into real-world experiences and considerations for practitioners and researchers. The paper concludes by outlining future steps envisioned for the ongoing implementation of smart maintenance within the RNLN.

Keywords: Organisational transition; Smart Maintenance; Predictive Maintenance; Condition Based Maintenance; Military-Maritime; Royal Netherlands Navy.

1. Data-driven maintenance for the current and future fleet

The Royal Netherlands Navy (RNLN) aims to bring new platforms into service across its force structure, including a combat support ship (CSS), anti-submarine warfare frigates (ASWF), air defenders, submarines, and various auxiliary vessels. With the ongoing pressure to reduce crew sizes aboard ships and the growing complexity of onboard systems, maintaining these future vessels presents significant challenges. Addressing these challenges necessitates the development of improved shore support capabilities, provided by the Directorate of Materiel Sustainment (in Dutch: 'Directie Materiële Instandhouding', abbreviated as DMI).

The integration of an increasing number of sensors onboard ships, combined with the emergence of learning algorithms, offers an opportunity to identify and diagnose failures at an earlier stage, better plan maintenance, and

Author's Biography
dr. Wieger Tiddens has extensive experience and knowledge on the implementation and development of predictive maintenance. His passion is to achieve the maintenance of tomorrow. Within the Royal Netherlands Navy's Data for Maintenance group, he works on data driven asset management and Predictive Maintenance for the current and future fleet.
Lt (ME) Sophie ten Zeldam MSc has a background as an engineer officer on board of various naval vessels. She has a master's degree in maintenance engineering and operations. Within the Royal Netherlands Navy's Data for Maintenance group, she bridges the gap between operations and development, paving the way for innovative maintenance solutions in the military-maritime domain.
Cdr (ME) ret. Bart Pollmann has fulfilled a lifetime military career in various marine engineering jobs, both at sea and in support and policy roles. From a maintenance perspective, his passion is to develop and implement solutions to improve the maintainability of future navy ships, allowing for trends of increased system complexity and reduced crew sizes.
Dennis Curvers BSc is an experienced Information Management Professional with a background in Chemistry and Quality Management. Complemented with keen analytical skills and a practical approach, he finds his way in getting reliable information to the right people at the right time. Within the Royal Netherlands Navy's Data for Maintenance group, he puts his experience into practice with a focus on Data Acquisition, -Infrastructure and -Governance for the current and future fleet.
LtCdr Jan Zegers MSc made, after an operational career, the switch to IT and data science. He is involved in the Royal Netherlands Navy's Data for Maintenance Group from the beginning, as part of developing and implementing the use of data science and AI within the navy, resulting in a Maritime Data Science Capability. In the group he works on the IT solutions and Data Governance.

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reduce (corrective) workload aboard ships through data analysis. Consequently, the RNLN is actively transitioning from traditional periodic maintenance, characterized by a high reliance on periodic checks and corrective actions, towards a more proactive approach. This shift entails a greater emphasis on condition-based maintenance (CBM) and predictive maintenance (PdM) strategies, based on advanced condition monitoring and data analysis.

Data-driven maintenance offers the opportunities to radically change the view on the RNLN's maintenance process. The application of these approaches of data-driven maintenance is however rather limited in the maritime industry (Tiddens, Braaksma, *et al.*, 2022). Many organisations have a high ambition to accurately predict failures of individual systems in their fleet, but this ambition does not match with the low quality of failure data and the very limited availability of machine (condition or sensor) data.

This also holds for the RNLN. Aiming for a data-driven maintenance organisation triggers the RNLN to collect and store more and more data from its ships. Data has traditionally been stored on-board for only days or weeks. Nowadays, the value of long term (onshore) storage is recognized, not only for maintenance but also as input for the design of new ships. The Defence Vision 2035 (Netherlands Ministry of Defence, 2020) recognizes this and indicates that efforts should be made to prevent the risk of drowning in a sea of information. The defence organisation needs to modernise. This, however, should be achieved from a base that has suffered from years of cutbacks combined with a shortage of personnel for the way the NLMOD (Netherlands Ministry of Defence) is currently organised. Change is therefore needed, both in the RNLN's maintenance organisation, the DMI, as well as in the procurement of new naval ships, which is carried out by the Command of Materiel and IT (COMMIT). The RNLN aims to orchestrate maintenance, new construction projects and maintenance knowledge within the military-maritime domain. Adequate maintenance and close cooperation with civil partners should guarantee the continuity of maritime maintenance. It is therefore essential that COMMIT as designer and the RNLN as user and maintainer work closely together.

The 'Data for Maintenance' (in Dutch: 'Data voor Onderhoud', abbreviated as DvO) initiative therefore set out in 2019 to develop a structured programme to introduce data driven maintenance within the RNLN. Setting up such a structured programme is required since it takes time to identify the technology's potential performance with targeted experiments, to integrate the technology into the existing hardware and processes, and to further improve the quality of analyses via processes of learning-by-doing (van de Kerkhof, 2020).

Figure 1: Artist rendering of a Holland-class ocean-going patrol vessel.

While a significant amount of research has concentrated on the development of data-driven models and techniques (Lee *et al.*, 2014) the successful implementation of data-driven maintenance remains elusive for many organizations (Grubic *et al.*, 2011). Achieving successful implementation of data-driven maintenance necessitates addressing both technical as well as organizational barriers.

On the one hand, there are the technical barriers. These challenges range from sensor techniques for data acquisition and the required data infrastructure to the development of validated (machine learning) algorithms to process this data. In earlier work, Tiddens, Pollmann, et al. (2022) presented the technical roadmap of the DvO-programme. This paper presented how one of the Holland-class ocean-going patrol vessels (Figure 1), the HNLMS

Groningen, has been the ‘DvO fieldlab’ from day one. The fieldlab is used to develop the DvO programme in five strategy lines: data acquisition, data infrastructure, data governance, data analysis and asset management.

On the other hand, there are organisational (and human) barriers to consider. These challenges seem understudied in current literature. Most research studies within the field of data-driven (or predictive) maintenance predominantly emphasize technical dimensions, often disregarding organizational considerations (Garg and Deshmukh, 2006; Kerkhof *et al.*, 2016; Tiddens, Braaksma, *et al.*, 2022; Veldman *et al.*, 2011). Organizational and human factors involve getting support from top management and creating an environment where change is welcomed in the organization (Bokrantz *et al.*, 2017; Lundgren *et al.*, 2023). They also include dealing with changes in culture and behaviour (Akkermans *et al.*, 2016), managing knowledge and helping employees develop their skills (Akkermans *et al.*, 2016), making sure decision-makers are open to using predictive maintenance technologies (Shafiee, 2015) and designing these technologies with people in mind to improve their well-being (Neumann *et al.*, 2021).

These social and technical implementation barriers cannot be seen in isolation since the interdependencies between the implementation issues are important (Burton *et al.*, 2020). This suggests that the implementation of data-driven maintenance innovations has a greater impact on the interaction between technology and knowledge rather than solely on the technology itself. This dynamic interplay, termed social innovation, accounts for up to 50-75% of the success of innovation initiatives (Volberda *et al.*, 2013).

In the current paper, our focus is on developing an implementation strategy to effectively introduce and promote the adoption of data-driven maintenance within the RNLN organization: a social roadmap. Developing an implementation strategy to effectively introduce data-driven maintenance within the RNLN organization requires identifying relevant criteria and steps. Research on data-driven maintenance implementations recall the importance of including the interdependencies between various implementation issues (Burton *et al.*, 2020). The social roadmap should therefore include all relevant implementation issues and their interdependencies. Most importantly, it should align with the RNLN’s technical roadmap for implementing data-driven maintenance (Tiddens, Pollmann, *et al.*, 2022). The development of a social roadmap can be guided by a design science research (DSR) approach. DSR seeks to create innovative artefacts that are useful for coping with human and organizational challenges by following an iterative process of development and testing (Hevner *et al.*, 2004).

Our paper is structured following a DSR approach. Above, the problem is identified and motivated. Section 2 examines the organizational challenges related to the introduction of data-driven maintenance and explores solutions outlined in existing literature. We then proceed in Section 3 to outline the initial steps towards designing a social roadmap. These will be accompanied by practical examples illustrating the challenges and social dynamics associated with implementing smart maintenance within the RNLN. Finally, we conclude by outlining the envisioned future steps for the ongoing implementation of data-driven maintenance within the RNLN.

2. Organisational challenges in the introduction of data-driven maintenance

The implementation of new technology within organizations can be examined through various lenses. In this study, we focus on four lenses: maturity models, work system approaches, technology acceptance models, and change management models. These lenses offer different perspectives on organizational change and technology adoption. By applying these lenses to the specific context of the RNLN, we derive design principles that guide the development of a social roadmap tailored to the specific context of the RNLN. These design principles encompass strategies for assessing organizational readiness, optimizing work systems, understanding user acceptance, and managing organizational change effectively.

2.1. Maturity models

Maturity models are structured frameworks that offer organizations a simple but effective possibility to assess and evaluate their capabilities and practices. Maturity models help to pinpoint crucial elements within a company that are vital for successful implementation and establish a set of criteria necessary to reach a specified level (Wendler, 2012). While these models are valuable for fully integrating new technology throughout an organization by identifying improvement opportunities, they often lack adequate validation (Wendler, 2012). Within the RNLN’s technical roadmap, the DvO-programme encompasses four maturity levels: concept development on HNLMS Groningen, concept evaluation on HNLMS Den Helder, concept realisation on the ASW-frigates, and concept optimalisation on the future submarines. Kerkhof et al. (2016) developed a descriptive maturity model consisting of five steps for the implementation of CBM, which can be extended to data-driven maintenance, by asset owners like the RNLN. Their model underscores eight categories of organisational aspects crucial for data-driven maintenance implementation: strategy and goals; decisions, structure; budget and capacity; processes and documentation; governance; knowledge and skills; and culture.

Mooij (2023) conducted a preliminary maturity scan within the RNLN's maintenance organisation using the descriptive maturity model of Kerkhof et al. (2016). The RNLN has a long history of structured use of condition monitoring technologies, including vibration monitoring and oil analysis conducted by a specialized department. This established practice has played a pivotal role in laying the groundwork for the introduction of data-driven maintenance within the organization. Mooij's scan showed that CBM is perceived as a proven technology but is not yet structurally embedded in all maintenance decisions. Further, Mooij posited that the RNLNL's maturity can be described on the continuum between 'reactive CBM' (level 2 out of 5) and 'planned CBM' (level 3 out of 5) since a significant part of the maintenance is still focused on corrective maintenance. To integrate data-driven maintenance, Mooij (2023) identified a clear need for a structured work process embedded within the organisational structure. This process should clarify the new maintenance decision-making process, integrating traditional indicators like calendar time and running hours with (near) real time condition indicators from data-driven models.

2.2. Work-system approaches

As the organization advances along the maturity ladder, the adoption of data-driven maintenance brings about transformation within the maintenance organisation. These evolving organizational characteristics should be incorporated into the implementation strategy (van Oudenhoven *et al.*, 2023). To identify factors influencing the acceptance of data-driven maintenance, Van Oudenhoven et al. (2023) utilize an adapted work system approach (Carayon, 2009). Their approach considers five domains: technology, focusing on data-driven decision support; individual, encompassing one's physical and psychological characteristics; tasks, relating to the job at hand; organization, encompassing the organizational conditions under which tasks are performed; and environment, pertaining to the physical surroundings. The interplay among these domains influences an individual's behaviour and performance, which can be influenced by the introduction of new tools and technologies, such as data-driven maintenance. Van Oudenhoven et al. propose four key support factors: establishing an appropriate level of human control for decision-making, fostering trust between decision-makers and the model, providing adequate cognitive resources to handle the system's high cognitive demands, and assigning decision-making responsibilities and capabilities to the appropriate organizational unit.

Berket (2023) applied van Oudenhoven et al.'s work system approach to study how the five domains influence the acceptance of the decision support tool that is developed within the DvO-programme. Berket found that the domains 'individual', 'organisation', and 'tasks' have a negative effect on the usage of the application and outweigh the positive loads in the work system. Berket suggests that the most effective way to facilitate usage within engineering sections in the DMI organisation is to introduce a data analyst role within each engineering section and provide training to improve technological competence within the organisation. These interventions reduce demands in three domains: 'task', due to a high workload, data-driven maintenance and learning to work with a new application is currently seen as an extra activity; 'individual', engineers do not often have a high affinity with data and are not digital literate; and finally 'technology', data-driven maintenance is still immature and a new decision support tool is therefore experienced as incomplete and difficult to use.

Vermeulen (2023) also applied van Oudenhoven et al.'s work system approach to change agents that are used within the DvO-programme. Alike Mooij (2023) and Berket (2023), Vermeulen recognizes the pitfalls of a bureaucratic organisation that suffered from long-term budget cuts, which has a high average workforce age and a high perceived workload. Vermeulen (2023) gestured towards the idea that little knowledge about how to use data seems available within the organization and data ambassadors are still divided when looking at their attitude towards data usage. Some really see the potential where others are not yet convinced that right now is the time to start working data driven. Vermeulen (2023) concludes that the concept of data ambassadors can be better supported by improving the selection process of potential ambassadors. This can be realised by including middle management in the selection process, selecting persons that fit the role and only apply the concept to departments with a high data availability. Finally, these ambassadors should be better supported by middle management and the DvO-programme should better support them in specific post-intervention meetings or training activities.

2.3. Technology acceptance models

Technology acceptance models are among the most extensively utilized frameworks for understanding IT adoption and have demonstrated high predictability in IT adoption and usage (Venkatesh and Bala, 2008). The

Unified Theory of Acceptance and Use of Technology (UTAUT) posits that performance expectancy, social influence, and effort expectancy influence an individual's behavioural intention to use a technology (Venkatesh *et al.*, 2003). Subsequently, behavioural intention and facilitating conditions determine technology usage, while individual difference variables such as age, gender, experience, and voluntariness moderate the relationships within the UTAUT model.

Brus (2022) used the UTAUT model to identify social barriers for implementing data-driven maintenance within the RNLN. Based on 12 interviews, he found that employees seem generally sceptic about new innovations and seem to question whether the RNLN’s organisation is suitable for implementing data-driven maintenance. Further, since the programme is relatively new within the organisation, many employees are unacquainted with the programme and have a large variety of expectations of data-driven maintenance. Finally, employees view data-driven maintenance as a new addition to their current work activities, instead of a tool that is integrated in their current work processes.

2.4. Change management models

Kotter’s (1995) eight-step process for achieving successful organizational change provides a structured approach to overcoming organizational difficulties. This process emphasizes creating a sense of urgency and vision for change within the organization. Effective implementation relies on strong leadership and motivation to overcome resistance, with top management playing a pivotal role. Following Kotter's approach, to enhance acceptance of data-driven maintenance and reduce scepticism, organizations should focus on achieving incremental successes through small projects and communicate these short-term wins throughout the company. Kotter's eight sequential steps include creating a sense of urgency, building a guiding coalition, forming a strategic vision, enlisting a volunteer army, enabling action by removing barriers, generating short-term wins, sustaining acceleration, and instituting change.

Additionally, Maali et al. (2022) modeled the relationships between key change management strategies and the level of successful change adoption. Their study underscores the importance of implementing five change management strategies concurrently: change agent effectiveness, establishing a realistic timeframe, communicating benefits, setting measured benchmarks, and senior leadership commitment. Among these strategies, change agent effectiveness and a establishing a realistic timeframe are identified as the two most effective organisational change management strategies (Maali *et al.*, 2022).

3. The development of a Social Roadmap for the adoption of data-driven maintenance within the RNLN

Six guiding design principles have been derived from the four perspectives on organizational change and technology adoption discussed in Section 2. Table 1 illustrates how elements from these four perspectives are integrated into the six guiding design principles. This section outlines the initial steps towards developing a social roadmap based on these principles.

3.1. Principle 1: Combining vision and urgency for change with opportunities to create an overall strategy

The DvO-programme originated from a convergence of opportunities that coincided in a specific starting moment in time: April 2019. This convergence included technical opportunities in data storage and analysis within the RNLN, a visionary outlook from top management regarding the utilization of these technical capabilities in an organisational programme, a halt on budget cuts allowing for innovation within the RNLN and allocating budget, and, most importantly, the formation of a multidisciplinary leading team, bypassing the usual organizational formalities (such as a formal place in the organization and job positions).

The first step of the DvO-programme has taken an integrated approach by creating a vision for implementing data-driven maintenance within the organisation. This aligns with Kotter’s (1995) principles by creating a sense of urgency and shaping a strategic vision for organisational change. This resulted in a broadly accepted technical roadmap of the DvO-programme (Figure 2) serves as an instrument to promote the adoption of data-driven maintenance tools. The implementation timeframe, spanning from 2019 to 2035 as depicted in the roadmap, is crucial for setting realistic expectations and ensuring progress aligns with organizational goals. This timeframe, outlined by Maali et al. (2022), corresponds to the maturity steps illustrated in the roadmap.

The roadmap is utilized in presentations aimed at maintaining commitment from senior leadership, in line with Maali et al.'s change management strategy, and move from top management support to top management engagement. Additionally, it facilitates the dissemination of information within the organization, fostering a sense of urgency and a shared vision for change, consistent with Kotter's principles.

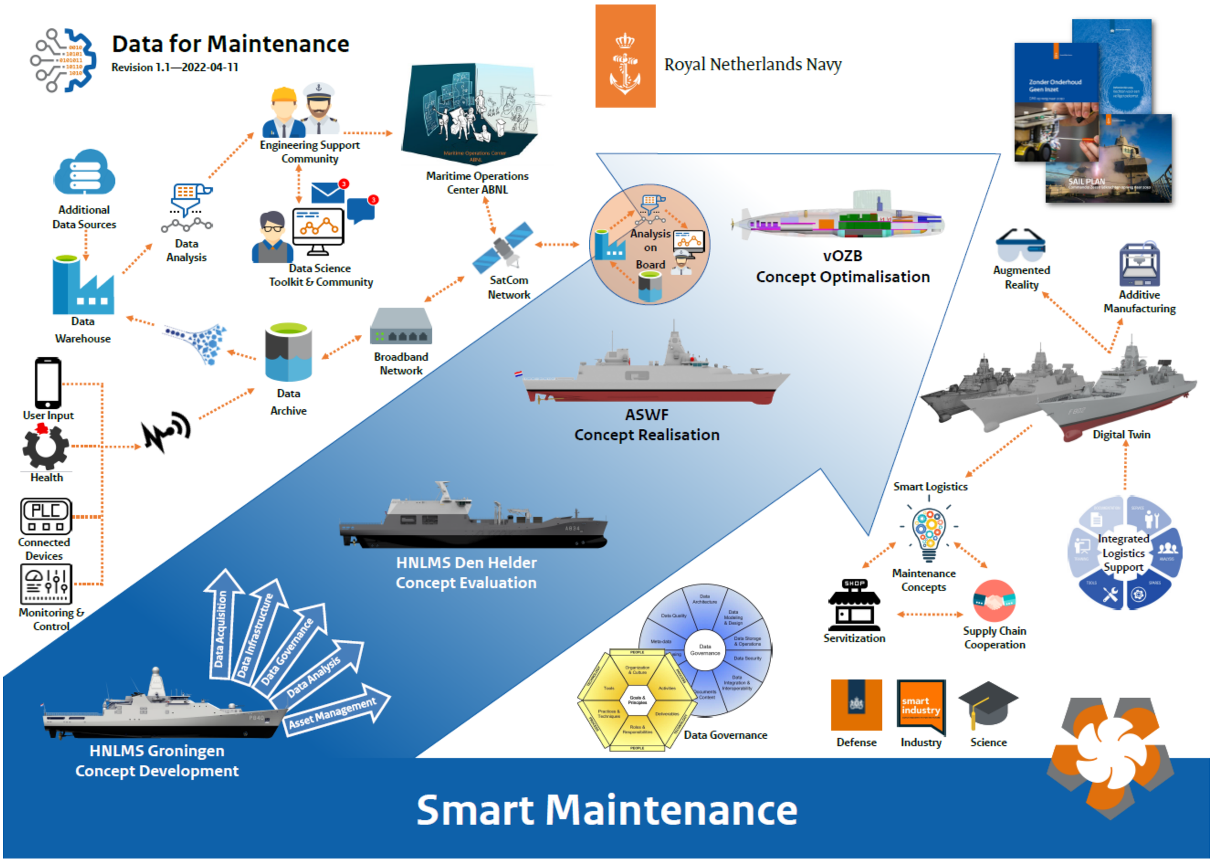

Figure 2. The RNLN's Smart Maintenance technical roadmap of the DvO-programme, see Tiddens, Pollmann, et al. (2022) for a detailed description.

3.2. Principle 2: Tailoring implementation strategies to target user groups and supporting stakeholders

The objective is to direct the implementation initiative towards potential users of data-driven solutions while ensuring continued stakeholder involvement. The UTAUT theory underscores that technology usage is determined by behavioural intention and facilitating conditions, with individual differences moderating these relationships. Potential users include maintenance engineers overseeing the how, when, and why of maintenance activities within the DMI and technical specialists within COMMIT (offering advice on modifications and the application of knowledge for future fleet design), and technical personnel aboard ships (at the organic maintenance level),

Supporting stakeholders, on the other hand, are individuals who do not directly benefit from data-driven tools but are needed to contribute to and facilitate the program. These stakeholders are primarily found within industry partners involved in developing new solutions, standardisation, data exchange, and service-based contracts, COMMIT (providing specifications for new build ships and facilitating design for data-driven maintenance), management overseeing maintenance processes, and IT partners within the organisation.

Different implementation strategies are employed for these user groups and supporting stakeholders. The initial phase of the program has primarily targeted maintenance engineers ashore within the DMI, who are the early adopters of data-driven tools. Subsequently, a specific software tool has been developed to provide insights into the collected data, featuring timeseries plots, descriptive analytics offering insights into system usage aboard ships, and offers the possibility to integrate predictive analytics.

Users: Maintenance engineers within DMI and technical specialists within COMMIT

The initial phase of the program has predominantly concentrated on onshore maintenance engineers within the DMI, primarily with a use-case driven approach (Principle 3), followed by the development of an internally developed decision-support tool. This tool aids maintenance engineers in fault-finding processes utilizing available

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data, providing descriptive and diagnostic analyses and technical specialist in providing insights in usage of equipment primarily. The primary objective has been to engage early adopters and incorporate their feedback into the DvO-programme. A key takeaway has been the importance of exercising caution in making commitments to ensure sustained engagement of these engineers in the programme: moderation.

Users: Technical personnel aboard naval vessels

For technical personnel onboard ships, a collaborative effort with industry partners is underway to develop an adaptable, comprehensive, and automated analysis solution. This solution is primarily designed to facilitate short-term operational responses and offer detailed system insights using a real-time data archive, in a disconnected environment. Crucially, these data-driven tools are integrated into existing software systems to ensure a seamless user experience. An additional requirement is to ensure that these tools offer similar functionalities to their onshore counterparts to make sure that maintenance engineers that assist in maintenance or fault finding aboard can work with these systems.

Supporting stakeholders: Industry

The transformation towards data-driven maintenance positions within original equipment manufacturers (OEMs) and service providers (SPs) increasingly need to offer services and performance-based contracts, instead of fixed maintenance contracts and selling spare parts, a concept known as servitization. The increasing trend towards servitization underscores the growing importance of facilitating the sharing of relevant data subsets among stakeholders.

Middelbrink (2023) delved into the role of legal and administrative mechanisms in facilitating data exchange between the RNLN, OEMs, and SPs. Middelbrink revealed that barriers to data exchange often stem from misconceptions, particularly regarding the legal framework. Moreover, there exist several unfounded fears surrounding data sharing, intensified by varying perceptions and interests both between and within organizations, leading to a tendency to share less data than possible and/or needed for optimal product support. Middelbrink (2023) emphasizes the necessity of a clear legal framework and open dialogue among parties to establish concrete agreements on data exchange. Such measures not only mitigate uncertainties but also foster trust, a critical component for successful data exchange and collaboration.

Supporting stakeholders: COMMIT (design authority)

The role of COMMIT is critical in defining data-driven requirements for new-build ships and significant modifications, particularly in the context of design for data-driven maintenance. Engineers and project teams must have a realistic understanding of the potential of data-driven technologies. Data-driven tools can facilitate the development of innovative crew and maintenance concepts, while fostering new modes of collaboration with OEMs and SPs, such as through servitization concepts.

Supporting stakeholders: Management overseeing maintenance processes

Management within the DMI plays a crucial role in facilitating the DvO-programme by providing the necessary space for innovation to flourish. This entails ensuring that their organizational structure and work processes are transitioning towards data-driven decision-making practices (Principle 6). One potential approach is to incorporate a dedicated data analyst role within each section, while also making data-driven operations a central theme. Additionally, management serves as a link between the DMI and supporting stakeholders within COMMIT. This ensures alignment and collaboration across different organizational levels, further fostering the success of the innovation initiative.

Supporting stakeholders: IT- partners within the organisation

IT partners within the organization, both in COMMIT and the RNLN play a crucial role in supporting the programme by providing robust solutions for data exchange (e.g., ship-to-shore), data storage and processing, a data analysis platform, and an IT platform capable of running data-driven tools. These technological infrastructures are essential to enable seamless data-driven operations and decision-making.

3.3. Principle 3: Starting small and showing the benefits using small use-cases

Since the start of the programme, use-cases have served as the primary means of addressing organization-submitted challenges. Resolving these use-cases has significantly contributed to the DvO-programme's success in achieving short-term wins, which is in line with Kotter (1995). Resolving use-cases creates a form of merchandise that can be used within the programme or by top management to demonstrate the value of data-driven maintenance. Initially, typical use-cases focused on resolving relatively straightforward fault-finding issues, such as understanding the behaviour of an installation leading up to a failure. However, over time, the focus has shifted towards providing deeper insights into naval ship operations, operational profiles, and insights like optimal settings to minimize fuel consumption (e.g., trim settings).

Collaborating with universities and offering graduate positions has been instrumental in addressing more complex use-cases. Graduates are well-suited to tackle complex problems, as they often have sufficient time available and are required to demonstrate their ability to solve complex issues to obtain their diploma. The DvO-programme provides them with a unique opportunity to work in an innovative department within the RNLN. To date, more than 25 students have contributed to creating data models, solving questions from the organization, and shaping the innovation programme.

3.4. Principle 4: Creating involvement of change agents

To ensure the RNLN has enough maintenance engineers well-versed in using the capabilities of data-driven models, a dedicated course has been established. This course aims to educate engineers from DMI and COMMIT about the DvO-programme and various aspects of data-driven maintenance while enhancing their digital literacy. By equipping engineers with knowledge, attitudes, insights, and basic skills, they can effectively utilize digital solutions. The provision of digital literacy through such courses is an iterative learning process, improving with each iteration. As highlighted by Berket (2023), individuals within the organization appear to have limited familiarity with data and seem to have low digital literacy. Given the embryonic stage of data-driven maintenance, new support tools are often perceived as challenging to use.

In the realm of change management, the significance of change agents is well-recognized. Kotter (1995) suggests the establishment of a volunteer army, while Maali et al. (2022) emphasize the effectiveness of change agent roles as a crucial strategy. They argue that successful change agents should assume responsibility for leading, supporting, communicating goals, and engaging in all stages of the implementation process. We refer to our change agents as data ambassadors, with the aim of having at least one ambassador in every engineering section within the DMI. These ambassadors are tasked with communicating the programme's objectives and assisting colleagues in utilizing data-driven tools. To become an ambassador, individuals are required to complete the DvO-course. However, the voluntary nature of participation in the course was sometimes unclear, which adversely affected its success. Nevertheless, data ambassadors have proven effective in promoting the programme's objectives and supporting the movement especially in sections where data is already available.

Initially, the course heavily focused on data-driven model development, based on perceived interest from participants. However, it became apparent that this approach was overly complex for the audience, necessitating a shift towards emphasizing the practical application of these models. Consequently, the course has evolved to centre around participants' specific use cases, providing them with directly applicable learning experiences within their own work environments.

As highlighted by Vermeulen (2023), future efforts should prioritize the improved selection of potential candidates and enhanced support for these ambassadors throughout their journey.

3.5. Principle 5: Bridging the gap between start-up and scale-up

The first four principles establish the groundwork for transitioning from a start-up phase to a scale-up phase, marking a crucial step in the evolution of the DvO-programme. During the start-up phase, emphasis was mainly placed on experimentation and demonstrating value through use-cases. However, as the program progresses, it must evolve into a more mature organization, where data governance and internal processes are in order. This shift is essential for bridging the gap between change agent involvement (Principle 4) and organizational implementation (Principle 6), fostering trust within the organization by delivering reliable and reproducible results.

Data-driven maintenance within the RNLN is built upon an established foundation of condition monitoring. Nevertheless, Mooij's maturity scan indicates that current practices lean towards reactive or planned CBM. To fully leverage the potential of condition monitoring and data-driven models, a significant organizational shift is required. Using the innovation funnel is thereby important. The DvO-programme is gradually steering the organization in this direction by seizing opportunities as they arise and prioritizing the exploration and development of promising initiatives. This funnel approach is crucial in a resource-constrained programme. The programme proves to be essential in taking proactive steps to initiate the transition, even if the organization and its IT infrastructure are not yet fully prepared for the transition.

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One key guiding principle learned within the DvO-programme is moderation. It is essential to encourage creativity and engagement while addressing concerns to prevent disengagement. Moderation is important to temper unrealistic expectations. Moderation is also important as not every department may have access to sufficient data or data-driven models. Adopting a gradual approach, starting from descriptive to diagnostic methods, aids in overcoming challenges and building upon the existing foundation of condition-based maintenance.

3.6. Principle 6: Instituting change by developing a work process for data-driven maintenance

The final principle of Kotter (1995) is instituting the change in the organization. Mooij (2023) argued that embedding condition indicators derived from data-driven models in the way of working of the RNLN is essential. A structured work process should be embedded within the organisational structure. This is also in line with Van Oudenhoven et al. (2023) who argues from a work-system approach that focus should be laid on creating trust between decision-makers and the data-driven models. Moreover, Van Oudenhoven et al. stress the importance of assigning decision-making responsibilities and capabilities to the appropriate organizational unit. Further, similar as discussed for Principle 5, documentation must be established regarding decision-making processes and finding the right balance between relying on a monitoring system and the judgment of engineers.

Presently, analyses derived from condition monitoring, serve as supplementary input for scheduling maintenance activities or providing instructions to limit or optimize usage, typically in consultation with installation managers within DMI. In the future, maintenance decisions such as repairs or replacements should not merely be supported by these new models but be entirely dependent on them. This requires abandoning traditional plans based on factors like calendar time or running hours in cases where effective data-driven models are available, necessitating a mindset shift. Consequently, the implementation of data-driven maintenance demands effective change management, as it entails replacing existing methods with novel, yet incompletely understood, technologies. This change may impact employee engagement, responsibilities, and necessitate a mindset shift that may not be readily accepted by all individuals within the organization.

In our vision, this transition necessitates painting a realistic picture by explaining how it works and clearly stating what is already achievable and what remains to be accomplished. It involves creating practical solutions that deliver results. Work-system approaches provide valuable insights into positively influencing people's behaviour towards data-driven maintenance. These approaches teach us that it is crucial to strike the right balance between relying on a monitoring system and the judgment of engineers. The presence of maintenance engineers who understand the capabilities of data-driven models is essential for assessing current risks associated with assets, while data professionals are needed to develop digital solutions capable of performing monitoring tasks. Integrating these individuals and systems into the organizational structure is particularly important in an organization like the RNLN, where current maintenance strategies are deeply entrenched in tradition.

In the current first steps towards a full integration of data-driven maintenance, maintenance engineers primarily depend on relatively straightforward, descriptive, and diagnostic data-driven analyses. However, with the introduction of more advanced data-driven models in the near future, factors such as human control for decision-making, trust between decision-makers and the model, and adequate cognitive resources to handle the system's demands need to be carefully addressed within the program.

To integrate data-driven decision making in the organisational structure, Mooij (2023) conducted design sessions within the DMI. By involving decision-makers from various organisational layers, she worked in an iterative design science process towards a widely supported work process for data-driven maintenance within the RNLN (Figure 3). This process shows how a measure-analyze loop is conducted before a notification is made that will consequently be allocated to either the ship's crew or a maintenance engineer ashore. Note that this measure-analyze-notify-allocation sequence can either be conducted in-person, for example in the case of a manual inspection or measurement, or automatically by an accepted and verified data-driven model. Mooij (2023) argued that next to a straightforward maintenance execution process based on data-driven models, a work-process should entail knowledge-building improvement loops to improve data-driven models (the algorithm improvement process of Figure 3).

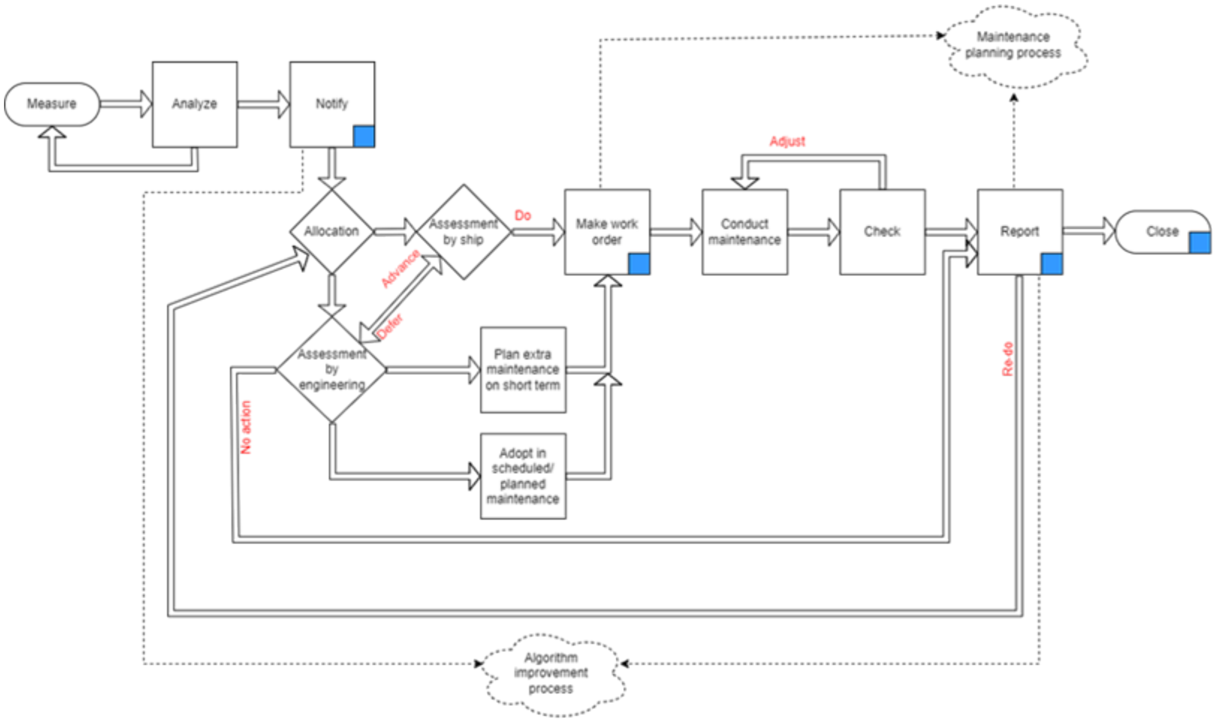

Figure 3. Proposed work process for data-driven maintenance within the RNLN (Mooij, 2023). The blue squares indicate activities in the company ERP system.

4. Conclusions and further directions

The current paper presented the foundation for the development of a social roadmap that complements the implementation programme of DvO with the earlier presented technical roadmap. Through a structured approach, derived from four perspectives on organizational change and technology adoption, six guiding design principles have been determined for the transition towards data-driven maintenance specific to the context of the RNLN. This paper showed that key principles such as moderation, trust-building, and targeted implementation have proven successful in overcoming challenges and driving momentum.

The successful adoption of data-driven maintenance requires careful consideration of human factors, organizational culture, and change management strategies. The engagement of maintenance engineers, management, technical specialists aboard naval vessels, engineers within COMMIT, and industry partners is essential for ensuring the effective implementation.

Moreover, the development of data-driven tools to support maintenance decision making and the use of use-cases as a vehicle for problem-solving and generating short-term wins has proven to be effective in demonstrating the value of data-driven approaches. Collaboration with universities and the involvement of graduate students have enriched the program by addressing more complex use-cases and bringing fresh perspectives to the table.

Looking ahead, continued focus on education and training, developing data-driven tools, stakeholder engagement, and iterative improvement will be crucial for advancing the DvO-programme and realizing its full potential. Further research should be conducted, using work-system approaches, to study optimal implementation strategies of data-driven tools for technical people aboard ships and integration of the six proposed design principles in a complete social roadmap.

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Design Principle	Maturity models		Work-system approaches			Technology acceptance models	Change management models	
	van de Kerkhof (2020)	Mooij (2023)	van Oudenhoven et al. (2023)	Berket (2023)	Vermeulen (2023)	UTAUT analysis Brus (2022)	Kotter (1995)	Maali et al. (2022)
1: Roadmap for vision and urgency	strategy and goals;					managing expectations, employees are unacquainted with the programme	creating a sense of urgency, building a guiding coalition, forming a strategic vision, sustaining acceleration	establishing a realistic timeframe, setting measured benchmarks, and senior leadership commitment
2: Differentiate in users and stakeholders						performance expectancy, social influence, and effort expectancy		
3: Show benefits with use case							generating short-term wins	communicating benefits
4: Data ambassadors	knowledge and skills; culture.			provide training to improve technological competence	improve selection process of ambassadors, better support ambassadors		enlisting a volunteer army	change agent effectiveness
5: Trust and digital literacy			human control for decision-making, trust between decision-makers and the model, cognitive resources to handle the system's cognitive demands.	low affinity with data, low digital literacy, concept is still immature, and support tool is experienced as difficult to use.		behavioural intention and facilitating conditions determine technology usage (UTAUT)		
6: Instituting change	decisions, structure, processes and documentation, governance.	structured work process embedded within the organisational structure	assigning decision-making responsibilities and capabilities to the appropriate organizational unit.	introduce a data analyst role within each engineering section,	only apply the concept to departments with a high data availability	integrated in their current work processes, organisation is suitable for implementing data-driven maintenance	instituting change, enabling action by removing barriers	

Table 1. Analysis showing the origin of the six guiding design principles for the social roadmap based on the four perspectives of Section 2

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