Navigating the Unknown: Knowledge Management in Machine Learning-Driven Product Development

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Abstract: The Digital Fish Simulation Project is a machine learning-driven innovation initiative aimed at optimizing fish production processes by developing simulation-based tools for digital modeling of fish behavior. Set within the context of the seafood industry's increasing demand for sustainability, precision, and efficiency, the project operates in a domain characterized by limited prior expertise and significant biological variability. As such, knowledge creation must be dynamic, interdisciplinary, and continuously evolving. This article explores the project from a knowledge management perspective, applying Nonaka and Takeuchi's SECI model of organizational knowledge creation and the Manulab–Industry Competence Building Process as theoretical frameworks. The study focuses on how structured knowledge management practices, embedded from the earliest stages, enable successful navigation of uncertainty and foster innovation in machine learning-based product development. Workshops were employed as the primary research method, functioning not only as operational project checkpoints but also as structured environments for facilitating interdisciplinary collaboration, surfacing tacit knowledge, externalizing insights, and iteratively refining concepts and prototypes. Through this action research methodology, the study captures the dynamic interplay between knowledge creation activities and project advancement. Preliminary findings indicate that, unlike traditional automation projects where knowledge transfer follows linear trajectories, machine learning-driven innovation demands multiple, parallel SECI cycles running simultaneously across different knowledge domains. Sustained involvement of industry partners from the earliest stages, coupled with interdisciplinary teamwork among engineers, biologists, simulation specialists, and students, has proven critical for effective knowledge creation. Trial-and-error learning, real-time adaptation, and continuous feedback loops emerged as key mechanisms for accelerating organizational learning. The article concludes with recommendations for future research, emphasizing the need to explore structured models for parallel SECI cycle management, interdisciplinary knowledge transfer optimization, and the institutionalization of trial-and-error learning processes. The findings contribute to a deeper understanding of how knowledge management practices must evolve to support sustainable, human-centric innovation in emerging machine learning-driven industrial environments.

Keywords: Simulation-based product development, Knowledge management, Seafood industry innovation, Machine learning, Industry 4.0, Industry-academia collaboration

1. Introduction

This article presents an analysis of the preliminary results and current status of a research project that leverages simulation as a tool for knowledge creation in machine learning-driven product development within the seafood industry. The project's core objective is to develop a simulation environment that supports innovation and customization of fish production lines. This includes the integration of fish processing machinery and transport systems, digital soft-body models of fish, AI-based generation of synthetic datasets for different fish species and varieties, as well as advanced machine learning and related algorithms. The simulation environment is intended to support the design, testing, and innovation of fish production lines. Its anticipated benefits include accelerated innovation, reduced time to commissioning, and faster achievement of full industrial performance. While the technical aim of the project focuses on the development of digital fish models and the optimization of production lines through simulation, this article specifically explores how structured knowledge management (KM) processes can support innovation in environments characterized by high uncertainty and limited prior expertise.

The project operates in a context where traditional, tacit knowledge about automation in fish processing is largely lacking. Therefore, knowledge creation must be dynamic and collaborative, involving interdisciplinary efforts across academia, industry partners, and students. Drawing on Nonaka and Takeuchi's model of organizational knowledge creation, and further developed through the Manulab–Industry Competence Building Process, this research investigates how knowledge can be generated, validated, and integrated into machine learning-based product development (Nonaka and Takeuchi 1995; Hansen *et al.* 2023). A wide range of knowledge domains and competencies are involved in the project, including: 1) biologists' understanding of fish anatomy and responses to various conditions; 2) physicists' ability to convert biological insights into measurable physical data, including the design of measurement systems; 3) data experts' capabilities in developing scanning technologies and data handling methods; 4) simulation experts' knowledge of platforms and simulation environment design; 5) industrial practitioners' practical insights into real-world fish production lines. Expertise in areas such as automated measurement technologies, advanced data tools for scanning, machine learning, simulation, and appropriate lab procedures is crucial for project success. *Based on these knowledge challenges, this article examines how well the Manulab–Industry Competence Building model supports machine learning-driven product development. The research outlines and reflects on key learnings from this case study.*

This article is structured as follows: the Background section presents the challenges of knowledge creation in fish processing innovation. The Method section explains the research approach based on structured workshops used as a research method. The Theoretical Framework outlines key concepts from knowledge management theory and introduces the Manulab–Industry Competence Building Process. The Case Description provides insights from the ongoing Digital Fish Simulation Project, focusing on early-stage knowledge creation and interdisciplinary collaboration. The Discussion section analyses the preliminary findings in relation to knowledge management strategies for machine learning-driven projects. The Conclusion summarizes the main contributions and proposes directions for future research. The article ends with an Ethics Declaration and an AI Declaration, following the ECKM submission requirements.

2. Background

The development of fish production lines has historically been based on practical experience and tacit knowledge accumulated through hands-on trial and error. Equipment has often been designed, tested, and verified using available dead fish in workshop settings, providing limited insights into how systems would perform under real operational conditions. Once installed aboard vessels, these production lines typically undergo years of incremental adjustments before achieving acceptable efficiency levels of 85–90%. This long commissioning phase results in substantial costs, operational disruptions, and increased financial risks for both vessel owners and equipment suppliers.

Traditional development models, while valuable in low-uncertainty environments, struggle when applied to contexts marked by biological variability, changing regulations, and rapid innovation cycles. The seafood industry increasingly faces demands for higher production efficiency, greater sustainability, and faster time-to-market — challenges that require new approaches to knowledge creation and application.

In response to these needs, the current research project adopts a simulation-driven methodology designed not just to optimize technical performance but to build organizational knowledge systematically. By embedding knowledge management principles into every phase of development, the project moves beyond isolated technical improvements toward holistic innovation processes. The aim is to create a simulation-based platform that reduces reliance on physical prototyping, accelerates learning cycles, and integrates biological complexity into production design. These goals align with a broader transformation seen across manufacturing industries in the wake of Industry 4.0. The advent of intelligent, connected technologies has reshaped knowledge management, shifting it from static, repository-based systems toward dynamic, adaptive infrastructures. Historically, KM focused on the manual documentation of explicit knowledge, with limited responsiveness to rapidly evolving environments (Zhang *et al.* 2025). Today, with the integration of artificial intelligence, cyber-physical systems, and advanced data analytics, modern KM platforms support real-time decision-making and continuous learning by incorporating both tacit and explicit knowledge (Del Vecchio *et al.* 2018).

Central to this evolution is the role of data as a strategic asset. Data-driven KM systems now leverage machine learning, big data analytics, and natural language processing to extract insights from heterogeneous sources such as sensor data, operational logs, and expert input. This enables organizations to detect anomalies, predict trends, and enhance responsiveness across complex systems (Zhang *et al.* 2025). In this way, KM becomes a critical enabler of innovation, resilience, and continuous improvement—capabilities that are especially relevant in smart manufacturing and biologically complex sectors like seafood processing (Machado, Winroth and Ribeiro da Silva 2020; Romero *et al.* 2016).

At this early stage, significant progress has been made in assembling preliminary digital fish models and testing various simulation environments. Researchers and industry partners at the Norwegian University of Science and Technology (NTNU), Campus Ålesund, have collaborated to produce soft, flexible digital fish models within discrete-event simulation frameworks (Banks *et al.* 2010) and game engine environments. Initial results demonstrate the feasibility of replicating realistic fish behaviour in a digital setting. However, empirical limitations—particularly concerning fish stiffness, friction coefficients, and dynamic interaction properties—highlight the pressing need for robust biological data collection (Kleppe *et al.* 2024; Giske *et al.* 2023).

These findings reveal a key insight: effective development in machine learning-driven product innovation depends on structured, interdisciplinary knowledge creation. Engineers, marine biologists, simulation developers, and industrial practitioners must work together continuously, sharing and iterating knowledge in real time rather than relying on handovers between isolated domains.

Beyond technical outcomes, the project's approach also supports broader sustainability goals by minimizing reliance on dead fish for prototyping, reducing waste, and enabling more sustainable, resource-efficient production workflows (Giske *et al.* 2023). By integrating Nonaka and Takeuchi's knowledge creation model into its methodology and adapting it to the realities of machine learning-based innovation, the project lays the groundwork for a new way of developing industrial systems—one that emphasizes agility, collaboration, and continuous learning.

3. Method

This study adopts an applied research approach, using structured workshops as the primary research method to investigate how knowledge management practices—specifically, the SECI model and the Manulab–Industry Competence Building Process—can be operationalized to manage a machine learning-driven innovation project (Ørngreen and Levinsen 2017). The research is conducted by a core team of four researchers: three are affiliated with the Norwegian University of Science and Technology (NTNU), and one works as a Research and Development (R&D) manager in industry while holding a part-time position at NTNU. Together, the team is engaged in both the management of the Digital Fish Simulation Project and the study of how knowledge is created, shared, and institutionalized throughout its phases.

Workshops have been organized at critical project milestones, serving as structured reflection points where knowledge creation activities are observed, documented, and analyzed. These workshops are not only part of the project's operational activities but are explicitly used as data collection events for the research.

The workshops are designed to: enable direct socialization between researchers, students, and industry professionals, surfacing tacit knowledge; facilitate externalization of insights through joint discussion, documentation, and shared problem-solving; track how concepts are created, justified, and embodied in prototypes; analyze how interdisciplinary collaboration shapes knowledge emergence and management; support empirical investigation of how SECI cycles operate in a machine learning-driven project context.

Participants in the workshops include representatives from multiple knowledge domains: simulation technology, mechanical engineering, automation, marine biology, and industrial fish processing. Each workshop focused on discussions related to key work packages:

- **WP1: Data collection** – Investigating how empirical biological data is collected and transformed into structured knowledge assets.
- **WP2: Model development of digital fish** – Exploring the translation of physical measurements into dynamic simulation models.
- **WP3: Simulation environment development** – Analyzing the validation processes for integrating real-world interactions into virtual environments.
- **WP4: Industrial case studies** – Reflecting on the preparation and application of knowledge in industrial pilot settings.
- **WP5: Project management and communication** – Studying coordination, knowledge dissemination, and strategic alignment activities.

Data collected during workshops include meeting notes, prototype evaluations, observational reports, and reflections shared during discussions. This material is systematically analyzed to understand how knowledge management practices influence project development, collaboration dynamics, and the progression from uncertainty to structured innovation.

Through this workshop-based research methodology, the study captures both the intentional and emergent aspects of knowledge creation within a real-world, interdisciplinary, machine learning-driven product development initiative.

4. Theoretical Framework: Knowledge Creation in Machine Learning Contexts

Innovation projects driven by machine learning, especially in emerging industrial domains, present unique challenges for knowledge creation. Unlike traditional product development projects that build upon established expertise and follow relatively linear knowledge transfer processes, machine learning initiatives often start from a position of limited or nonexistent prior knowledge. In these cases, effective innovation requires structured approaches to managing uncertainty, building new knowledge collaboratively, and accelerating organizational learning across multiple domains.

A useful lens for understanding knowledge creation in such environments is Nonaka and Takeuchi's (1995) SECI model. This model conceptualizes knowledge creation as a dynamic and iterative process, involving four modes of knowledge conversion: Socialization (tacit-to-tacit knowledge transfer), Externalization (tacit-to-explicit), Combination (explicit-to-explicit), and Internalization (explicit-to-tacit). Through successive SECI cycles, organizations generate new knowledge by continuously spiraling between tacit and explicit forms.

In traditional industrial projects, SECI cycles often unfold sequentially, with phases of concept development, validation, and industrialization following an ordered progression. However, in machine learning-driven projects, the need for rapid iteration, cross-disciplinary integration, and real-time adaptation leads to multiple SECI cycles operating simultaneously across different domains. Knowledge does not move smoothly from one phase to another; instead, it evolves dynamically, shaped by continuous feedback loops among academic researchers, engineers, industry practitioners, and end-users.

Recognizing these demands, the Manulab–Industry Competence Building Process was developed as an adaptation and operationalization of Nonaka and Takeuchi's theory for Industry 4.0 and 5.0 contexts (Hansen *et al.* 2023). This model expands the SECI framework by structuring knowledge creation into six interconnected phases, specifically designed to foster dynamic, cross-organizational collaboration in environments characterized by high uncertainty:

- **Gemba Walks:** Creating opportunities for sharing tacit knowledge through direct observation and dialogue between researchers, engineers, and industrial practitioners at the actual work sites.
- **Creating Concepts:** Developing new ideas collaboratively by synthesizing diverse tacit knowledge and making it explicit.
- **Justifying Concepts:** Testing and refining new concepts against empirical data, industrial requirements, and strategic goals.
- **Building Prototypes:** Iteratively translating validated concepts into physical or digital prototypes that can be tested and further improved.
- **Industrial Installation:** Implementing validated solutions within operational industrial environments, integrating feedback from real-world application.
- **Operating and Upgrading:** Continuously learning from operations, iterating improvements, and embedding new knowledge into organizational practices.

In contrast to traditional automation projects, where industry partners often become actively involved only during the validation or implementation stages, the Manulab model emphasizes continuous engagement of all partners—academia, industry, and system integrators—across all phases. This enables knowledge to be created, tested, and refined collaboratively in real time, aligning closely with the needs of machine learning-driven innovation where uncertainty and complexity demand flexibility and speed.

In the context of the Digital Fish Simulation Project, this theoretical framework provides essential guidance. The project does not simply apply simulation tools to existing problems; it operates in a largely unknown domain where fundamental knowledge about biological properties, material interactions, and system behavior must be constructed as part of the innovation process itself. By embedding structured knowledge management practices into project management workflows, the team ensures that learning is continuous, interdisciplinary, and cumulative—critical factors for success in machine learning-based product development.

Thus, the SECI model and the Manulab–Industry Competence Building Process together offer a coherent theoretical foundation for understanding how knowledge is created and managed in this project. They illuminate why sustained interdisciplinary collaboration, parallel SECI cycles, and adaptive iteration are not just advantageous but essential for navigating the challenges of machine learning-driven innovation.

5. Case Description: The Digital Fish Simulation Project

The Digital Fish Simulation Project represents a dynamic effort to create new knowledge in machine learning-driven product development, applying simulation and physical measurement to one of the most variable domains—biological seafood processing. The project is planned to run for three years, from November 2024 to June 2027. At the time of writing, the project is in its first six months of development, currently focused on iterative prototyping, knowledge building, and setting the foundation for later industrialization.

5.1 Gemba Walks: Understanding the Unknown

At the outset, researchers, students, and industry partners engaged in Gemba walks across fish processing plants, onboard trawlers, and directly in the field. These sessions were crucial for immersing the academic team in the realities of industrial fish processing and biological variability. One particularly important activity was organizing field trips where students actively participated in fishing wild cod, collecting fresh samples needed for early-stage physical measurements (Figure 1). Through these hands-on experiences, the project team could observe the biological diversity of fish populations, understand handling challenges, and refine their approaches to data collection. These practical engagements helped surface critical tacit knowledge from both the industrial and biological perspectives, framing the project's initial direction.

Figure 1: Students collecting wild cod for research

5.2 Creating Concepts: Testing Ideas Across Disciplines

With no established roadmap to follow, the team quickly moved into a creative, exploratory phase. The primary challenge was identifying what physical data would be necessary to build realistic digital fish populations for simulation in Isaac Sim—and how to collect it reliably under industrial conditions (NVIDIA 2025). In the very first weeks of the project, students, researchers, and industry partners made an initial visit to a land-based fish processing facility, where farmed cod was used to test early prototypes (Figure 2).

Figure 2: First friction jig test with farmed cod at processing facility

This provided accessible fish specimens to begin testing concepts in a real but controlled environment. One of the first friction jigs—manually operated—was tested here, sparking the project's iterative prototyping process. In parallel, preparations began for measuring stiffness under laboratory conditions. A cross-disciplinary team—including researchers from NTNU, research institution Moreforskning, and industry—gathered at the biological lab to plan and develop the first stiffness jigs (Figure 3). This session involved testing bending setups and evaluating fish-handling techniques, marking a key step in turning early concepts into practical experimental systems.

Figure 3: Interdisciplinary team preparing stiffness measurements in biological laboratory

5.3 Justifying Concepts: Learning Through Trial and Error

As early prototypes emerged, rapid testing cycles became central to project progress. Each iteration of the friction jig and measurement systems was evaluated in real-world or near-real-world conditions, with immediate feedback guiding refinements.

In one key session, students tested an improved version of the friction jig using wild cod freshly delivered by a local fisherman (Figure 4). This setting allowed the team to validate whether the modifications—such as improved surface materials, better angle adjustment, and more stable measurement procedures—produced reliable and realistic results closer to industrial needs.

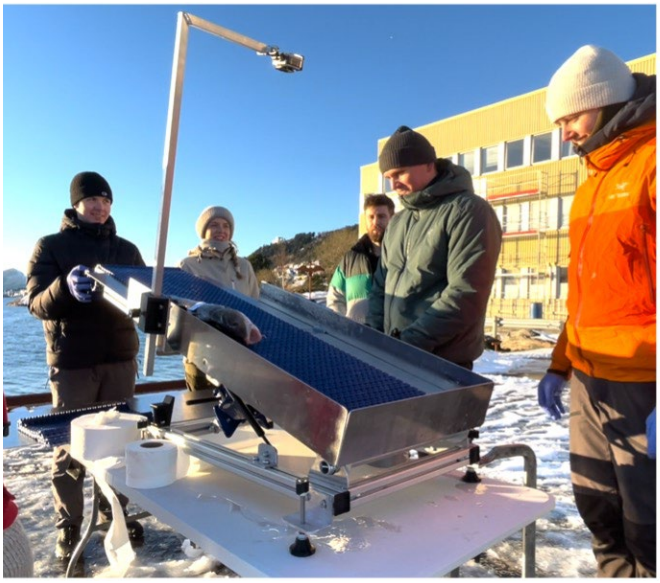

Figure 4: Students testing improved friction jig with wild cod

6. Building Prototypes: Toward Functional Measurement Systems

Through ongoing collaboration and successive iterations, the project has progressed toward fully functional prototype systems for 3D scanning, friction measurement, and stiffness evaluation. As insights accumulated through testing and feedback, physical setups became increasingly refined, and the connection between digital simulation and biological measurement became more tangible.

One key session took place in the biological laboratory, where students and researchers jointly tested both the improved friction jig and the photogrammetry-based 3D scanning setup (Figure 5). The simultaneous testing of multiple systems allowed for comparison, coordination, and shared problem-solving — aligning digital model requirements with physical data collection methods.

Figure 5: Testing friction jig and 3D scanning setup in biological laboratory

This phase of the project marked a shift from isolated experiments to coordinated prototype testing. By bringing together students from engineering, automation, and marine biology with academic researchers and external partners, the lab became a shared space for real-time learning and mutual adjustment — a central arena for combining, internalizing, and refining knowledge across disciplines.

6.1 Preparing for Industrialization: The Next Steps

While full-scale industrialization has not yet begun, the shape of the final measurement solutions is becoming increasingly clear. Several versions of friction and stiffness jigs, along with scanning setups, have been tested and refined based on biological input, simulation requirements, and practical constraints.

In a recent workshop held at the Manulab facility, students, researchers, and industry representatives from both biological and engineering backgrounds gathered to evaluate the prototype systems (Figure 6). This collaborative evaluation session focused on identifying improvements needed for scaling, improving measurement consistency, and ensuring alignment between physical data collection and simulation performance. These evaluation activities represent a critical transition between iterative prototyping and future industrial deployment. They also reinforce the role of shared physical and organizational spaces—such as Manulab—as enablers of structured interdisciplinary knowledge creation. The knowledge generated during this phase will guide the next steps in preparing field-ready systems for data collection onboard fishing vessels.

Figure 6: Prototype evaluation at Manulab with interdisciplinary team

7. Discussion

The early stages of the Digital Fish Simulation Project offer valuable insights into how knowledge management practices can be adapted to support machine learning-driven innovation under conditions of uncertainty. Several key lessons emerge from the project's experience so far, illustrating the relevance and utility of the theoretical frameworks outlined earlier.

8. Parallel SECI Cycles in Practice

One of the most striking features of the project is the way knowledge creation has unfolded through multiple, parallel SECI cycles rather than following a traditional, linear progression. Socialization, externalization, combination, and internalization processes are not confined to distinct stages but occur simultaneously across different domains: biological data collection, simulation modeling, prototype development, and industrial evaluation. The iterative development of the friction and stiffness measurement jigs involved simultaneous sharing of tacit knowledge, externalization into design choices, combination of empirical findings with simulation, modelling, and internalization of learning into improved prototype designs.

9. Sustained Interdisciplinary Collaboration

The project emphasizes the importance of continuous collaboration across knowledge domains. In contrast to traditional projects, where industry partners primarily contribute during validation, this project sees industry engineers, researchers, and simulation experts jointly engaging from the earliest stages of concept development through to prototype testing. This intensive engagement accelerates knowledge emergence and ensures practical relevance of new knowledge, reflecting the evolving demands of machine learning-driven innovation.

10. Knowledge Creation Through Trial and Error

The trial-and-error approach has proven to be a powerful driver of knowledge creation. Instead of being seen as setbacks, failures in prototype development have been embraced as essential inputs into the ongoing SECI cycles. Each iteration enhances understanding, refines methods, and strengthens the collaborative learning process. This learning-by-doing resonates with Nonaka and Takeuchi's vision of dynamic, spiraling knowledge creation and operationalizes the Manulab–Industry Competence Building Process.

11. Building a Foundation for Industrialization

While still in the early stages, the project's prototype systems represent valuable knowledge artifacts, crystallizing interdisciplinary collaboration into tangible innovations. By embedding structured knowledge management practices into everyday project activities, the project team ensures that early investments in knowledge creation will support later phases of scaling and industrial deployment.

12. Conclusion and Recommendations for Further Work

The early phases of the Digital Fish Simulation Project demonstrate how structured knowledge management practices, when carefully embedded within project workflows, can support innovation in machine learning-driven product development even under conditions of high uncertainty. By operationalizing Nonaka and Takeuchi's SECI model through the Manulab–Industry Competence Building Process, the project has fostered dynamic, interdisciplinary collaboration, enabled continuous knowledge creation, and accelerated the development of prototypes suitable for future industrial application. Several key lessons have emerged:

- **Multiple SECI cycles must run in parallel** to accommodate the need for rapid, cross-domain knowledge integration.
- **Sustained interdisciplinary collaboration** is critical; knowledge workers from academia and industry must be actively engaged at every stage.
- **Trial-and-error learning** must be embraced as an essential engine of innovation, not as a deviation from planned processes.
- **Early and continuous industry involvement** transforms projects from linear, handover-driven processes into collaborative ecosystems of knowledge creation.

By embedding these principles into its operations, the Digital Fish Simulation Project has built a solid foundation for further development. Although the project is still in its early stages, the evolving prototypes for 3D scanning, friction measurement, and stiffness evaluation already represent valuable knowledge assets that will inform future scaling and deployment efforts. Based on the experiences gained so far, several directions for future research in knowledge management within machine learning-driven projects are recommended:

- **Structuring Parallel SECI Cycles in Machine Learning Projects**. Further research should investigate how concurrent SECI cycles can be structured, coordinated, and supported systematically.
- **Managing Trial-and-Error Learning as a Formal Knowledge Process**. Methods for systematically capturing, evaluating, and institutionalizing learning from iterative prototyping should be explored.
- **Enhancing Interdisciplinary Knowledge Transfer**. Frameworks for measuring and optimizing knowledge flows between diverse disciplinary domains should be developed.
- **Evaluating industry–academia knowledge co-creation mechanisms**. Research should examine how early and continuous co-creation partnerships can be sustained across full project lifecycles.
- **Designing knowledge management tools for simulation-driven innovation**. Practical tools such as reflection workshops, knowledge repositories, and collaborative platforms could support dynamic knowledge flows.
- **Understanding organizational learning across project phases**. Longitudinal studies could track how early-stage knowledge is adapted or institutionalized through scaling and industrialization phases.

By pursuing these directions, both the project team and the broader research community can contribute to a deeper understanding of how knowledge management strategies must evolve to support machine learning-based innovation.

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References

Banks, J., Carson II, J. S., Nelson, B. L. and Nicol, D. M. (2010) *Discrete-event system simulation, International version.* Pearson Education, Upper Saddle River, London.

Del Vecchio, P., Di Minin, A., Petruzzelli, A. M., Panniello, U. and Pirri, S. (2018) Big data for open innovation in SMEs and large corporations: Trends, opportunities, and challenges, *Creativity and Innovation Management,* 27(1), pp. 6-22.

Giske, L. A. L., Kleppe, P. S., Rezaei, F., Glomsrud, A., Mork, O. J. and Hansen, I. E. (2023) Development of Digital Fish Simulation Model, *Procedia CIRP,* 119, pp. 1053-1058.

Hansen, I.-E., Mork, O. J., Kleppe, P. S. and Giske, L. A. L. (2023) Towards Industry 5.0: Developing Knowledge and Skills in a Research and Innovation Lab, *European conference on knowledge management,* 24(1), pp. 509-517.

Kleppe, P. S., Karlsen, B., Lersveen, F. P. and Giske, L. A. (2024) Soft Body Simulation of fish in Norwegian Fish Processing Factories with Omniverse.

Machado, C. G., Winroth, M. P. and Ribeiro da Silva, E. H. D. (2020) Sustainable manufacturing in Industry 4.0: an emerging research agenda, *International Journal of Production Research,* 58(5), pp. 1462-1484.

Nonaka, I. and Takeuchi, H. (1995) *The Knowledge-Creating Company: How Japanese Companies Create the Dynamics of Innovation.* Oxford University Press.

NVIDIA (2025). Available at: https://developer.nvidia.com/isaac/sim.

Romero, D., Stahre, J., Wuest, T., Noran, O., Bernus, P., Fast-Berglund, Å. and Gorecky, D. Towards an operator 4.0 typology: a human-centric perspective on the fourth industrial revolution technologies. *proceedings of the international conference on computers and industrial engineering (CIE46), Tianjin, China*, 29-31.

Zhang, W., Zhang, W., Daim, T. and Yalçın, H. (2025) AI challenges conventional knowledge management: light the way for reframing SECI model and Ba theory, *Journal of knowledge management,* 29(5), pp. 1618-1654.

Ørngreen, R. and Levinsen, K. T. (2017) Workshops as a research methodology, *Electronic Journal of E-learning,* 15(1), pp. 70-81.