THESIS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

GENERATING ARCHITECTURAL KNOWLEDGE IN DIGITAL INNOVATION NETWORKS

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ABSTRACT

This thesis investigates the generation of architectural knowledge within digital innovation networks, focusing on the collaborative integration of diverse component knowledge to create new digital products. Architectural knowledge, or the understanding of how individual components are integrated into a coherent whole, is particularly important to align and coordinate actors in interorganizational networks with highly heterogeneous knowledge bases. However, little research has investigated how such knowledge is generated when the innovation involves digital components that are inherently malleable.

Through qualitative, longitudinal single-case studies of two distinct networks, this thesis investigates how architectural knowledge is generated across different innovation strategies. Findings indicate that given the malleable nature of digital components, architectural knowledge is highly dynamic, as desirable component interactions, contextual requirements, and new value opportunities may only emerge during the innovation process. Specifically, this thesis offers a refined definition of architectural knowledge in digital innovation as *knowledge of how digital and physical components synergistically contribute to overarching architectural goals within specific use contexts to create current and future value opportunities.*

The required capabilities for innovation networks to generate such knowledge are fundamentally similar to those in non-digital innovation. However, they need to facilitate knowledge integration across more disparate component knowledge domains, higher paces of architectural knowledge refinement, and increased design flexibility. Findings are synthesized in a theoretical framework on architectural knowledge generation in digital innovation networks.

The thesis contributes to the literature on digital innovation, innovation networks, and organizational design by explaining knowledge dynamics in digital innovation networks and offering practical implications for actors in these networks and other actors such as supporting funding agencies.

Keywords: *digital innovation, innovation networks, architectural knowledge, combinative capabilities, case study, layered modular architecture, architectural innovation, radical innovation*

LIST OF APPENDED PAPERS

This thesis is based on the work contained in the following papers:

1. Bumann, A., & Teigland, R. (2021). *The Challenges of Knowledge Combination in ML-based Crowdsourcing – The ODF Killer Shrimp Challenge Using ML and Kaggle*. Proceedings of the 54th Hawaii International Conference on System Sciences (HICSS).

2. Bumann, A. (2022). *No Ground Truth at Sea – Developing High-Accuracy AI Decision-Support for Complex Environments*. Proceedings of the 56th Hawaii International Conference on System Sciences (HICSS).

3. Bumann, A., Sandberg, J., Teigland, R. (under revision for 2nd submission round at AJG- level 4* journal). Theorizing Digital Innovation Network Orchestration: Navigating the Tension Between Leveraging Generativity and Bounding Innovation.

4. Bumann, A., Mansoori, Y. (Manuscript, under peer review at AJG-level 3 journal). Generating architectural knowledge in interindustry digital innovation: the case of a maritime navigation decision-support system.

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"most of these nautical officers are not the brightest. So, it's important that we make the system really, really easy to use" (ECDIS developer during project meeting, 2021)

I've always found this quote funny. Before entering academia, I've worked as one of those nautical officers, and when I first heard this quote, my reaction (and that of former colleagues when I tell them) was to laugh, shrug, and say "well, he's not wrong". He's definitively not wrong on the second part – support systems for operators in complex environments should be easy to use! Somebody should write a paper on that, or something. And is he correct on the first part that nautical officers are not the brightest? I don't know, but if that was true, then this thesis is proof that intelligence is not the only thing needed to complete a PhD. It also takes a good support network, and I'm lucky enough that I encountered a number of people during the last five years who contributed to this work in various ways.

First off, thanks to my PhD supervisors Robin Teigland and Johan Sandberg. You have created an environment that allowed me to discover what research can be; you've given me the freedom to find my own directions; and you've provided me with the tools, intellectual guidance, encouragement, and mentorship to succeed. I have learnt a tremendous amount from working with both of you, including what kind of researcher I want to be. I'm glad I got to work with both of you.

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Some of these topics have been more relevant to this thesis than others, but learning about all of them has made the PhD process more interesting and enjoyable.

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Finally, and last but not least, thanks to my friends in Sweden and abroad, and my family, who have been with me during this process. To my mother, father, grandma, and late grandparents, if there are two things that you all have in common, it is that you taught me that knowledge is always worth pursuing, and that you have shown unconditional support throughout this process. For both, I am very grateful.

Adrian

Gothenburg, September 2024

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Table 1 - Overview of key concepts used in this thesis.

Concept	Definition
Architectural knowledge	"Knowledge about the ways in which the components are integrated and linked together into a coherent whole" (Henderson & Clark, 1990).
Architecture	Basic structure of a system that describes what component are part of the systems and what their roles are (Baldwin & Clark, 2000, p. 77).
Combinative capabilities	Abilities that allow an organization/network "to synthesize and apply current and acquired knowledge" (Kogut & Zander, 1992, p. 384), encompassing systems capabilities, coordination capabilities, and socialization capabilities (De Boer et al., 1999; Van Den Bosch et al., 1999).
Component	Used synonymously in this thesis with 'module', i.e. "a unit whose structural elements are powerfully connected among themselves and relatively weakly connected to elements in other units" (Baldwin & Clark, 2000, p. 63).
Component knowledge	"Knowledge about each of the core design concepts and the way in which they are implemented in a particular component" (Henderson & Clark, 1990).
Digital innovation	The "carrying out of new combinations of digital and physical components to produce novel products" (Yoo et al., 2010, p. 725).
Digital innovation network	A collaborative arrangement of organizations formed to engage in digital innovation.
Inclusionary product hierarchy	The architecture of a product or system that is organized in a fixed and nested manner, i.e., a single component is always part of one component in the hierarchical level above and is composed of multiple components in the hierarchical level below (Clark, 1985). Contrasted with → Layered Modular Architecture.
Innovation strategy	Approach an organization/network adopts for technological innovation by reconfiguring components and/or interfaces to differing extents, classified into incremental, modular, architectural, radical innovation (Henderson & Clark, 1990).
Interface	Procedures for exchanging necessary information about the functional interactions between components, indicating "how a [component] interacts with the larger system" (Baldwin & Clark, 2000, p. 64).
Layered modular architecture	The architecture of a product or system that is characterized by distinct, loosely coupled layers, each dedicated to a specific functional domain (Yoo et al., 2010). Contrasted with → Inclusionary Product Hierarchy.
Modularity	A design principle that builds on the ideas that 1) a system is composed of modules that are interdependent within and across modules, and 2) the complexity of a system can be managed by breaking it up and hiding information behind an interface (Baldwin & Clark, 2000).
Value path	Strategic routes through which digital innovation creates and captures value by connecting digital components in novel ways; the product-agnosticism of digital technology enables generating new value paths both during design and while in use, and allows it to simultaneously be part of multiple value paths (Henfridsson et al., 2018).

1 INTRODUCTION

1.1 Research Motivation

Digital technology plays a critical role in today's world, as it reshapes industries and creates new value propositions. At the core, such digitalization is enabled by the layered and modular nature of digital technology, which increases flexibility, interoperability, and the range of combinatorial opportunities in innovation.

Digital innovation occurs not exclusively, but increasingly, in innovation networks, i.e., collaborative arrangements of diverse organizations that aim to create value through innovative digital products or services. Such collaboration is beneficial for organizations because it provides access to unique technologies and knowledge that would be difficult to acquire independently. For instance, traditional manufacturers like Volvo collaborate with technology companies to access specialized technology knowledge (Svahn et al., 2017), and public innovation funding agencies increasingly foster interdisciplinary collaborations to explore how digital applications can help address complex societal or environmental challenges (World Economic Forum, 2022). Within these networks, innovation does not stem from a single idea or organization but rather emerges through the dynamic integration of the knowledge of all network members (Lyytinen et al., 2016).

Prior research indicates that collaboration is significantly more challenging when individuals and organizations come from different knowledge backgrounds, as opposed to when they share similar expertise. Many practitioner studies show that organizations increasingly partner with others (BCG, 2022; Deloitte, 2021), but they also indicate that a majority of these collaborations fail (Cecchi-Dimeglio et al., 2022; Guzzini & Iacobucci, 2017; Hughes & Weiss, 2007). Despite the interoperability of digital technologies making it easier to develop new solutions by combining components from different industries, managing these diverse collaborations remains complex. Given the critical role of such innovation networks in addressing complex issues, and the significant investments made by organizations and funding agencies[1], understanding how to successfully manage collaborations within these networks, particularly when they involve diverse knowledge domains, is important.

The importance of knowledge in innovation is well established. Central to this thesis is the concept of architectural knowledge, i.e., knowledge about how components are integrated to form a coherent architecture (Henderson & Clark, 1990). The concept is rooted in the architectural view of innovation

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[1]The most recent research initiative of the European Union, 'Horizon Europe', includes a budget of €95.5 bn and explicitly encourages interorganizational collaboration. Compared to the previous initiative 'Horizon 2020', the focus has shifted "from establishing a larger number of small partnerships to fewer and larger ones, capable of making a strong impact on their policy area" (European Commission, 2021, p. 3), indicating the perceived benefits from knowledge diversity in such collaborations.

that considers technological innovation as a (re-)configuration of components and/or interfaces that connect components. Together, components and interfaces form a coherent architecture that fulfills specific functions. Such reconfiguration can involve differing degrees of change in components and/or interfaces to create innovation. For instance, a table fan could be innovated upon by developing more efficient blades, reconfiguring its individual components (such as motor, blade, casing) into a ceiling fan, or creating entirely new bladeless designs.

Previous studies have explored different approaches that help generate architectural knowledge in innovation processes. For instance, when innovation involves mature technologies, it is likely that dominant designs have emerged that guide innovators in creating new variations (Murmann & Frenken, 2006). Within interorganizational collaboration, literature has explored how central network orchestrators or systems integrators can guide architectural knowledge creation by providing overarching design rules (Brusoni et al., 2001; Dhanaraj & Parkhe, 2006). However, these approaches are not feasible when the to-be-developed architecture is novel, complex, and requires diverse knowledge bases. In this case, innovators face high uncertainty because they can neither fall back on existing design knowledge nor nominate a single person that can guide system development. Thus, a larger emphasis is put on a network to possess combinative capabilities, i.e., abilities to combine diverse component knowledge to generate new architectural knowledge (Kogut & Zander, 1992).

In essence, this thesis views innovation in interorganizational networks as the *combination of diverse component knowledge of network members to create new architectural knowledge*. This combination is facilitated by the network's combinative capabilities. Such capabilities are not 'one-fits-all-solutions'; rather they need to be aligned with the network's innovation strategy (Henderson & Clark, 1990), i.e., whether the network aims to repurpose existing, well-established component technologies or rethink entirely new designs.

1.2 Problem Statement

As digital technology becomes increasingly pervasive, the importance of innovation networks' abilities to integrate technology components from varied domains also grows. While the concept of technology fusion is not exclusive to digital innovation – for instance, fiber optics result from merging glass, cable, and electronic components (Kodama, 1992) – the inherent layered and modular design of digital technology facilitates such cross-domain innovation. Digital innovation networks are established not just to generate business value but are also often created to address environmental or societal challenges through digital means (Heathcote-Fumador et al., 2024). Therefore, the capacity of these networks to generate and refine architectural knowledge by harnessing diverse component knowledge is important for successful innovation in all areas of society.

However, prior Information Systems (IS) literature, while acknowledging the dynamic and emergent innovation trajectories of such networks and comparing them to "anarchic" garbage-can-like organizations (Lyytinen et al., 2016; Nambisan et al., 2017), falls short of explaining how knowledge dynamics specifically unfold in these contexts and which organizational capabilities are needed to facilitate successful digital innovation. Although the concept of combination - bringing together different elements to create something new - is fundamental to innovation (Schumpeter, 1934), the IS literature has predominantly focused on the technological aspect of component combination, with less emphasis on the combination of technology-related knowledge (Hund et al., 2021). Conversely, despite extensive literature on knowledge management in various contexts (see Zahra et al., 2020), there is scant research exploring how the malleable nature of digital technology influences knowledge processes.

Given the importance of knowledge for innovation, this gap is surprising. Yet, without further exploration of the knowledge dynamics of digital innovation, IS research lacks necessary tools to address critical questions, such as: What knowledge should innovators acquire or develop while collaboratively developing new digital product architectures, and why? How can innovation networks be designed to facilitate effective knowledge generation? And how do those configurations evolve over time?

The concepts of component knowledge and architectural knowledge are useful for this research objective because they offer an explicitly technology-centric lens on knowledge processes (Henderson & Clark, 1990; Sanchez & Mahoney, 1996). However, in the process of writing this thesis and attempting to operationalize the concept of architectural knowledge, a secondary research gap emerged in that the concept is anchored in the modularity literature that predates digital phenomena. Specifically, the concept was developed and mainly applied to technological innovations characterized by an inclusionary product hierarchy, where components are organized in a nested, singular design hierarchy. However, the architectural configuration of components in digital product architectures diverges because digital components are inherently malleable, product-agnostic, and can be simultaneously part of multiple value paths (Henfridsson et al., 2018; Lee et al., 2020). Thus, it is useful to explore how seminal definitions of architectural knowledge endure within the context of digital innovation and to understand the implications of digital technology's layered and modular nature on this concept, including what drives effective learning about new architectures (Henderson & Clark, 1990).

1.3 Research Objective and Approach

This thesis seeks to explore how actors with diverse component knowledge, within collaborative digital innovation networks, generate shared architectural knowledge of how these components can effectively interact to create novel and value-adding digital products. The inherent complexity of combining expert knowledge across knowledge boundaries is compounded in the context of digital technologies. While the IS literature acknowledges this heightened complexity, there is a gap in understanding how to effectively facilitate this process. In response to prior calls in digital innovation literature for a "*deeper understanding of how developing specific types of knowledge can support strategies for and practical advice on how to identify, prioritize, access, and recombine knowledge*" (Hund et al., 2021, p. 14), the objective of this thesis is to investigate two research questions:

RQ1: How should architectural knowledge in the context of digital innovation be defined given the malleability of digital components?

RQ2: How is architectural knowledge generated in digital innovation networks with different innovation strategies?

To provide such insights, I draw on the modularity, digital innovation, and knowledge management literature, and on four appended papers that are the result of two qualitative, longitudinal, single-case studies of two digital innovation networks. Both networks present collaborative engagements of diverse organizations aiming to create new digital products: artificial intelligence (AI) systems for marine environmental monitoring and maritime navigation, respectively. The two networks differed in their innovation strategy, with one network pursuing architectural innovation by integrating existing components possessed by network members and one network pursuing radical innovation by exploring a wide range of potential components and combinatorial opportunities.

1.4 Central Argument

The red thread that runs through the two study contexts is the linkage of 1) digital product innovation, 2) knowledge combination in innovation networks, and 3) iterative adaptation and refinement of design goals. The overall argument in this thesis can be outlined as follows:

1. Every product or system can be understood as an architecture, composed of individual components connected through interfaces or linkages.
2. Digital technologies possess distinct properties of homogeneity and reprogrammability, which fundamentally change the nature of digital product architectures by allowing components to transcend the constraints of physical materials, such as size, form, and function. This flexibility facilitates more adaptable and emergent innovation processes.
3. Due to the modularity of digital technology and the blurring of industry boundaries, the locus of digital innovation is increasingly shifting towards interorganizational networks that enable the combination of diverse technologies and knowledge.
4. The successful combination of diverse knowledge requires the network to possess combinative capabilities, i.e., the abilities to integrate component knowledge to develop new architectural knowledge. Architectural knowledge is knowledge about the ways in which the components are integrated and linked together into a coherent whole.

5. Architectural knowledge in digital innovation includes both relational knowledge to align product-agnostic components within the product architecture and with external conditions in complex use contexts; and strategic knowledge to anticipate emerging value opportunities enabled by digital technology's generative potential.
6. The generation of such architectural knowledge occurs by a network enacting its combinative capabilities in the form of systems, coordination, and socialization capabilities.
7. Systems capabilities involve procedures that facilitate codification of extant architectural knowledge and the adaptation of organizational task structures to evolving design needs.
8. Coordination capabilities involve collaborative processes that facilitate development of technical interfaces that reduce the need for inter-actor knowledge transfer and boundary-spanning practices that translate complex component knowledge across epistemological domains.
9. Socialization capabilities involve cultural norms and informal processes that support the pursuit of short- and long-term objectives and informal leadership by individuals with integrative expertise.
10. The specific application of these capabilities depends on the network's innovation strategy, which reflects varying degrees of exploring new components/interfaces and exploiting existing ones, thereby requiring a focus on either reducing uncertainty or enhancing integration efficiency.
11. The generation of architectural knowledge is a continuous, iterative process that leads to the refinement of component knowledge, potential adjustments to the innovation strategy, and the discovery of new value opportunities at both component and architectural levels. The pace in which iterations occur is high in digital innovation due to the malleability of digital technologies facilitating intra-component adaptation and responses to changing external conditions.
12. Generating, holding, and enhancing architectural knowledge is critical for the development of a digital product architecture that is cohesive, functional, adaptable, and sustainable over time.

1.5 Structure of this Thesis

The thesis is structured as follows:

- Chapter 2 provides an overview of what we can assume to be known about the research topic based on prior literature. Specifically,
    - 2.1 presents how digital product architectures differ from non-digital ones, and how this impacts innovation processes and interorganizational innovation networks.
    - 2.2 describes the concept of architectural knowledge, its role in different types of technological innovation, and its generation, and synthesizes this in a conceptual framework.

- Chapter 3 presents and discusses the research design.
- Chapter 4 provides a summary of the appended papers.
- Chapter 5 presents a discussion concerning RQ 1 & 2, implications for research and practice, and limitations and future research avenues.
- Chapter 6 presents the conclusion.
- Finally, the appended papers are presented in full.

2 BACKGROUND

2.1 Digital Innovation and Digital Innovation Networks

2.1.1 Digital Product Architectures

The last decades have seen a substantial shift in how digital technologies impact innovation regimes (Lyytinen, 2022). Until the 1990s and early 2000s, digital technology typically played a narrowly defined role in product design, for instance regulating gas and oxygen ratios in a carburetor (Lee & Berente, 2012). Since then, digital technology has become infrastructural, and the process colloquially referred to as 'digitalization' refers to the imbuement of all kinds of products, processes, and experiences with digital capabilities. The reason why digital technology affords such large-scale change can be traced to the basic properties of digital material that differentiate it from physical material.

While there has been extensive theorizing about the nature of digital material (Baskerville et al., 2020; Faulkner & Runde, 2013; Kallinikos et al., 2013; Tilson et al., 2010), there are two features relevant to digital product innovation. **First, digital material is *homogeneous*** in that all digital objects are subject to the same basic representation scheme. Fundamentally, all digital material is semiotic in nature as any digital object consists of bits composed of 0 and 1. While physical technology requires a tight coupling between signal and device (e.g., photo – camera, sound – gramophone), a digital object can represent any type of analog signal as long as it adheres to the same data standards (Faulkner & Runde, 2013).

Second, **digital material is *reprogrammable***, in that it can be edited in real-time. This is afforded by the von Neuman architecture that combines a memory unit and a central processing unit storing both data and instructions how to manipulate data (Yoo et al., 2010). In contrast to physical technology, this affords digital devices a separation between the functional logic of the device from the physical embodiment of the device. For instance, a modern smartphone can perform a variety of functions (e.g., navigation, photo editing, information retrieval) based on installed apps, and these apps can be installed or deleted to change the phone's functions.

Consequentially, digital artifacts are more granular than physical artifacts**.** Granularity refers to "*the minute size and resilience of the elementary units or items by which a digital object is constituted*" (Kallinikos et al., 2013, p. 360). For non-digital entities, granularity is typically lower given their physical and less divisible nature. The granularity of digital objects is characterized by their fundamentally binary and numeric makeup, which allows for detailed decomposition into very small, precise fragments (Faulkner & Runde, 2013). This fine granularity permits modifications at any level of detail. For instance, compared to physical audio storage media like cassette tapes, an mp3 music file can be edited instantaneously, infinitely, and to varying extents down to the bit-level.

A key premise in this thesis is that these **characteristics of digital material result in differences in the configuration of physical and digital product architectures**. In this thesis, I refer to architecture as the *structure of a technological system that is made up of various components and the* *relationships between them*. Such relationships are defined through interfaces[2] (Baldwin & Clark, 2000). This view of an architecture builds on the notion of modularity which refers to the extent to which a system can be decomposed into smaller parts, or modules, which can be independently developed and then combined into a complete entity (Simon, 1962). As modularity increases, each component gains greater independence, being isolated from changes in other components (Baldwin & Clark, 2000).

Physical products can be understood as an architecture. Design scholars have described the architectural configuration of physical products as *inclusionary product hierarchy* (Murmann & Frenken, 2006) or single design hierarchy (Clark, 1985), where relationships between architecture and its components are nested and fixed, with each component belonging to a single higher-level component and comprising multiple lower-level components (Murmann & Frenken, 2006; Simon, 1962). For example, a bicycle is an overarching architecture with components like steering, braking, or drivetrains, which in turn comprise lower-level components such as wheels, further broken down on a lower level into rims, tires, spokes, etc. This reflects a top-down design that starts with a product design which is then broken into subcomponents. The design of individual components is driven by the functional requirements of the overall architecture, i.e., the components are designed to be product-specific (Yoo et al., 2010).

Physical products can be designed with different degrees of modularity, i.e., different degrees to which components are loosely coupled and can be independently developed, tested, and replaced (Ulrich, 1995). Generally, it is more difficult to manage and manipulate an integral, unified entity than its individual components (Ethiraj & Levinthal, 2004; Simon, 1962). Hence, a modular product architecture reduces complexity and increases design flexibility to create new product variations in response to changing environments (Baldwin & Clark, 2000). For developer teams, a modular architecture allows dividing work tasks more efficiently and isolating design changes within the technical boundary of a single component without requiring substantial changes to other components (Baldwin, 2007). However, physical products are ultimately constrained by their immutable design characteristics, requiring that interfaces are designed *a priori* with specific functions tailored to the particular product they serve (Yoo et al., 2010). For instance, spare parts from one bicycle manufacturer rarely fit bicycles from other manufacturers, and even less so for products from different industries. Negotiating standards for physical components (e.g., ISO 4210 for bicycle parts) can enhance

[2] Numerous scholars, including Plato, Wittgenstein, Focault, Herbert Simon, or Christopher Alexander, have concerned themselves with the nature of architecture and how it is different from physical structures, design, or art. The definition used in this thesis and by Baldwin & Clark (2000) emphasizes the relationships between elements in an architecture, rather than their functions. This contrasts with another seminal definition in organizational studies that considers architecture as "*the scheme by which the function of the product is allocated to physical components*" (Ulrich, 1995, p. 422).

interoperability but typically does not extend across functional boundaries of different industries (Kallinikos et al., 2013).

The principle of modularity applies both to digital and physical product architectures. However, the characteristics of digital material allow digital components to be combined without physical constraints. Thus, modularity "*runs much deeper and wider in digital objects and technologies*" (Kallinikos et al., 2013, p. 360). **A digital product can be understood as a *layered modular architecture*** that constitutes a temporary coupling between specific components in different layers (device, network, service, and content) (Yoo et al., 2010). The device layer includes physical hardware and software, e.g., operating systems, which bestow logical capabilities onto hardware. The network layer includes physical components and logical transmission standards, e.g., cables and TCP/IP network standards, which handle data transmission. The service layer hosts functional software, e.g., computer applications, which facilitate device usage and information access for users. This information, e.g., data or metadata, exists within the content layer.

The layered modular architecture has several implications of how components are arranged (Hund, 2022; Wang, 2022; Yoo et al., 2010). First, **digital components are *product-agnostic***, in that they can be utilized across organizational or domain boundaries and for purposes they were not initially designed for. The relative independence of each layer enables flexible combination and recombination of components within and across layers without deterioration, blurring product boundaries (Yoo et al., 2010). In this regard, digital innovation does not follow a predefined, top-down design. Instead, the layered modular architecture reflects a bottom-up design that is inductively enacted through the iterative assembly of various components across multiple layers, without a predetermined final product configuration (Henfridsson et al., 2018; Hylving & Schultze, 2020). As product boundaries become more ambiguous, the functionality attributed to a product or component increasingly hinges on its specific application. For instance, ChatGPT and other Large Language Models have been utilized for various applications, such as writing SQL queries, chatbots and text-based adventure games (Shardin, 2020). Similarly, data sets are often repurposed for uses beyond their original collection intent (Guenther et al., 2017).

Second, while the relationships between the product and its components are fixed in an inclusionary hierarchy (Murmann & Frenken, 2006), **the coupling between digital components in a LMA is *contingently obligatory***, in that the relationships among components in a product architecture are not defined *a priori* but rather depend on their specific combination (Henfridsson et al., 2018; Wang, 2022). Component variation in an inclusionary hierarchy is confined within the scope of an architectural scheme (Tushman & Murmann, 1998). In contrast, components in a layered modular architecture exhibit relations of exteriority (De Landa, 2006), as their meaning or function changes in conjunction with its relation with other components in a specific architectural arrangement. Digital interfaces like APIs can cover a broader range of functions, are often designed to be independent of any specific function and can be added to existing products. Their non-material nature means that digital interfaces do not physically obstruct other interfaces (Gawer, 2021; Kallinikos et al., 2013). Therefore, digital technology provides an open-ended value landscape where value is created by establishing and dissolving connections between different digital components across different layers (Henfridsson et al., 2018). In other words, the modularity of digital technology affords "*a virtually infinite number of potentially valuable recombinations*" of individual digital components (Brynjolfsson & McAfee, 2014, p. 77). For instance, a car navigation computer combines car sensors, digital map contents, and real-time traffic information. These components have contingently obligatory relationships as they have been developed independently from each other, follow their own evolutionary trajectories, and may be independently embedded in other product architectures.

These characteristics make up an architecture that enables generativity, i.e., "*a technology's overall capacity to produce unprompted change driven by large, varied, and uncoordinated audiences*" (Zittrain 2006, p. 1980). This is facilitated by each layer adhering to its own design hierarchy, enabling modifications to be implemented largely independent from design choices in other layers (Yoo et al., 2010). Consequentially, digital technologies exhibit higher technological complexity due to emergence (Benbya et al., 2020). Complex systems are "*made up of a large number of parts that interact in a non-simple way*" (Simon 1962, p. 468), with emergence being the "*arising of novel and coherent structures … during the process of self-organization*" (Goldstein, 1999, p. 49). In a layered modular architecture, configurations emerge through continuous feedback loops and iterative refinements, often leading to serendipitous innovations and new functionalities (Lee et al., 2020; Nylén & Holmström, 2019). This continuous evolution is not typically present in traditional physical architectures where interactions between components are predetermined and remain constant after assembly. Viewing technological complexity from this perspective, a car manufactured today embodies a more complex architecture than one from the 1980s. Although the architecture of an older car is highly complicated, with many interrelated parts, their functions and relationships are fixed once the design is finalized. In contrast, modern cars can incorporate new functions during their use, such as through software updates, or by finding new uses for existing digital capabilities, like a fuel analysis feature that evaluates driving data. Leveraging such emergent properties and ongoing adaptability is crucial for maintaining the relevance of modern technological systems (Benbya et al., 2020).

Figure 1 illustrates the different architectural configurations and design implications in an inclusionary product hierarchy and in a layered modular architecture.

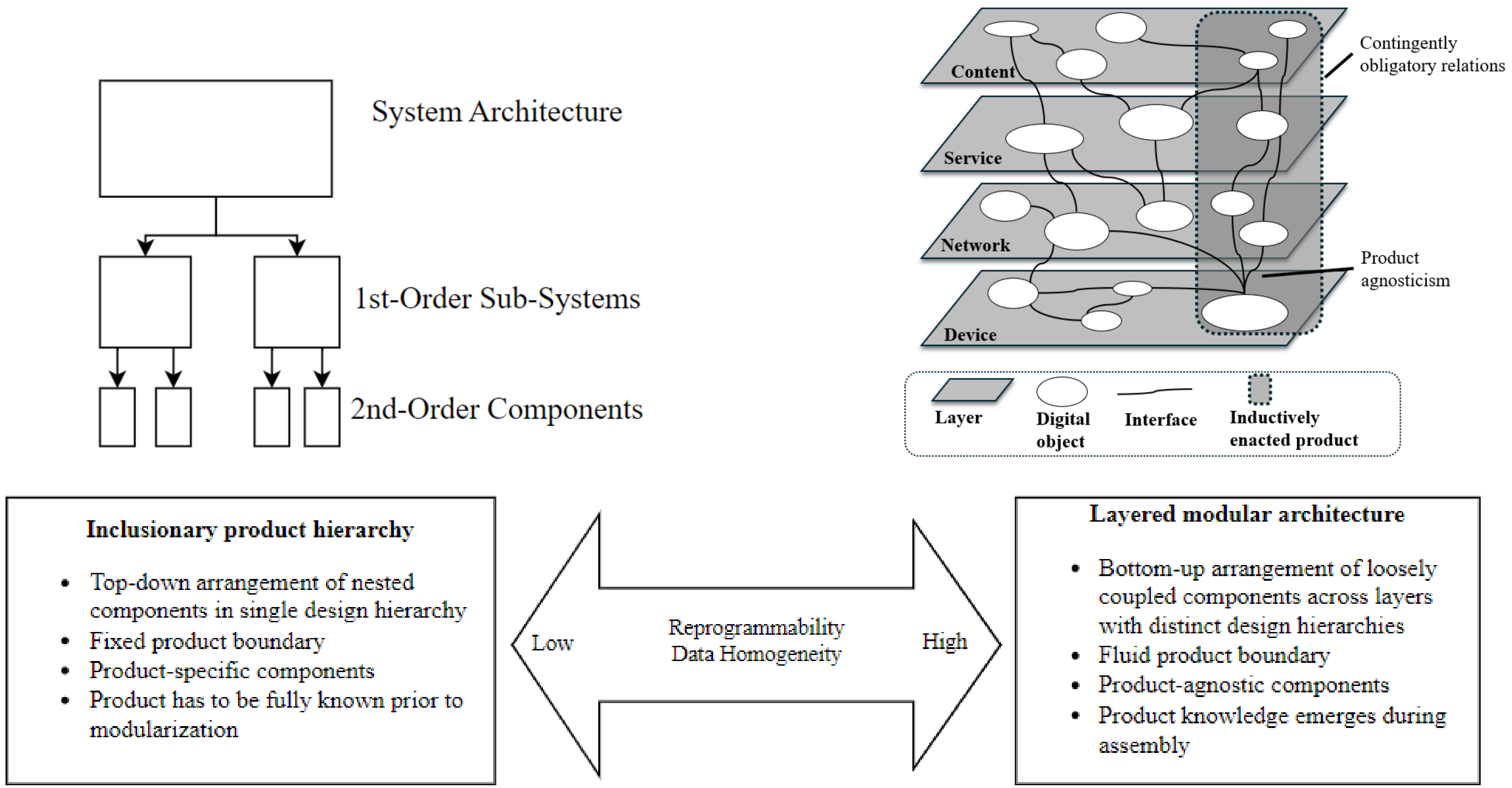

Figure 1 – Architectural configurations in three-level inclusionary hierarchy and layered modular architecture (adapted from Henfridsson et al., 2018; Hund, 2022; Murmann & Frenken, 2006; Yoo et al., 2010)

2.1.2 Digital Innovation as Process

So far, I have presented why and how architectural configurations differ between digital and physical technologies. I now turn to outlining the implications of those differences on innovation processes.

The concept of digital innovation has gained much traction in the last decade amongst both researchers and practitioners. Despite that popularity, the application of the concept in academic research is not always uniform, and it has been used to describe digital innovation as a process, a context (Urbinati et al., 2022), or an outcome (von Briel et al., 2021). **In this thesis, I focus on digital innovation as the process of** “*the carrying out of new combinations of digital and physical components to produce novel products*” (Yoo et al., 2010, p. 725).

IS researchers have emphasized the distinction between "digital innovation" and IT innovation. Similar to the distinction between digitization and digitalization, IT innovation describes the use of digital technologies to supporting existing operational processes and organizational goals; digital innovation seeks to transcend traditional boundaries and introduce transformative sociotechnical changes (Baiyere et al., 2020). Tilson et al. (2010, p. 2) have described this transition as “*from digitizing the cow paths to unleashing generativity*”. Rather than replacing analog with digital technology, the generative potential of digital technology is used to create new infrastructures, business models, and capabilities. For instance, the transition from paper charts in maritime navigation to raster navigational charts (RNC) represents IT innovation, as it involves digitizing paper charts into electronic images without adding new functionalities. On the other hand, vector-based electronic navigational charts (ENC) exemplify digital innovation. They not only digitize the physical aspect of nautical charts but also incorporate dynamic features such as real-time updating, interactive route planning, and integration with other digital systems. Thus, the introduction of ENC had a transformative impact on operational navigation practices.

Hence, **digital innovation is an inherently sociotechnical, context-dependent process**. Lyytinen (2022) notes that successful digital innovation involves not only embedding of digital technology into other technological systems (both digital and physical) but also embedding it within social structures, such as cultural and institutional norms, regulations, and social habits. He emphasizes that these embedding processes occur relatively independent from each other in distinct contexts and under different logics. Each of these embedding processes presents a distinct ‘leverage point’ for further and more extensive digital innovation (Bogers et al., 2022).

Digital innovation is an **unbounded, continuous process**. Digital products are perpetually incomplete and ‘ever-in-the-making’ (Lehmann & Recker, 2022) due to the malleability of digital technology. In perpetually changing environments, this incompleteness is leveraged for generativity (Garud et al., 2008). Opportunities for new value paths may not be apparent beforehand but emerge serendipitously (Nylén & Holmström, 2019).

Given their product-agnosticism, **the purpose of digital components within a product architecture is up for interpretation**. Consequently, the distinct function, i.e., the socially agreed upon meaning (Faulkner & Runde, 2013), of the same component may vary across different settings. When actors or collectives reinterpret the fundamental function of digital components, they endow these objects with a 'technical identity' that defines "*their use, and "fit" generally within the social world*" (Faulkner & Runde, 2019, p. 1283). This 'technical identity' is invariably linked to the object's form, encompassing its technical attributes and capabilities. The intertwining of technical (i.e., form) and social (i.e., function) determines the sociotechnical character of a digital component, i.e., "*when it is assigned a meaning, namely a purpose for applying it, whereby the purpose is determined by social actors"* (Hund et al., 2021, p. 5). Consequentially, this places higher demands on developers to engage in a cognitive process of generalization and specialization (Henfridsson et al., 2014) to determine product-specific functions of product-agnostic technology (Kandaurova & Bumann, 2023; Wang et al., 2022).

Finally, the use of digital technology in innovation produces a variety of tensions (Svahn et al., 2017; Tilson et al., 2010). In particular, the hybridity of digital and physical components can lead to clashes in opposing architectural logics. Empirical studies have outlined different responses, such as resolving issues on layer with changes on another layer (Lee et al., 2020), adapting organizational structures to elevate the role of systems integrators (Hylving & Schultze, 2020), or building up integrative capabilities to reconcile such tensions (Lee & Berente, 2012).

2.1.3 Knowledge Dynamics in Digital Innovation Networks

So far, I have described how the unique characteristics of digital technologies alter the way product architectures are configured and lead to new approaches in innovation processes. These changes are particularly evident in the context of digital innovation networks, where the collaborative efforts of multiple organizations converge to create new digital products. Such collaborations typically aim for more complex innovation projects which require the combination of diverse knowledge under high uncertainty.

Traditionally, innovation has predominantly occurred within organizational boundaries, driven by a single R&D department or a few individuals (Drucker, 2002). In contrast, **digital innovation increasingly takes place across organizational boundaries** (Nambisan et al., 2017) in contexts such as open innovation (Chesbrough, 2003), innovation networks (Lyytinen et al., 2016), distributed innovation (Yoo et al., 2008), or digital ecosystems (Selander et al., 2013). What these contexts have in common is that the innovation process involves an often loosely organized and dynamic collective of actors with differing knowledge bases (Nambisan et al., 2017).

This thesis focuses on digital innovation networks, defined as collaborative arrangements among organizations to create novel products that "*are either embodied in information and communication* *technologies or enabled by them*" (Lyytinen et al., 2016, p. 49). Specifically, I examine networks with distributed control and highly heterogeneous knowledge bases, sometimes referred to as 'doubly distributed' (Yoo et al., 2008) or 'anarchic' innovation networks (Lyytinen et al., 2016). While digital innovation does not occur exclusively in such networks, the interoperability of digital technologies and lowered cost of communication infrastructure facilitates such arrangements (Altman et al., 2015; Yoo et al., 2012). These networks provide access to knowledge, resources, and technologies otherwise difficult to acquire and allow for innovation at the intersection of multiple knowledge boundaries (Sandberg et al., 2015).

Public funding initiatives are often designed to incentivize such interdisciplinary innovation networks, particularly when market mechanisms alone are insufficient to spur such collaborations (Levén et al., 2014). For instance, the EU's Horizon 2020 program has funded such projects across diverse fields like agriculture, photonics, and life sciences (European Commission, 2024). However, public funding is not a prerequisite for such networks. Non-publicly funded examples include scientific communities such as CERN (Tuertscher et al., 2014), complex project networks like the Bilbao Guggenheim museum construction (Boland et al., 2007), and industry-wide networks exploring use cases for emerging technologies like the Internet of Things (IoT) (Prince et al., 2014) or ubiquitous computing environments (Andersson et al., 2008).

IS scholars have frequently highlighted the complex dynamics in digital innovation networks with heterogeneous knowledge bases and distributed control. Nambisan et al. (2017) compare such networks to garbage-can organizations where "*problems (or needs) and solutions 'float around' waiting to be temporarily matched for action potential and capabilities orchestrated within the organization*" (p. 230). Lyytinen et al. (2016, p. 69) note that the inclusion of digital technologies in the innovation process, "*no matter how innocent the original intent of the innovation network might be, is likely to lead to fundamental and continuing reconfiguration of the innovation networks, eventually moving organizations towards anarchic forms*".

Digital innovation networks may take different approaches to technological innovation. While recombination is the core principle for innovation (Schumpeter, 1934), it can range from refining existing designs to introducing entirely new concepts that significantly depart from past practices (Freeman, 1982; Simon, 1962). Henderson & Clark (1990) outline four innovation strategies based on changes to core design concepts (components) and their linkages (interfaces) (Figure 2). These innovation strategies reflect different degrees of uncertainty because they either retain or diminish the usefulness of existing technological knowledge[3] (Sanchez & Mahoney, 1996).

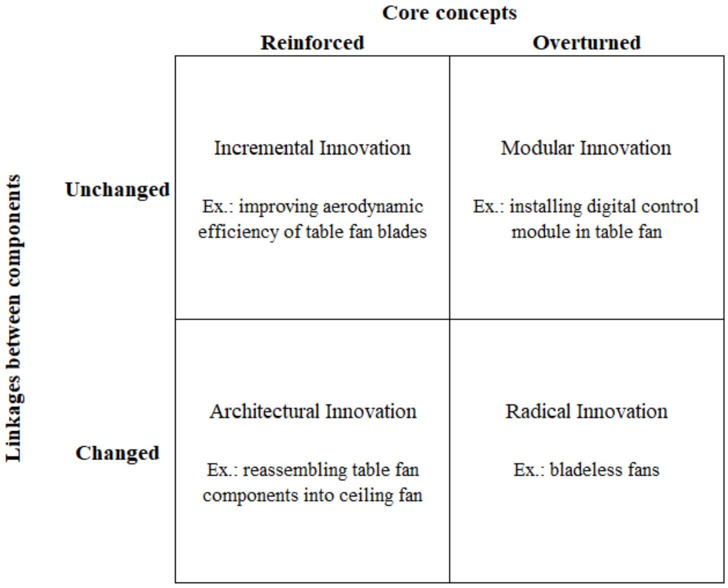

Figure 2 – Four types of innovation strategies (adapted from Henderson & Clark, 1990)

Incremental innovation refers to innovation in an existing design where core design concepts are reinforced and linkages between components are unchanged. Such innovation exploits previously uncaptured potential of established designs (Henderson & Clark, 1990). *Modular innovation* entails high changes on a component level that can be accommodated in an existing architecture while the interfaces between components remain relatively stable (ibid). Assuming that the underlying system is designed as modular and nearly decomposable, changes are largely localized and do not significantly affect the overall functioning of the system. In that case, innovators need to acquire new knowledge to understand functionalities of newly introduced components, while retaining architectural knowledge (Sanchez & Mahoney, 1996). *Architectural innovation* exhibits low changes in core concepts but high changes in interfaces. While components may undergo alterations, the underlying core concepts persist. For instance, reassembling the components of a table fan (motor, blades, control system, etc.) into a ceiling fan represents architectural innovation by creating a new product without altering the fundamental components. By changing the interactions and relationships between components, architectural innovation often reveals latent interdependencies and requires a re-evaluation of how components work together (Xie et al., 2016). *Radical innovation* involves significant changes in both

[3] This broad dichotomy between leveraging existing resources and seeking new opportunities can apply to any creative endeavor, similar for instance to the effectuation principles of 'bird in hand' and 'lemonade' (Sarasvathy, 2008). An everyday example would be a chef creating a new dish by utilizing only the ingredients available in her kitchen or exploring a food market for inspiration.

core concepts and interfaces. Radical innovation is often associated with resource heterogeneity and a lack of strict control (Carlo et al., 2012; Lyytinen et al., 2016). Radical innovation aims to introduce fundamentally new design principles (Dosi, 1982) that are characterized as unique, markedly different from existing alternatives, and novel, which makes the application of previous knowledge challenging (Bijker et al., 1987; Carlo et al., 2012). Hence, radical innovations require a heightened level of knowledge exchange among different specialists because innovation novelty reduces the potential for preemptive modularization (Mikkola, 2003) and increases the frequency of potential errors (Carlile & Rebentisch, 2003)[4].

Generally, innovation networks are more inclined to pursue architectural or radical innovation, largely due to the transaction cost dynamics associated with different types of innovation (Meissner et al., 2021). Incremental and modular innovations confined to specific components typically incur lower transaction costs for an organization managing these processes internally, compared to outsourcing or collaborating (Baldwin & Clark, 2000). This is because their established knowledge bases are sufficient to handle such minor changes. However, architectural and radical innovations require a greater variety of knowledge that may exceed the capacity of any single organization (Meissner et al., 2021). The mirror hypothesis supports this approach, suggesting that when innovation surpasses the capacity of a single organization, extending innovation efforts across organizational boundaries becomes logical. This hypothesis posits that organizational structures should parallel the technical architecture of products, indicating that collaboration across organizational boundaries might be needed for complex innovations (Colfer & Baldwin, 2016; Hao et al., 2017). However, such collaboration also introduces an additional 'tax' on transaction costs, particularly when there is a significant disparity in knowledge and high uncertainty (Meissner et al., 2021). Successful collaboration thus depends on well-designed processes that facilitate information transfer and minimize this transaction cost 'tax' (Langlois, 2006; MacDuffie, 2013).

Hence, the integration of diverse knowledge is a universal challenge in digital innovation networks. Translating varied and distributed knowledge across epistemological boundaries is inherently difficult (Dougherty, 1992; Tuertscher et al., 2014). This is compounded by the emergent nature of digital

[4]The boundaries between these types of innovation strategies are not always clear-cut, and their classification can vary depending on the hierarchical level of analysis (Murmann & Frenken, 2006). A modular innovation at one level can be seen as architectural or radical at another level. For instance, azimuth propulsion technology on ships is a modular innovation within the ship’s architecture but a radical innovation at the component level due to its departure from traditional propeller designs. Ultimately, the question regarding when incremental changes in components constitute a fundamentally different system becomes a philosophical one that cannot be easily answered, as illustrated by the parable of the Ship of Theseus (Chomsky, 2009). Nonetheless, these categories of innovation strategies are still useful in providing a theoretical lens to describe different approaches to technological innovation by different degrees of exploration and exploitation of technology components and/or interfaces.

innovation, as it is difficult to know what type of knowledge and interactions will be most relevant *a priori* (Yoo et al., 2010). To understand how diverse knowledge bases can be leveraged to collaboratively create innovative digital products, I turn to the concept of architectural knowledge.

2.2 Architectural Knowledge in Technological Innovation

2.2.1 What is Architectural Knowledge?

Knowledge is a key driver for innovation. The literature on the Knowledge-Based View (KBV) of organizations is diverse but generally 1) shares a common focus on internal and inter-organizational processes and acknowledges that 2) value is generated from things an organization can do (such as routines, capabilities, and competencies) that are difficult to replicate, and 3) such things emerge from the collective knowledge of individuals spread within or across organizations, which needs to be effectively combined and reconfigured in various ways (Grant, 1996; Kogut & Zander, 1992; Teece et al., 1997; Zahra et al., 2020).

Organizational scholars have proposed a variety of classifications of knowledge. One common distinction is between *tacit* and *explicit knowledge*, where tacit knowledge is personal, context-specific, and difficult to articulate, whereas explicit knowledge is easily shared and documented, encompassing facts and concepts (Nonaka, 1994). Knowledge can also be categorized based on its locus as *individual knowledge* possessed by single members of an organization, and *collective* knowledge, which transcends individual members and is embedded in an organization's practices and norms (Grant, 1996). Other distinctions include *declarative knowledge* ("know-what,") versus *procedural knowledge* ("know-how") (J. R. Anderson, 1983; Kogut & Zander, 1992); *core knowledge* ("that is at the heart of, and forms the foundation for, a particular service") versus *integrative knowledge* ("knowledge of how to integrate, different activities, capabilities, and products") (Helfat & Raubitschek, 2000, p. 963); *relational knowledge* ("know-with", or understanding the connections and relationships between different entities) (Alavi & Leidner, 2001; Halford et al., 2010); or *strategic knowledge* ("used by an agent to decide what action to perform next, where actions have consequences external to the agent") (Gruber, 1989, p. 5).

In the context of technological innovation, and central to this thesis, Henderson & Clark (1990) coined the terms of **architectural knowledge and component knowledge**. Architectural knowledge refers to knowledge about how components are integrated and function together as a whole. Component knowledge refers to knowledge about core design concepts, and how they are implemented in a particular component (Henderson & Clark, 1990). Both architectural and component knowledge include declarative and procedural forms of knowledge. Component knowledge tends to be explicit and readily codifiable, for instance through technical specifications (Matusik & Hill, 1998).

In contrast, architectural knowledge is tacit in nature and represents a deeper, less easily articulated understanding of system integration. Within organizations, it is **distributed** as it spans across organizational units and is collectively maintained due to its wide scope. Typically, no single person has a complete grasp of all architectural knowledge, making it difficult to codify (Henderson & Clark, 1990). An organization's distinct history shapes its architectural knowledge through a path-dependent, endogenous process influenced by specific events (Tallman et al., 2004). Consequently, architectural knowledge is unique to each firm, embodying organization-wide, tacitly understood, and privately held insights. Thus, "*no two firms have the same architectural knowledge*" (Matusik & Hill, 1998, p. 698).

Furthermore, architectural knowledge is inherently incomplete. Given the impracticality of achieving a fully decomposable architecture where components operate without any mutual dependencies, latent interdependencies, i.e. component interactions that are not fully known, inevitably exist (Sanchez & Mahoney, 1996). Product development organizations can only be familiar with a portion of the component interactions crucial to the behavior of the system in development. Thus, architectural knowledge is always only 'relatively complete' in relation to an organization's current technological architecture and evolves as technology advances, component-level changes occur, and organizational goals shift (Leo, 2020). For instance, incorporating a new, heavier engine component into a car could uncover latent interdependencies, such as added stress on the suspension system or altered aerodynamics affecting fuel efficiency. This might require subsequent adjustments to the braking system or the chassis design to maintain performance.

Architectural knowledge becomes particularly important when organizations engage in complex innovation endeavors, such as architectural or radical innovation (Sanchez & Mahoney, 1996; Xie et al., 2016). In such cases, innovators need to determine new or reevaluate existing connections and interdependencies between components (Baldwin & Clark, 2000). This can be illustrated with the reconfiguration of a table fan into a ceiling fan as an example of architectural innovation. In a table fan, core components like the motor and blades are designed for stability and airflow in a specific direction. While these components are fundamentally the same in a ceiling fan, innovators need to reassess how they can interact to provide hanging support and broad air distribution. Such architectural innovation involves understanding new interdependencies (Henderson & Clark, 1990), such as airflow dynamics and structural stability. Thus, technological innovation that goes beyond component-level changes reduces the usefulness of existing architectural knowledge and requires innovators to make explicit previously implicit knowledge (Baldwin & Clark, 2000).

The concepts of component knowledge and architectural knowledge provide a simple yet powerful language to describe knowledge about both the parts and the whole of a technological system (Wang, 2021). As a result, the concept of architectural knowledge has been used across numerous studies to describe knowledge management regarding modular systems (s. Table 3). **Two limitations can be identified in the extant literature in relation to the objective of this thesis.**

First**, extant literature has focused predominantly on architectural knowledge within firms** rather than interorganizational networks (s. Table 3). This distinction is important as these two settings not only differ in context but also in the role of architectural knowledge. For a firm, a key challenge is *maintaining* and renewing architectural knowledge as a source of competitive advantage (Henderson & Clark, 1990; Matusik & Hill, 1998). Over time, organizations develop structures and information channels that mirror the structure of the product(s) they are designing. If these structures are overly rigid, architectural knowledge decays and organizations risk falling into the 'mirroring trap' (Cabigiosu & Camuffo, 2012; Tuna et al., 2018). For instance, if component development teams in a car manufacturer do not continuously share knowledge about their respective components, firm-wide architectural knowledge decays, reducing the firm's ability to innovate. In contrast, if multiple organizations collaborate in innovation networks, they need to *generate* shared architectural knowledge to ensure effective coordination (Andersson et al., 2008). Especially for first-time collaborations and in the early innovation stages, network actors will face high uncertainty on how different components can function together (Grant & Baden-Fuller, 2004). Therefore, such collaborations require shared information structures that help actors align their diverse interests by providing a clear model of the innovation (Bittner & Leimeister, 2014). Such a structure presents not only a clear technical description of the envisioned innovation but also helps align diverse interests and enables coordination as individual actors can decide whether, when, and how to act based on the information about other actors and components (Wang, 2021). For instance, Mikkola (2003) describes the first-time collaboration between Chrysler Jeep and an OEM tasked with developing a new windshield wiper controller. Despite having predetermined interface specifications for all components, Chrysler and the OEM lacked knowledge of how the components would function as an integrated system within the car. The initial development failed, with the wiper even catching fire under certain conditions. Success was only achieved after intensifying information exchange between the parties and making explicit the previously implicit knowledge about latent interdependencies.

A second limitation in extant literature on architectural knowledge is the conceptual rooting in, and subsequent focus on, physical product innovation. For instance, Baldwin & Clark (2006) describe architectural knowledge as knowledge about 1) the mapping of functions to components, 2) the interfaces between components, and 3) intended and unintended behavior of the system. This implies that the function of a component is narrowly defined and constrained by the nested and fixed arrangement in an inclusionary hierarchy (Clark, 1985; Ulrich, 1995). This assumption is problematic because, as noted in 2.1.1, the architectural configuration for physical products differs from digital products, for instance in the separation between function and form (Yoo et al., 2010). And while the concept of architectural knowledge has been applied in some digital innovation studies (Attour & Peruta, 2016; Kindermann et al., 2022; Wang, 2021), none have specifically explored if and how digital materiality challenges existing notions of the architectural knowledge concept.

A noteworthy attempt to **understand architectural knowledge better in inter-organizational IT innovation** was made by Andersson et al. (2008). They explicitly acknowledge the bottom-up generation of architectural knowledge as a result of combining diverse component knowledge (Figure 3). They suggest that architectural knowledge encompasses three dimensions: *technology capability* *awareness* (perception of the capabilities and limitations of a specific digital component), *use context sensitivity* (understanding of work contexts in which a digital component shall be deployed), and *business model understanding* (understanding of opportunities for value creation afforded by applications of a digital component). This classification helps clarify the types of knowledge that digital innovation networks might initially lack. However, this categorization is broad enough to be relevant to both digital and non-digital innovation contexts and does not fully address the unique characteristics of digital materiality. Moreover, beyond noting that network members need 'boundary-spanning competencies' (cf. Attour & Peruta, 2016) and the importance of instantiations like IT standards, Andersson et al. (2008) provide limited guidance on the dynamics that generate architectural knowledge. This leaves a gap in understanding how architectural knowledge should be understood in the context of digital innovation and how it is generated in innovation networks.

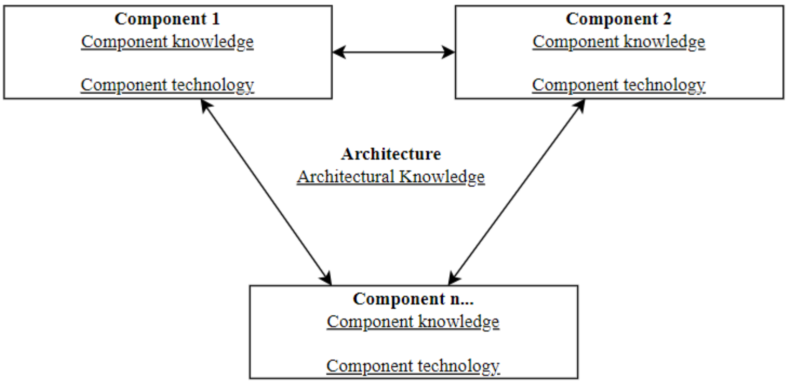

Figure 3 – Theoretical model of architectural knowledge in inter-organizational digital innovation (adapted from Andersson et al. (2008))

2.2.2 Combinative Capabilities for Generating Architectural Knowledge

As noted above, architectural knowledge in innovation networks must be generated *in novo* rather than maintained as in a single firm. How can organizations in innovation networks then create architectural knowledge that guides their collaborative actions to create a novel technological architecture? Two possible approaches can be identified from extant literature.

First, organizations may draw on existing architectural designs. As technologies mature, dominant designs emerge that encompass a set of design rules that guide innovators. For instance, Garud & Rappa (1994) find in their study on the technological evolution of cochlear implants that emerging dominant designs helped establish technical guidelines that set benchmarks for what features were essential. Existing architectural designs can also be understood more broadly in the form of technical industry standards (Andersson et al., 2008). For example, the standard NMEA 0183 defines standardized data exchange between marine electronic devices.

Second, literature on systems integration has suggested that a central actor may specify architectural guidelines that guide other actors. Such a system integrator 'knows more than they make', as their competencies extend their operational boundaries (Brusoni et al., 2001). For instance, manufacturers of technologically complex systems like Boeing or Volvo are engaged in large supply chains involving a variety of organizations and associated knowledge bases. To coordinate supplier actions, system integrators prescribe design rules. Similar dynamics exist in digital platform ecosystems where platform providers design technical boundary resources, like APIs or SDKs, to guide third-party developers in their periphery (Gawer, 2021; Skog et al., 2021).

However, **neither of these two approaches is feasible** when the envisioned architecture is particularly novel and there is little extant architectural knowledge to draw on (Tuertscher et al., 2014). In such scenarios, the process of defining component configurations and their interconnections becomes highly speculative, with each component choice potentially influencing the feasible arrangements of others in unpredictable ways (Ethiraj & Levinthal, 2004). Additionally, when the innovation involves diverse knowledge bases, there may be no single actor who can possess a holistic understanding of all components and their interactions. **This is further complicated by the implications of digital technology on innovation processes.** As noted above, a layered modular architecture differs from inclusionary hierarchies in various ways, for instance in the product-agnostic nature of its components and their contingently obligatory coupling across layers (Hylving & Schultze, 2020; Yoo et al., 2010). In contrast to inclusionary hierarchies that require detailed knowledge of the entire product design and the modular interfaces between components (Baldwin & Clark, 2006), such *a priori* function-component mapping is difficult in digital innovation (Henfridsson et al., 2014).

Therefore, digital innovation networks require capabilities that allow their members to dynamically integrate their component knowledge to generate shared architectural knowledge. Kogut & Zander (1992) introduced the concept of *combinative capabilities*, abilities that allow organizations "*to synthesize and apply current and acquired knowledge*" (p. 384). According to them, knowledge creation is not separable from an organization's (or network's) "*current abilities. Rather, new learning, such as innovations, are products of a firm's combinative capabilities to generate new applications from existing knowledge. By combinative capabilities, we mean the intersection of the capability of the firm to exploit its knowledge and the unexplored potential of the technology*" (p.391). Combinative capabilities are impacted by an organization's (or network's) higher-order organizing principles that are expressions of how activities are organized. The result of combinative capabilities is cumulative knowledge on a higher order of hierarchy (e.g., from individual to group-level) that provides new opportunities for value creation. In that sense, **combinative capabilities can be understood as**

organizational abilities for knowledge combination, instantiated through processes[5]. For instance, Koruna (2004), confusingly using resource combination as synonymous with knowledge combination, write "*combinative capabilities can be defined as a firm's ability to make efficient use of its resources by combining internal resources or internal and external resources to create new resource combinations that are rare, valuable, hardly imitable and non-substitutable*." Hence, leveraging modularity to create new product variations is an expression of combinative capabilities.

The concept of combinative capabilities has been criticized for its broad scope. For instance, Koruna (2004) notes that "*Kogut and Zander never went beyond defining what their understanding of combinative capabilities is and only stressed their importance*" (p. 541). **De Boer et al. (1999) further specify three types of combinative capabilities: systems, coordination, and socialization capabilities**. They note that "*a firm developing new architectural knowledge can use these three capabilities to integrate component knowledge located within its own organization*" (De Boer et al., 1999, p. 385)

System capabilities encompass structured processes, guidelines, and instructions that facilitate the integration of explicit knowledge (De Boer et al., 1999). Van den Bosch et al. (1999) define system capabilities as the extent to which actions are pre-programmed before their implementation, indicating that these capabilities are standardized, explicit, and modifiable by management. This includes designing organizational structures and linkages between actors to align with strategic objectives and allow for the exchange of explicit knowledge via formal communication channels, such as written documents, IT systems, and guidelines. According to Van den Bosch et al. (1999), the primary advantage of system capabilities lies in their ability to reduce the need for further communication among different organizational actors. Galbraith (1973) suggests that enhanced system capabilities reduce the necessity for collaborative decision-making since many responses are predetermined.

Coordination capabilities refer to coordination of knowledge flow, increasing the exchange and integration of knowledge across actors and different levels of hierarchy (Henderson & Cockburn, 1994). These capabilities are path-dependent as they evolve over time, and are cultivated through methods such as cross-functional collaboration or inclusive decision-making practices (Jansen et al., 2005; Van Den Bosch et al., 1999). For instance, Baldwin & Clark (2006) note that "architects can experiment with putting the system together in different ways, in each case measuring how its performance changes.

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[5] Knowledge and capabilities are broad concepts and thus, researchers have conceptualized their relationship in various ways to describe different phenomena. While combinative capabilities specifically can be understood as organizational abilities *to combine* knowledge, other capability-related concepts see knowledge combination as *antecedent* or *moderator* for capabilities. For instance, Teece (2007), Karabag & Berggren (2017), and Grant (1996) describe knowledge combination as a requirement to develop 'dynamic', 'innovation', or 'organizational' capabilities respectively; Zahra & George (2000) describe knowledge integration as moderating effect between organizational performance and absorptive capacity.

They can also study the system under different conditions and meter its internal operation to see what levels of activity or stress arise at different junctures" (p. 5). These methods may be pre-designed or emerge organically through interaction.

Socialization capabilities refer to the capacity of organizations to cultivate a common ideology that provides their members with a sense of identity and helps in interpreting shared realities (van den Bosch et al., 1999). When well-developed, these capabilities enable members to align around a cohesive set of beliefs, shared values, and commonly accepted norms for behavior within organizations. As a result, socialization capabilities tend to be more pronounced in organizations characterized by a strong sense of identity. Such organizations benefit from a clear understanding of each member's strengths in specific tasks, minimizing the need for individuals to seek out task-relevant information and reducing unnecessary duplication of knowledge across the organization. However, overly strong organizational cultures may also act as cognitive constraints that limit the ability to recognize and adapt to significant external changes.

Combinative capabilities should align with an innovation network's innovation strategy. Leo (2020) notes that, given the inherent incompleteness of architectural knowledge, any innovation calls for organizations to be ambidextrous in both exploiting extant and exploring new architectural knowledge. The extents of exploration and exploitation however depend on the pre-specification of technological components that should serve as building blocks. In architectural innovation, there is more certainty about existing components and thus component knowledge, whereas in radical innovation, core design concepts may be defined only loosely, and various component technologies may be considered to fulfill that role. For instance, wind sails, kites, or Flettner rotors on modern cargo ships are all different component technologies developed to pursue the radical design concept of using wind power to augment traditional propulsion systems (Atkinson et al., 2018). In radical innovation, network members still possess unique domain knowledge, but it may be leveraged for a larger variety of potential components. For instance, a museum curator may not have much technical expertise, but he possesses unique knowledge on, e.g., how art data is recorded and on what digital platforms it is publicly available.

I synthesize the above literature in a conceptual framework (Figure 4, Table 2) to clarify the relationships between component knowledge, architectural knowledge, innovation networks and strategies, and combinative capabilities. In this model, component knowledge provides the foundational knowledge resources, combinative capabilities act as the process through which these resources are recombined, and architectural knowledge represents the holistic understanding of the technical system that emerges from this process.

While this framework reflects a rich body of literature on product innovation and knowledge management, its theoretical categories were established prior to the ubiquity of digital technology and its impact on innovation management practices. Consequently, the ways in which digital technologies sustain and change the underlying principles of architectural knowledge and combinative capabilities are still not fully examined. In an extensive review of digital innovation literature, Hund et al. (2021) contend that "*while the concept of recombining digital and physical components is central to digital innovation research, the recombination of organizations' most important asset, knowledge, has so far been neglected in digital innovation research, even though it has been repeatedly emphasized across disciplines as essential for innovation*" (p. 14).

Therefore, I explore:

RQ1: How should architectural knowledge in the context of digital innovation be defined given the malleability of digital components?

RQ2: how is such architectural knowledge generated in digital innovation networks with different innovation strategies?

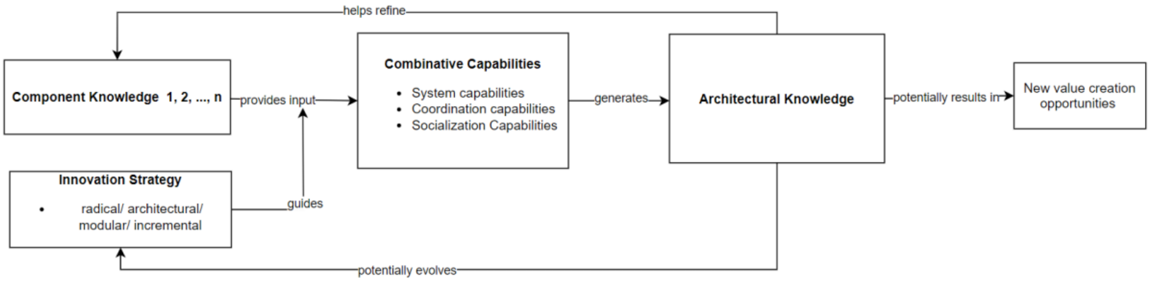

Figure 4 – Generating architectural knowledge in digital innovation networks

Table 2 – Overview of concepts in Figure 4

Concept	**Description**
Component knowledge	Understanding of specific components that serve as potential building blocks for a new technological system or product. This knowledge includes the functionalities, operations, and characteristics of individual parts. It is held by different members of the innovation network. It can differ in specialization, in that it can be tied to a specific, proprietary technology or to general domain knowledge. For instance, a SKF engineer has detailed component knowledge about SKF's patented ball bearings, and a marine biologist has a broad understanding of marine technologies like ocean sensors or public databases. The component knowledge bases serve as elemental input for technological innovation.
Combinative capabilities	A network's ability to synthesize, combine and apply existing component knowledge in novel ways. Combinative capabilities encompass systems, coordination, and socialization capabilities that are instantiated through various procedures, processes, or cultural and informal elements in the network.
Innovation network strategy	Describes the approach an innovation network pursues to technological innovation by differing degrees in changing components and/or interfaces, categorized by radical, architectural, modular, and incremental innovation (Henderson & Clark, 1990). Innovation network strategies guide how combinative capabilities are applied.
Architectural Knowledge	The outcome of effectively applying combinative capabilities is enhanced architectural knowledge of how various components interact with each other and how they are integrated to function as a cohesive system. Architectural knowledge includes the overall structure, design principles, and the relationships between different parts of the system. Given the inherent incompleteness of architectural knowledge, the generation process is continuous. New architectural knowledge helps refine component knowledge, for instance when new component requirements emerge, and potentially evolves the innovation network, for instance when the innovation strategy shifts from radical to architectural because selection of core components becomes more defined.
New value creation opportunities	New opportunities for value creation, such as new business models or improved operational processes, result from the exploitation of architectural knowledge. For instance, Boland et al. (2007) describe how architectural knowledge generated during an interorganizational construction project led to several secondary value opportunities, e.g., in the form of new techniques for fire safety or steel processing.

Table 3 – Overview of architectural knowledge in organization studies and information systems literature

Source	**Empirical context and method**	**View of architectural knowledge**	**Management of architectural knowledge**
(Henderson & Clark, 1990)	Conceptual, with illustrations from photolithographic alignment equipment manufacturers	"knowledge about the ways in which the components are integrated and linked together into a coherent whole" (p. 11)	Architectural knowledge is accumulated through experience and is not always explicitly documented, making it difficult to recognize and creating potential blind spots to see opportunities or threats from architectural changes
(Sanchez & Mahoney, 1996)	Manufacturing firms (conceptual)	Knowledge of how components function and interact in a product	Embedded coordination of system development through pre-defined, stable interfaces reduces need for top-down management
(Andersson et al., 2008)	IT innovation network for road transportation (single case)	Knowledge of "the integration and linkages between each of the components" (p. 22), resulting from of integrating diverse components and associated knowledge	Architectural knowledge generation facilitated by boundary-spanning competence and IT standards
(Mikkola, 2003)	OEM – supplier network in automotive (single case)	System-level knowledge that requires integrating diverse knowledge bases	Modularization facilitates component outsourcing but requires close & frequent communication channels to enable shared understanding of interface requirements
(Lyytinen et al., 2016)	Digital innovation networks (conceptual)	Digital innovation networks involve diverse knowledge bases that "become assembled through the interaction of diverse actors into new knowledge combinations of resources" (p. 50)	Knowledge translation and social dynamics in digital innovation networks become more non-linear due to higher knowledge diversity and decentralization of control
(Tuertscher et al., 2014)	Interdisciplinary network for building CERN particle detector (single case)	Architectural knowledge for emerging, complex technologies requires knowledge integration across epistemic communities and is challenging	Technological novelty and knowledge diversity complicate nominating a single systems integrator; boundary infrastructure, i.e., a variety of shared assets, helps to make knowledge transparent and accessible and enables to pockets of shared knowledge across diverse knowledge communities that allow practical decomposition of system architecture
(Tuna et al., 2018)	Pharmaceutical firm (single case)	Architectural knowledge decays when organizational and technological structures are aligned too rigidly	Interdependent generation of component knowledge and architectural knowledge facilitated through learning-before-doing, learning-by-doing, integration decisions, and partial mirroring of organizational and technological structures
(Brusoni et al., 2001)	Aircraft industry (single case)	Architectural knowledge needed to coordinate loosely coupled networks of component suppliers	Organizations acting as system integrators maintain in-house capabilities to generate design knowledge and related capabilities for a broader set of components than those they immediately design and produce
(Lee & Berente, 2012; Lee & Veloso, 2008)	Automotive industry (patent analysis)	Distribution of architectural knowledge and component knowledge in supply chains reflect division of labor	Higher uncertainty in product development due to introduction of digital components leads to broader distribution of architectural knowledge in supply chain networks
(Henfridsson et al., 2014)	Automotive firm (single case)	Architectures can be understood as aggregation of decomposed components or as network of loosely coupled solution patterns	Digital innovation benefits from cognitive 'network-of-patterns' frames to facilitate design flexibility and generalization-specialization
(Wang, 2021)	Digital innovation ecosystems (conceptual)	Layers of layered modular architecture stretches across multiple levels of operation, ranging from organizations, industries, to sociotechnical landscapes	Innovation ecosystems need a collective structure (e.g., value proposition, organizing vision, product architecture) that represents the part-whole relations of individual actors with other actors and the overarching ecosystem
(Puranam et al., 2012)	Organizations (conceptual)	"Designers' knowledge of how to divide, allocate, and measure tasks" (p. 420)	Organizational ties between network members are required for epistemic interdependence, i.e., communication in near-real-time between network members,

			for when one member needs to predict another member's actions to choose their own best course of action; predictive knowledge thus can substitute architectural knowledge
(MacDuffie, 2013)	Global automotive manufacturing industry (conceptual)	Modularity facilitates component outsourcing but requires firms to maintain architectural knowledge	Architectural knowledge is generated through learning and mastering potential interdependencies across modules by creating 'thin crossing places' at module boundaries
(Baldwin & Clark, 2000)	Conceptual, with illustrations of semiconductor industry	Modularity facilitates partitioning knowledge across different parts of an organization or system	Knowledge sharing is facilitated by interdependent testing on system- and module-levels, experimentation, well-defined interfaces
(Azzam et al., 2020)	UK manufacturing industry (survey)	Architectural knowledge is the source of a firm's capability to develop new products in the form of architectural innovation	Drawing on Nonaka (1994), architectural knowledge generated by socialization (create environments encouraging individuals to share tacit knowledge); externalization (convert tacit into explicit knowledge); combination (aggregate new explicit knowledge with existing knowledge); internalization (embed technical know-how into mental models)
(Baldwin & Clark, 2006)	Conceptual, with illustrations from computer manufacturers	Source of firm's competitive advantage by modularizing systems and outsourcing component-level activities	Identification of bottlenecks between components in complex system architecture
(Zhang et al., 2023)	Chinese firms (survey)	Modular and architectural knowledge search as distinct strategies for radical innovation	Architectural knowledge search enhanced by emphasis on understanding customer needs and creating customer value
(Leo, 2020)	Conceptual	Architectural knowledge as requirement to enable intra-firm product & organizational modularity (mirroring)	Architectural knowledge is inherently and continuously incomplete, enabled by cumulative prior experience, dominant designs, communication across component developers,
(Oshri et al., 2019)	IT procurement of European firms (survey)	Architectural knowledge as capacity to coordinate procurement of interdependent IT from diverse vendors	Architectural knowledge enabled by single IT vendor acting as system integrator
(Autio et al., 2018)	Entrepreneurial ecosystems (conceptual)	Architectural knowledge more difficult to transfer in ecosystems than component knowledge	Cross-industry architectural knowledge in entrepreneurial ecosystems enabled by spatial proximity, e.g., coworking spaces, makerspaces, etc.
(Matusik & Hill, 1998)	Firms (conceptual)	Architectural knowledge is a source of competitive advantage; is inherently tacit and collective	Firms should use their absorptive capacity to enhance their architectural knowledge by using contractors, but must prevent knowledge leaks to maintain competitive advantage
(Yayavaram, 2008)	US firms (patent analysis)	Architectural knowledge is an enabler for firms' search for technological innovation	By reconfiguring existing knowledge, "a firm can 1) change the way it recombines existing knowledge components and 2) integrate new knowledge components with existing components" (p. 2)
(Yayavaram et al., 2018)	US semiconductor manufacturers (patent analysis)	Search for new architectural knowledge is a motivating factor for creating firm alliances	"The likelihood of alliance formation increases when two firms are similar in domain knowledge and dissimilar in architectural knowledge" (p. 2277)
(Tallman et al., 2004)	Regional clusters (Conceptual)	Architectural knowledge guides relationships amongst firms in regional clusters and develops over time through interactions	Cluster-level architectural knowledge increases firms' absorptive capacity for component knowledge and increases collective competitive advantage by preventing component knowledge flow across cluster boundaries
(Attour & Peruta, 2016)	Digital business ecosystem (single case)	Architectural knowledge as prerequisite to coordinate integration of components from diverse actors in digital business ecosystem	Actors with boundary-spanning competence facilitate architectural knowledge generation by acting as systems integrator
(Asmussen et al., 2016)	Manufacturing firms (simulation model)	Architectural knowledge needed to coordinate offshoring manufacturing activities	Firms must complement architectural knowledge with contextual knowledge of local markets to successfully relocate business processes to other countries

(Currie & White, 2012)	Teams in medical unit (single case)	Operational performance by multidisciplinary teams requires architectural knowledge as integration of diverse component knowledge	Architectural knowledge in diverse teams enabled by knowledge brokering, i.e., linking professional practices, enacted by team members with high legitimacy
(Finn & Waring, 2006)	Teams in medical unit (multiple cases)	Architectural knowledge encompasses knowledge about interdependent organizational structures	External disruptions to team composition and procedures hinders effective accumulation of architectural knowledge
(Barbaroux, 2011)	NATO task force (single case)	Architectural knowledge is interdependent with organizational structures and information linkages between functional units	Decentralized information flows as part of digital transformation in hierarchical organizations requires distributing architectural knowledge
(Jaspers & Ende, 2010)	Firms (conceptual)	Architectural knowledge for complex products is scarce and difficult to generate and maintain in-house	Open innovation and systems integration helps acquire external knowledge and translate it into architectural knowledge
(Grunwald & Kieser, 2007)	SAP strategic alliances for product innovation (multiple cases)	Goal of product innovation alliances is often to generate new knowledge, not to acquire each other's knowledge	Create efficient learning routines that focus on collaboratively creating new knowledge building on complementarities of existing knowledge
(De Boer et al., 1999)	Firms in multimedia ecosystem (multiple cases)	Architectural knowledge is the reconfiguration and integration of existing component knowledge	Firm's combinative capabilities and organizational form should align to successfully reconfigure component knowledge
(Kindermann et al., 2022)	Digital innovation ecosystems (conceptual)	Architectural knowledge in digital innovation ecosystems distributed and involves heterogeneous knowledge bases	Creation of architectural knowledge is dispersed among various actors; deployment of digital platforms that integrate various subsystems to codify architectural knowledge in a "single source of truth" facilitates coordination

3 METHOD

As the specific methodological approaches used in my studies are detailed in the appended papers, my objective in this section is to offer an overview of the methodological decisions I have made and their influence on my research trajectory. I start with a discussion of my rationale for selecting interpretive, longitudinal case studies as a tool for scientific inquiry. Next, I describe the methodology employed for data collection and analysis. I close with a reflection on the role of my research regarding broader societal challenges.

3.1 Research Design

I have chosen a qualitative approach for this thesis, using exploratory research questions and data collection through interviews, observations and archival documents, to develop theoretical perspectives (Flick, 2009). Unlike quantitative research that relies on numerical data and the development of theoretical constructs from the interpretation of these numbers to understand phenomena (cf. Bryman & Bell, 2011), qualitative research allows researchers to "*explore a wide array of dimensions of the social world, including the texture and weave of everyday life, the understandings, experiences and imaginings of our research participants, the ways that social processes, institutions, discourses or relationships work, and the significance of the meanings that they generate*." (Mason, 2002, p. 1).

All appended papers are based on one of two longitudinal, single-case studies of digital innovation networks. A single-case study is considered appropriate for exploratory research where little theory exists and current perspectives seem inadequate due to a lack of empirical evidence (Eisenhardt, 1989). Typically, case study research involves combining different methods of data collection like observations, interviews and archival data (Maxwell, 2013). Focusing on single cases in contrast to multiple cases has allowed me to gain rich and in-depth insights relevant for the aim of the thesis, and uncover the complexity related to the phenomenon. The longitudinal character of the studies has allowed me to track changes and compare intentions with outcomes in the process (van de Ven & Poole, 1995).

To investigate knowledge dynamics in digital innovation networks, I have taken an *interpretive stance* (Walsham, 2006). An interpretive stance in IS research aims to produce "*an understanding of the context of the information system, and the process whereby the information system influences and is influenced by the context*" (Walsham 1993, p. 4). It assumes that IS-related phenomena can be understood through accessing the subjective and intersubjective meanings that actors assign to them (Orlikowski & Baroudi, 1992). This contrasts with case studies adopting positivist or critical perspectives (Klein & Myers, 1999; Orlikowski & Baroudi, 1992). IS research is deemed positivist when it involves formal propositions, measurable variables, hypothesis testing, and extrapolation of findings from a sample to a broader population. IS research is considered critical when its primary goal is to conduct social critique, highlighting and challenging the restrictive and oppressive aspects of the current conditions. Critical research is emancipatory in that it aims to dismantle the causes of unnecessary alienation and control to better enable the fulfillment of human potential. Critical theorists believe in the capacity of individuals to actively change their socio-economic circumstances but acknowledge that this capacity is often limited by social, cultural, and political constraints, as well as by natural laws and resource scarcity (Klein & Myers, 1999). An interpretive approach is suitable for this thesis because it allows for investigating digital innovation as a result of actors creating path-dependent, subjective, and context-dependent architectural knowledge. Taking an interpretive stance has influenced how I have conducted my studies and come to generalize from the findings.

First, I aimed to understand phenomena "by iterating between considering the interdependent meaning of parts and the whole that they form" (Klein and Myers, 1999, p. 72). That is, I iterated between specific events, developer actions and interactions, and micro-processes, and the broader context of the innovation network and its organizational and design goals to understand the phenomenon of collaborative digital innovation. This empirical understanding was the input for the theorizing process where various theoretical concepts from organizational studies and IS literature served as overarching analytical lenses to make sense of these observations.

Second, I aimed to include the institutional and historical contexts that influenced the research settings (Klein & Myers, 1999). Considering the role of context helps understand boundary conditions and why processes unfold in specific ways (Pettigrew, 1990) and enhances generalizability and usefulness of research results (Davison & Martinsons, 2016). Neither of the studied innovation networks were created in a vacuum, but rather are part of broader digitalization trends in marine ecology and maritime transportation. This helped, for instance, understand how decisions in OceanAI to focus on open data was influenced by institutional pushes to promote such data, or how Neptune's implementation of predictor-sharing functionalities built on prior EU projects to promote ship-ship information exchange (cf. Lind et al., 2021). In the appended papers, I have strived to provide thick descriptions of the research settings to give the reader an understanding of these contexts.

Third, I aimed to critically reflect on how data from (non-)participant observation and interviews were "socially constructed through interaction between researchers and participants" (Klein & Myers, 1999, p. 72). The extended periods of observation enabled me to establish strong relationships with most network participants. Additionally, my active participation in OceanAI and my professional proximity to Neptune's context presented me with unique perspectives as a researcher. Interviewees' accounts are unavoidably shaped by their interactions with me, influenced by my presence and engagement. Navigating these dynamics presents a universal challenge in qualitative research, and this research is no exception. To mitigate potential biases and clarify my positionality, I aimed to present myself as a neutral observer during interviews, distancing my identity from that of a network member or nautical officer, to foster a more authentic understanding. Nonetheless, it is plausible that my relation to the networks have spurred inter-subjective understandings that differ from conventional interpretations of such innovation networks.

Fourth, I aimed to be aware of the possibility of multiple interpretations among members in the studied networks (Klein & Myers, 1999). Even when individuals participate in the same events, they may perceive and interpret these events differently. This was particularly salient in interviewee accounts of OceanAI, as it involved members with differing expectations, technological frames, and motivations. Hence, I strived to investigate the reason for potential incongruences and acknowledged them in both empirical descriptions and analysis of the papers. The conceptual framing in paper 3 of a tension between the need for ambiguity and innovation boundaries is partially derived from this investigation.

Fifth, I aimed to relate ideographic details, i.e., the specific, detailed elements that make up the unique characteristics of my cases, to general theoretical concepts, or what Myers & Klein (1999) describe as principle of abstraction and generalization. An interpretive research approach emphasizes the use of theory as sensitizing device to view the world in a certain way, rather than something to be tested in a direct manner as suggested in positivist research (Yin, 2018). However, it is still important to relate theory and empirical observations to enable readers to grasp the logic behind the derived insights. Walsham notes that the validity of generalizations depends on the *"plausibility and cogency of the logical reasoning used in analyzing results from the case and drawing conclusions from it"* (p.75)." I have strived to include such generalizations in this cover paper and all appended papers, although assessing the "plausibility and cogency" ultimately rests with the reader.

3.2 Research Settings

In this section, I describe the two research settings and sampling logic.

3.2.1 Neptune

Paper 2 & 4: Neptune was a digital innovation network formed to develop a novel, AI-based decision-support system for maritime navigation. Neptune was comprised of five Northern European organizations from multiple industries and research institutes, including telecommunication, global navigation satellite system (GNSS) technology, metrology, maritime electronics, and data science. Active from early 2020 to mid-2022, Neptune received approximately €3m in public funding, allocated by its funding agency to foster innovative GNSS applications. The project's structure drew inspiration from similar interorganizational efforts within the maritime and automotive industries but marked a first-time collaboration for the majority of Neptune's members. Neptune's innovation strategy can be characterized as architectural innovation, with each member organization contributing specialized component technology previously developed outside the Neptune project. These components were then integrated into a novel system architecture intended to enhance maritime navigation decision-making processes.

I joined Neptune as non-participant observer in autumn of 2020 following an unsolicited inquiry to one of the network's members. I included Neptune as a second case for two reasons. First, I aimed to establish a comparative case study to enrich my research. At the time, I had already gained valuable insights from my engagement in OceanAI and wanted to study another innovation network with similar organizational arrangements but different objectives to compare and contrast my existing findings. Second, I was particularly interested in digital innovation in a maritime context due to my background as a navigational officer and my experience of the industry's shift towards digitalization following the 2012 grounding of Costa Concordia. During my time at sea, I witnessed the implementation of various new digital navigation aids to enhance the monitoring capabilities of shore-based teams and onboard situational awareness, such as cross-departmental dashboards or digital logbooks. Given that Neptune's decision-support system was designed for navigational officers, I was curious to explore the developmental dynamics and combine my professional knowledge as IS researcher and navigator.

3.2.2 OceanAI

Paper 3 and 1: OceanAI is a digital innovation network formed in 2019 with a broad focus on driving digital innovation in the blue economy. Similar to Neptune, OceanAI was funded by a funding agency as part of national initiative to drive AI innovation in various industries. At its launch, OceanAI included 21 organizations spanning public, private, and research sectors with diverse expertise in marine biology, data science, maritime transportation, and information systems (IS) research. Throughout my study, active participation varied, with 8-12 members regularly engaged. OceanAI’s innovation strategy can be characterized as radical innovation, as it aimed to explore new digital design concepts to address a variety of ecological challenges. While my study period focused on the exploration of AI decision-support systems and open innovation to monitor marine invasive species, subsequent innovation efforts focused on a variety of other subjects, such as predicting algae bloom, enhancing marine data collection through citizen science, and crowdsourcing the design of marine sensor technology. While paper 1 refers to OceanAI by its non-anonymized term, this thesis always uses the term OceanAI for clarity.

I joined OceanAI as an active participant at its launch in 2019 when I commenced my PhD studies. Given that my principal supervisor was one of OceanAI's project managers, I was able to gain deep insights into the network context and good access to other network members. In addition to my engagement with OceanAI, I reached out to several other innovation networks that were funded under the same initiative but focused on other innovation areas like forestry, space data, tax report processes, or natural language processing. This exploration revealed that while OceanAI's strategy of leveraging diverse expertise for digital innovation was a common thread among these networks, its emphasis on extensive exploration and novelty set it apart. In other words, OceanAI presented a common case in its objective but an extreme case (Yin, 2018) in its execution.

3.3 Data Collection and Analysis

Data collection and analysis was overall similar for both case studies (Table 4). Following recommendations for longitudinal case studies, data collection included (non-)participant observations, semi-structured interviews, and archival data to allow triangulation (Pettigrew, 1990).

Participant observation: I joined project meetings (involving all active network members) and developer meetings (involving smaller groups of developers). Due to the covid-19 pandemic, most of these meetings took place on Zoom. These meetings allowed me to follow the process and observe emerging challenges, shifting objectives, and social dynamics over time. In addition, I engaged in workshops, typically half- or full-day meetings to discuss strategic objectives or larger technical design decisions. Most workshops included internal network members but occasionally also involved external stakeholders like government agencies or representatives from shipping companies. In Neptune's case, I also joined several system tests conducted at sea on trial boats and in a bridge simulator. These were invaluable in getting me 'closer to the action' as I got to see many of the technical components, connections, and software employed by the various developers in real life and could observe how they integrated their components both with other components and in the boat architecture. Plus, it was plain fun to be out at sea. Overall, these workshops presented an opportunity to conduct many informal conversations with developers and I made extensive field notes (Yin, 2018).

Interviews: Semi-structured interviews were conducted with members from both innovation networks, consistent with purposeful sampling criteria (Flick, 2009) to ensure a broad range of perspectives on the innovation process were captured. This included individuals from different backgrounds and roles within the networks. Additionally, I interviewed six persons who participated in a crowdsourcing competition organized by OceanAI which provided insights into how knowledge was combined across network boundaries in an open innovation setting. Most interviews were conducted by me, although six interviews with OceanAI participants were carried out by another network member, who shared the transcripts with me, and seven interviews were conducted collaboratively with this individual. Interviews varied in length from 30 to 90 minutes and followed the "dramaturgical model" (Myers & Newman, 2007), beginning with an introduction to the research project and my role as a researcher, not a network member. To reduce social dissonance, I emphasized how interviews would be anonymized and not shared with other participants. The interview guide was designed to elicit detailed descriptions of the participants' activities and interactions within the network, leveraging the longitudinal study design to explore anticipated future actions and reflect on these in follow-up interviews, thus tracking changes and challenges over time.

Archival data: Finally, I had access to a large amount of internal communication and documents. Those were helpful in providing temporal snapshots of how innovation goals and development progressed over time. For instance, access to OceanAI's internal Kanban board and Slack communication with thematically named channels like #shippingdata was useful to track the evolution of development activities. Similarly, Neptune's large repository of reports to its funding agency allowed for a comparison of early design plans with final outcomes, revealing various development challenges and shifts in priorities that were further explored in later interviews.

Table 4 – Overview of collected data

Data	Neptune	OceanAI
Participant observation		31 project meetings (avg. ~1h) 35 developer meetings (avg. ~1h) 11 workshops
Non-participant observation	40 project meetings (avg. ~1h) 15 developer meetings for subsystem integration (avg. ~1h) 10 workshops 3 sea trials (9 days total) 1 system test in professional bridge simulator (2 days)	
Interviews	17 interviews (Neptune members)	36 interviews (OceanAI members) 6 interviews (Kaggle participants)
Archival documents	Documentation & presentations (incl. 37 reports to Neptune's funding agency with combined 1106 pages) Selected mail communication Developers' GitHub pages	Documentation & presentations Selected mail communication Internal communication on Slack channel

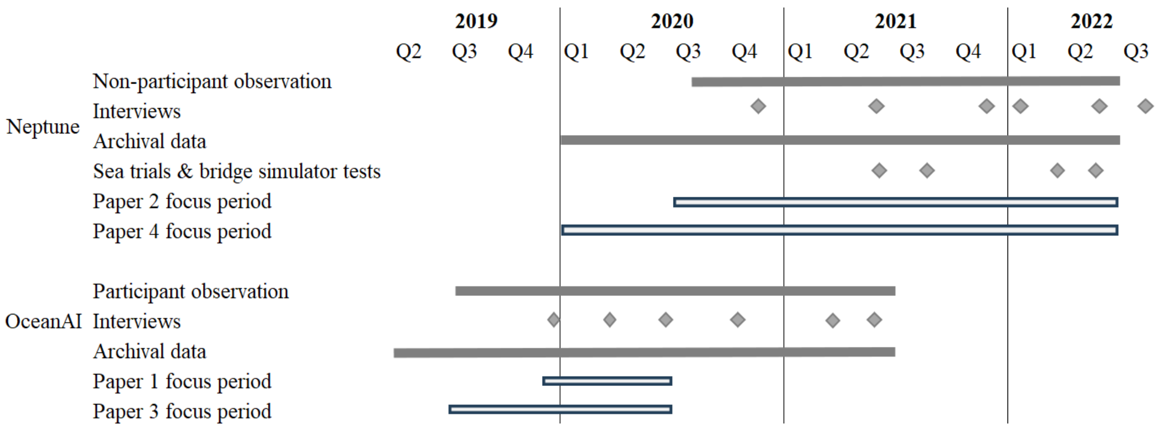

Figure 5 – Timeline of data collection and empirical focus of appended papers

The specific approaches to data analysis are described in detail in the respective papers. Therefore, I want to provide an overview of my use of theory and how I handled the data in general. Throughout the research process, I have engaged with a large variety of theoretical perspectives to investigate the broad phenomenon of digital innovation in interorganizational networks. In addition to the concepts used in the appended papers (Table 5), I explored various other concepts that served as sensible theoretical basis to inform my understanding of the empirical context. For instance, previous versions of paper 3 included concepts like sensemaking or technological frames, and paper I originally included a design science lens. As organizational phenomena emerge through complex relationships and are determined by their context, using these different concepts served as sensitizing devices that were useful to draw attention to important features of social interaction (Gehman et al., 2018). At the same time, theory can be a tool "*tools that weigh us down and preclude lightness*" (Weick, 1996, p. 312) in that it can prevent discovery of new meanings. Walsham (1995) compares the use of theory to using scaffolding during construction – it is useful during the process but can be removed once it has served its purpose. If only one theoretical perspective is adopted to investigate a research question, there is a risk for a limited view (Walsham, 2006). Therefore, I tried to be flexible during my research by revising my assumptions continuously through iterative cycles of data collection and analysis. Thus, the theoretical lens presented in this cover paper is the result of the research process and iteratively engaging with theory and the data, rather than an initially chosen lens.

As noted above, I was able to collect rich, varied, longitudinal data from both case studies. While this is overall advantageous, it also makes data analysis challenging. As Langley notes, "*process data are messy. Making sense of them is a constant challenge*" (Langley, 1999, p. 691). To that end, my analysis process was inspired by recommendations for longitudinal research (Pettigrew, 1990). The first step involved creating a visual map of case events to represent case events in a structured format. Visual maps are "*particularly attractive for the analysis of process data because they allow the simultaneous representation of a large number of dimensions, and they can easily be used to show precedence, parallel processes, and the passage of time*" (Langley, 1999, p. 700). Using Excel and the software Aeon Timeline, I assembled a large event sequent databases (Poole et al., 2000). For instance, the unfiltered timeline for Neptune included 332 events, such as development milestones, critical discussions or testing activities. Two specific examples for such events are "predictor developers warn not to overload ML model in order to facilitate standard creation" and "GNSS developers planning to test accuracy of 'maritimized' GNSS software in sea trial, foreseen main challenge reception". These events were further annotated with practical descriptors (e.g., data source or technological component) or broad theoretical descriptors to facilitate filtering. The goal was to get a holistic understanding of "*what happened and who did what when*" (Langley, 1999, p. 692). While these databases themselves were too unwieldy to guide analysis alone, they were an immensely useful intermediary step between the raw data and subsequent abstract conceptualizations (Langley & Tsoukas, 2017).

Subsequent analysis differed by paper, but overall followed common practices for thematic analysis (Braun & Clarke, 2006) and the Gioia methodology (Gioia et al., 2013). I reviewed data on a more granular level in Atlas.ti, a qualitative data analysis software, and familiarized myself with it and started making sense of it. During this step, I coded inductively first-order codes, searching for interesting features of the data relevant to the research objective. These codes were then collated into potential themes or second-order codes, which guided further analysis and helped engaging with theoretical concepts. A practical illustration of this can be found in Paper 2, Table 1; it contrasts general design goals for AI tools derived from literature with development challenges found in the empirical context, reflecting reflect second-order themes. Contrasting these two gave me a deeper understanding of the underlying tensions and guided further analysis that resulted in the abstraction of environmental constraints and identification of mitigating development actions. During this step, I further iterated between data and literature to relate these insights to larger bodies of research and identify specific gaps to which my insights could provide useful contributions.

Additionally, Paper 4 and 3 involve more holistic investigations on the innovation trajectories of both networks. In the analysis for these papers, I made stronger use of the visual map in conjunction with granular data in Atlas.ti to facilitate understanding between specific events and the overall process. I examined the process by its horizontal and vertical dimensions. Horizontal dimensions refer to "*the sequential interconnectedness among phenomena in historical, present, and future time*", whereas the vertical dimensions refer to "*the interdependences between higher or lower levels of analysis upon phenomena to be explained at some further level*" (Pettigrew, 1990, p. 269). On the horizontal level, this approach helped perform temporal bracketing (Langley, 1999) and trace how decisions or events at one point affected subsequent developments. Vertically, I explored how changes on a technical level reverberated through the network, affecting other components or preceding shifts within the organizational structure. Although not explicitly detailed in the papers, these analytical steps were useful in uncovering and conceptualizing the dynamics within the networks.

Analyzing data from the Neptune case presented distinct opportunities and challenges given the case's proximity to my professional background. Having worked as a nautical officer before entering academia has not only helped me entering an innovation project that might have been restricted for others, but also sensitized me to the challenges in developing digital tools for a complex sociotechnical context (Davison & Martinsons, 2016). I was not an active project participant, but the fact that I am a 'native' to the field still mattered (Brannick & Coghlan, 2007). My fluency in 'maritime lingo' helped me to understand technical documents involving industry-specific terms like COG, CPA, or NMEA 0182. It also lends me credibility when presenting my findings in writing or in conferences. Additionally, it helped me to detect inconsistencies between extant IS literature and my own observations. For example, the development of Paper 2 was inspired by insights gained during Neptune's sea trials and a noted scarcity in research exploring digital innovation in settings beyond the conventional office environment. While I believe this led to identifying an interesting research gap in conceptualizing natural forces as overlooked impact on AI design, one reviewer of this paper also voiced concerns about the potential lack of detachment. This resembles the sentiment of Langley & Klag (2019) who note that "*on one hand, we laud field proximity as a tenet of qualitative inquiry. On the other hand, we insist on professional distance to avoid "contamination" of findings*." There is a risk that my focus might be unduly influenced by familiar themes or that I might prematurely draw conclusions (Klein & Myers, 1999). For instance, I initially attributed Neptune's exclusion of a feature for calculating hydrodynamic effects to the complexity of such calculations due to the way these effects were presented during my nautical training. However, subsequent interviews revealed that the real challenge was the integration of necessary chart data, not the complexity of the calculations.

Anteby (2012) suggests that there is a taboo in organizational studies associated with researching a field that one is personally involved in because of a perceived lack of professional distance. He argues, however, that this misconception has led to subpar research by hindering the generation of new insights. Similarly, Faulkner & Becker (2008) note that in order to study female jazz musicians, one does not have to be a female jazz musician herself, but it matters if it that is the case. But they also reflect that this carries a risk of insider bias as they realized in their own study that their knowledge of jazz musicians was not as deep as originally assumed. Both Faulkner & Becker and Anteby note that the key to navigating this role is to maintain an open inquiry stance and be transparent about one's own involvement. In this thesis, I acknowledge these potential biases. Nonetheless, I believe that I have exercised due diligence in analyzing my data, validating assumptions with interviewees, and engaging with the literature to mitigate these biases.

3.4 Reflections on the Role of an IS Researcher

As a part of reflecting on my research design, I want to reflect on my role as IS researcher. Given the increasing importance of digital technologies in all areas of society, it is easy to argue for the relevance of this research, compared to, for instance, art historians. However, this current relevance also raises requirements for IS researchers to interpret the 'broader impact' of their inquiry and discovery. Pielke (2007) outlines four roles scientists can adopt in the intersection of science and policy: pure scientists, issue advocates, science arbiters, and honest brokers. While practical implications are detailed throughout my thesis and related papers, I have primarily taken the role of a 'science arbiter' and built these implications within the bounds of my empirical observations. In the following, I switch roles to an 'issue advocate' to discuss two societal issues and suggest directions for IS research and policies.

First, within the research of field of IS research I see a need for more critical research (Myers & Klein, 2011). IS research and practice are interdependent, and the way IS explores the role of technology in organizations and society impacts practitioners (Astley & Zammuto, 1992). Drawing on Habermas, Lyytinen & Klein (1984) note that IS research should not only increase organizational effectiveness but "*must also increase human understanding and emancipate people from undesirable social and physical constraints, distorted communication and misapplied power*" (p. 219). History has shown that technologies do not only become popular because of their usefulness but also from their perceived novelty (Wang, 2010). This technological optimism can lead to adverse effects on social and economic sustainability. For instance, the potential benefits of cryptocurrency are arguably disproportionate to its environmental impact and proliferation of criminal ecosystems. While the creation of hype can be a strategic move by companies and researching new technologies is essential, the IS field must maintain a critical stance. It should not merely follow transient technological trends for the sake of visibility but should uphold a vision that champions human flourishing (Hylving et al., 2023). Unfortunately, IS research has sometimes followed technological trends uncritically (Baskerville & Myers, 2009). For instance, Uber and Airbnb are often cited as positive digital business models despite their negative societal impact, and recent publications on NFTs and the metaverse rarely address ethical concerns or the past misconduct of tech companies like Meta. While my research has not actively contributed to these trends, I also have not made any attempts to include a more critical perspective either.

Second, the empirical context of digital innovation initiatives often harbors excessively optimistic expectations of technology's role in addressing climate change. While digital technologies should indeed contribute to solving these issues, an overreliance on them can overshadow more effective and immediate solutions. Technological optimism is often tied to a belief in proactionary principles which argue that technology should be used unless there are strong reasons to limit it, rather than needing justification for its use (Hedenus et al., 2018). This favors technologically driven solutions, like the futuristic but currently immature fuel cell technologies in automotive, over straightforward policy interventions, such as implementing a CO_2 tax or speed limits. This preference for innovation over regulation reflects a broader inclination to prioritize novelty and future possibilities over the immediate enactment of proven solutions. Such technological optimism has an opportunity cost. The report "Limits to Growth" that identified the environmental problems from untethered growth was already released in 1972, and many of its projections have proven accurate (Herrington, 2021). The persistence of climate change, despite decades of warnings and evidence, highlights the need for more radical policy approaches beyond only technological innovation.

The case studies in my thesis illustrate how digital innovation projects are motivated by the potential to address environmental issues. However, they also reveal the limitations and potential distractions of focusing solely on technological solutions. For example, while OceanAI aims to mitigate the impact of invasive species, broader issues like overfishing and ocean acidification require policy interventions that technology alone cannot resolve. Similarly, Neptune's AI system for maritime navigation claims to incrementally reduce fuel consumption, but broader systemic changes could potentially have a more significant impact on emissions.

I acknowledge my personal gains from this trend. After all, it enabled me to pursue a PhD through investigating emerging technologies. However, this acknowledgment does not diminish my critique that prioritizing technological solutions over perhaps less glamorous but more effective policy measures might lead to a misallocation of focus. This disproportionate emphasis on innovation, I fear, might be met with greater skepticism and regret by future generations than is currently the case.

3.5 Additional Publications

During my PhD studies, I have produced additional publications that I have not appended in this thesis but nonetheless represent the progress of my PhD research.

- Bumann, A. (2020). Integrating Bridge Resource Management into Organizational Culture. In J. Neff (Ed.), *Improving Bridge Resource Management*. PMC Media.

- Bumann, A., Teigland, R., Germishuys, J., Ziegler, B., Mattson, M., Olsson, E., Rylander, R., Lindh, M., Zhang, Y., & Linders, T. (2021). Predicting the spread of invasive marine species with open data and machine learning: Process and Challenges. *Bollettino Di Geofisica Teorica Ed Applicata*. IMDIS 2021 International Conference on Marine Data and Information Systems.
- Kandaurova, M., & Bumann, A. (2023). Governance in Implementing Weakly Structured Information Systems. *ECIS 2023 Research Papers*.
- Bumann, A. (2024.). Captains don’t Navigate with a Keyboard—Developing AI for Naturalistic Decision-Making. In I. Constantiou, M. P. Joshi, & M. Stelmaszak (Eds.), *Research handbook on artificial intelligence and decision making in organizations*. Edward Elgar Publishing.

4 THESIS CONTRIBUTIONS FROM APPENDED PAPERS

This chapter provides a summary of the appended papers. Table 5 provides an overview. Subsequently, it elaborates the contributions of these papers in relation to the theoretical concepts employed in this thesis.

Table 5 - Overview of appended papers

	Paper 1: Challenges of Knowledge Combination in ML-based Crowdsourcing	**Paper 2: No Ground Truth at Sea - Developing High-Accuracy AI Decision-Support for Complex Environments**	**Paper 3: Theorizing Digital Innovation Network Orchestration - Navigating the Tension Between Leveraging Generativity and Bounding Innovation**	**Paper 4: Generating Architectural Knowledge in Interindustry Digital Innovation**
Area of Concern	Knowledge combination in open innovation	AI development for complex environments	Network orchestration in digital innovation	Digital architectural innovation in interindustry collaboration
Research Question	What are the challenges to knowledge combination in domain-specific ML-based crowdsourcing?	What are the challenges designing a high-accuracy AI-based decision-support tool for a complex context subject to external physical sources of inaccuracy? And how do developers mitigate these challenges?	How do digital innovation networks navigate the tension between leveraging the generativity of digital technology and the need for innovation boundaries?	How is architectural knowledge generated in inter-industry digital innovation in the absence of a central systems integrator?
Theoretical Framing	Knowledge combination	AI design, Cybernetics	Network orchestration, Organizing Vision	Architectural theory of innovation
Unit of Analysis	Crowdsourcing challenge	Sub-set of actors in innovation network	Innovation network	Innovation network
Method	Longitudinal case study	Longitudinal case study	Longitudinal case study	Longitudinal case study
Data	Interviews, archival data, participant observation (OceanAI), non-participant observation (Neptune)			
Data Analysis	Thematic analysis	Thematic analysis	Gioia method & temporal bracketing	Thematic analysis & temporal bracketing
Empirical Context	OceanAI - developing AI models via open innovation platform	Neptune - developing AI component for maritime navigation decision-support system	OceanAI - exploring AI use cases for marine environmental monitoring	Neptune - integrating components in maritime navigation decision-support system
Contribution	Highlight challenges of combining expert knowledge across domains. Provide practical recommendations for interdisciplinary open innovation	Identification of challenges for AI development arising from complex natural use environments. Highlight role of domain knowledge, physical innovation, and HMI design to overcome challenges	Theoretical model for digital innovation network orchestration, including mechanisms that illustrate how changing network visions lead to orchestration practice adaptation	Identification of three mechanisms that facilitate generation of architectural knowledge in interindustry digital innovation

4.1 Paper 1

Bumann, A., & Teigland, R. (2021). *The Challenges of Knowledge Combination in ML-based Crowdsourcing – The ODF Killer Shrimp Challenge Using ML and Kaggle*. Proceedings of the 54th Hawaii International Conference on System Sciences (HICSS).

This paper explores knowledge combination in machine learning (ML)-focused crowdsourcing initiatives. In such open innovation environments, organizations (seekers) utilize digital platforms to engage a wide user base (solvers) to develop ML models tailored to specific needs. This involves formulating a particular challenge for resolution, engaging platform users, and assessing the algorithms they submit. Despite extensive exploration of open innovation, the dynamics of merging advanced technical knowledge with domain-specific insights in AI-centric open innovation have received little attention. Specifically, we investigate: *What are the challenges to knowledge combination in domain-specific ML-based crowdsourcing?* Empirically, we draw upon an in-depth investigation of OceanAI's efforts in organizing a crowdsourcing event on the ML crowdsourcing platform Kaggle.

The findings highlight various challenges in combining diverse knowledge across epistemological communities. These challenges emerge both during the initial problem formulation phase within the organization and as solvers interpret and tackle the problem applying their specialized knowledge. The incorporation of adjacent domain knowledge during problem formulation can help circumvent technical constraints. Knowledge combination is further facilitated by boundary objects that visualize complex AI functionalities and characteristics of the problem context. Additionally, the findings highlight the importance of individuals with boundary-spanning expertise to moderate seeker-solver relations and qualitatively evaluate applicability of submitted ML models. The findings contribute to understanding digital innovation processes and offers practical recommendations on integrating crowdsourcing into digital innovation, including on internal problem formulation, choosing suitable crowdsourcing platforms, community moderation, and qualitative evaluation of submitted algorithms.

4.2 Paper 2

Bumann, A. (2022). *No Ground Truth at Sea – Developing High-Accuracy AI Decision-Support for Complex Environments*. Proceedings of the 56th Hawaii International Conference on System Sciences (HICSS).

Nominated for Best Paper in the Knowledge Innovation and Entrepreneurial Systems (KIES) track.

This paper explores challenges and mitigation strategies when developing AI applications for natural use domains with high environmental complexity. AI tools have become increasingly ubiquitous in an ever-expanding range of contexts (Berente et al., 2021), but AI development in contexts characterized by dynamic physical forces has seen little attention in IS literature. Such physical forces constitute boundary conditions that AI developers must account for but cannot actively influence, implying different development strategies compared to AI development for bounded organizational settings. I conceptualize AI development as a three-stage process and investigate: *What are the challenges in designing a high-accuracy AI-based decision-support tool for a complex context subject to external physical sources of inaccuracy? And how do developers mitigate these challenges?*

Empirically, the paper focuses on the development of an AI predictor component for maritime navigation as one element in Neptune's overall technical architecture. This predictor had been initially developed for use in ship simulators and required extensive modification to be suitable for practical, real-world deployment.

The paper presents three interesting insights. First, it identifies various challenges that emerge when adapting an existing component to a new, more complex use context. While the AI predictor was technically functional from day 1, its functionality was constrained by the physical environment. This reflects a tension between feasibility and accuracy, i.e., the AI system's ability to accurately predict a ship's future trajectory by accounting for environmental variety (Ashby, 1956). To identify these challenges, developers needed to acquire holistic understanding of the use context conditions, including environmental forces, technical legacy systems, or different levels of variety during different stages of a ship's voyage. Determining a suitable balance between feasibility and accuracy was helped by tacit domain knowledge by experienced maritime navigators and testing the AI system in simulated and real-life settings. Overall, developers prioritized robustness of AI output quality over accuracy, illustrating that is both difficult and not necessary to account for all environmental variety in order for an AI tool to be useful.

Second, it illustrates the role of physical materiality in digital innovation outside of traditional organizational confines, adding nuance to prevalent assumptions that digital objects increasingly take precedence over their physical counterparts. The paper highlights several instances where physical elements had to be integrated into AI development to mitigate challenges, for instance by installing new antennas to produce accurate input data or by testing the AI system in a mockup ship simulator to integrate domain knowledge.

Lastly, I provide suggestions for appropriate Human-Machine-Interface (HMI) design for AI applications in naturalistic use contexts. As users need to make decisions under time pressure and with their intuition, HMI design should focus on providing reliable, easily interpretable information. If the AI output quality is sub-optimal, developers should implement an automatic switch to more robust, non-AI systems to avoid cognitive overload. This contrasts with common design principles like Explainable AI (XAI) that prioritize explaining underlying AI processes to the user. The implications of naturalistic decision-making in contrast to classical decision-making in AI development are further explored in a non-appended book chapter (Bumann, 2024.).

4.3 Paper 3

Bumann, A., Sandberg, J., Teigland, R. *Theorizing Digital Innovation Network Orchestration: Navigating the Tension Between Leveraging Generativity and Bounding Innovation*. (under revision for 2nd submission round at AJG-level 4* journal).

This paper explores how innovation networks deal with both the opportunities and uncertainty arising from the abundance of possible value paths provided by generative digital technology. We suggest that digital innovation networks face a key tension between flexibility and stability in formulating their vision and orchestrating the collaborative efforts of its participants: on one hand, leveraging the generative potential of digital technologies requires an open-ended vision as opportunities for recombinatorial innovation may emerge only serendipitously; on the other hand, certain boundaries are necessary to provide guidance to a diverse and dynamic array of network participants. Specifically, we investigate: *How do digital innovation networks navigate the tension between leveraging the generativity of digital technology and the need for innovation boundaries?*

Empirically, we draw on a 13-month period of OceanAI and their efforts to envision and realize an AI application for the purpose of marine environmental monitoring that aligned with the interests and capabilities of the network participants.

The first contribution of this paper is the illustration of how the generative potential of digital technologies can be a source of substantial uncertainty. While prior literature on digital innovation has predominantly portrayed this generative potential as a positive enabler for serendipitous innovation, the heightened complexity of having too many options has rarely been discussed. OceanAI's innovation trajectory was highly dynamic, characterized by multiple changes in direction and network participants. In their search for a suitable AI use case, OceanAI considered a broad variety of digital components, including various data sets, AI modelling techniques, APIs, sensor hardware, and crowdsourcing platforms. While this variety provided an open-ended value landscape with many opportunities for recombinatorial innovation, it also was a source of uncertainty regarding what opportunities to prioritize.

The second contribution is a theoretical model for digital innovation network orchestration. According to this model, innovation networks respond to the tension between generativity and the need for boundaries by oscillating between two types of visions: divergent visions characterized by ambiguity and idea plurality, and convergent visions that are more focused, coherent, and seek to produce tangible outcomes. A new vision guides the adaptation of network orchestration practices through three mechanisms: articulating problem-solution pairing, scoping digital resource space, and repositioning the network innovation locus. We illustrate how digital technology both facilitates and requires a higher pace of iterating between divergence and convergence.

4.4 Paper 4

Bumann, A. & Mansoori, Y. *Generating architectural knowledge in interindustry digital innovation: the case of a maritime navigation decision-support system*. (Manuscript, under peer review at AJG-level 3 journal).

Technological components from different industries are increasingly combined to create novel products. While such inter-industry architectural innovation reduces component-level uncertainty from using tried-and-tested technologies, it creates new challenges in generating new architectural knowledge on how these technologies should interact to form a coherent architecture. The development of the required architectural knowledge is especially challenging in digital innovation. While the malleability of digital technologies facilitates collaboration across increasingly heterogeneous industries, the resulting knowledge diversity complicates nominating a central systems integrator beforehand who can prescribe architectural design rules. Given these considerations, we investigate the *generation of architectural knowledge in inter-industry digital innovation networks, especially in the absence of a central systems integrator.* Empirically, we draw upon a 20-month, longitudinal case study of Neptune and its efforts integrate 5 diverse components (maritime electronics, radio telecommunication, AI system, GNSS technologies from automotive and metrology) into a novel system architecture for maritime navigation.

Findings show three key mechanisms that facilitate the generation of architectural knowledge in interindustry digital innovation. First, collaborative interface development facilitates knowledge translation and role negotiation amongst involved actors, and the resulting interfaces codify architectural knowledge and simplify component-level complexity. Technical boundary objects such as prototypes or simulation tools are useful in this process, enabling iterative exploration of subsystem integration and acting as bridges between individual components and the overall architecture. Second, system-level testing in real-world conditions enables making informed design decisions, detect latent component interdependencies, and verifies the integration of digital technologies within the physical world. Third, if there is no formally defined systems integrator, actors with domain knowledge relevant to the use context will take a more prominent role in guiding integration efforts. As they can evaluate the architectural design in a broader context, they can identify latent interdependencies, functional limitations, and guide appropriate component adaptation. In relation to the common description of systems integrators as those who “need to know more than they make” (Brusoni et al., 2001), we find that the reverse is true as well: “those who know more, become systems integrators”.

This paper contributes to digital innovation literature by detailing how architectural knowledge evolves through the discovery of desirable component interactions and navigating emerging tensions between digital and physical materiality. Additionally, it contributes to digital innovation network governance literature by emphasizing the importance of flexible governance structures that allow the role of systems integrators to organically emerge.

4.5 Synthesis of Paper Contributions

Together the papers illustrate digital innovation as a process of knowledge combination. Both networks, OceanAI and Neptune, consisted of diverse actors who collaborated to integrate various technological components into a new technical architecture. This technical integration required the exchange and combination of specialized component knowledge to generate new architectural knowledge. The key difference between the two networks was the degree to which components were predefined at the start of the innovation process. Due to the exploratory nature of my research design, not all papers were written with the theoretical concepts of architectural knowledge and combinative capabilities in mind. However, throughout all four papers, both concepts are useful because they allowed me to understand how multiple knowledge “building blocks” come together to form an overarching whole and how this knowledge combination depended on the networks’ combinative capabilities. This section synthesizes the paper contributions in relation to these two concepts (Table 6). First, I outline the type of knowledge that Neptune and OceanAI lacked and generated during their innovation process. Then I describe how they exercised their combinative capabilities to facilitate generating this architectural knowledge.

Neptune was established with the goal of architectural innovation. Each of the five network members possessed proprietary component technology, and Neptune’s envisioned outcome was a new system architecture that integrated these five components (papers 2 & 4). The project had strong initial conditions: each member had extensive component knowledge in their respective components, and Neptune members had outlined a detailed blueprint of the envisioned system architecture prior to development to fulfill funding agency requirements. Despite these advantages, it still took two years to develop a fully functional system with seamless interoperability among the components. While the functional interactions between components were relatively well-defined from the start (e.g., the GNSS transponder providing input data for the prediction algorithm), *there remained much uncertainty (i.e., a lack of architectural knowledge) on how these interactions should be specifically designed*. Many details regarding these interactions lacked an obvious answer and were only specified after much discussion and iterative testing, for instance to what extent input data fluctuations should be filtered to display accurate ship movements (paper 2 & 4), how data should be transmitted with limited network bandwidth (paper 4), or how complex information from the ECDIS on fixed objects could be transmitted as input data for the AI predictor to calculate hydrodynamic effects (paper 2). In some cases, developers were not even aware that certain component interactions were relevant (i.e., latent interdependencies) until unexpected bugs emerged, for instance because of non-uniform data formats or cable connections (paper 4).

Neptune’s case also highlights the challenges of adapting technologies developed for specific applications to entirely new contexts. As most components were developed for non-maritime applications, developers engaged in ‘maritimization’, i.e., adapting the components to the maritime context (paper 4). Thus, *architectural knowledge does not only relate to technical interoperability of multiple components but also understanding how product architectures perform under varied conditions and the constraints imposed by those conditions*. For instance, paper 2 shows how, although technically feasible to install an AI predictor initially developed for ship simulators on real ships, contextual factors such as the unreliable data quality from onboard sensors that were not designed for high-accuracy AI applications, required adjustments. As result, developers opted to use fewer input parameters than in simulators to ensure output quality. Additionally, both papers 2 & 4 illustrate how user needs were taken into account for architectural configurations. For instance, simulation tests with ship captains revealed that despite the system being functional on a technical level, it still needed various adjustments to align with the specific needs of experienced navigators, such as introducing automation settings in the ECDIS to automatically switch from AI to traditional predictor based on specific navigational conditions. Finally, some integration activities resulted in serendipitous component-level modifications beyond Neptune’s initial project scope. For example, ECDIS developers created a bow-crossing range feature in the ECDIS to calculate when another ship would pass in front of a ship. This feature was initially developed to validate functionalities of the AI predictor but was later implemented as a standalone feature following positive feedback from users (paper 4).

In comparison to Neptune, OceanAI followed a more exploratory, radical innovation strategy, initially defining only a few broad technological components like 'AI' and 'marine data’. Network members were diverse and possessed component knowledge relevant to various technologies within their domains. For example, data scientists knew about data storage and processing or AI modeling, while marine biologists knew about marine data infrastructure and sensor hardware. Thus, OceanAI members needed not only architectural knowledge on *how* different components would interrelate to produce a technical product to address environmental issues but also needed to determine *what* components were suitable in the first place. Paper 3 highlights how the 'what' and 'how' questions in OceanAI's innovation process were addressed not simultaneously but in a temporally distinct manner. In divergent phases, network members explored a broad range of components to understand which ones were ‘low-hanging fruits’ that could be easily used to address the larger issue of marine environmental monitoring. In subsequent convergent phases, the focus shifted on understanding how a more narrowly defined range of components could fit together.

Given such a broad focus, it is not surprising that initially envisioned architectural configurations had to be frequently revised as network members learned more about individual components and what potential combinatorial opportunities they offered. For instance, paper 1 describes how OceanAI members determined relatively quickly that they wanted to use a dataset of a specific marine species as a key component but had to revise several ideas on how to utilize it once the limitations in data quality became apparent. Paper 3 shows how some members had to re-evaluate their assumptions after learning more about the usefulness of AI models with 100% prediction accuracy. While this open-endedness occasionally caused confusion amongst OceanAI members, it also allowed for serendipitous repurposing of digital components to open up new avenues for innovation. For instance, paper 3 describes how OceanAI members recognized the broader utility of one component, the aggregated dataset originally created for an AI proof-of-concept, which helped launch an open-ended crowdsourcing challenge on Kaggle. Thus, while the malleability of digital components introduces uncertainty by broadening the range of potential architectural configurations, it also enables creative solutions that can adapt to new value opportunities.

The four papers also provide insights on what combinative capabilities digital innovation networks employ to facilitate the generation of architectural knowledge. Despite Neptune and OceanAI having very different innovation strategies, available knowledge resources, and innovation outcomes, they shared various common strategies in how they combined knowledge from diverse actors in novel ways.

In regard to *systems capabilities*, both networks created technical and organizational infrastructures to store and share relevant information across different organizations. This included regular meetings and the use of digital platforms, shared databases, and other collaborative tools. Through those means, network members could share relevant information about components, such as interoperability requirements or how components had been used in previous applications. For example, during Neptune's early phases, members shared extensive material on how their components, like the GNSS transponder used in automotive applications, had been utilized. This helped other members understand the basic capabilities of these components and explore potential integration strategies. Additionally, throughout their innovation trajectories, both networks shared information on similar technological solutions from other contexts to inspire innovation and reduce uncertainty. For instance, OceanAI's early activities were inspired by media reports on predictive AI used in forestry to monitor the spread of bark beetles (paper 3), while some of Neptune's members shared development notes from projects with similar objectives in achieving high-accuracy motion prediction in transportation (paper 4).

These infrastructures were not static throughout the networks' life span but were periodically adapted to meet the evolving demands for knowledge combination. This is only pragmatic, as innovation networks are loose organizational arrangements that are adapted as needed. In both cases, network members used this freedom to intensify or relax their collaborative efforts with different actors as needed. In paper 3, we describe this dynamic as 'repositioning the innovation locus', where in different stages of OceanAI's innovation process, a wider range of actors collaborate in creative ideation or a smaller set of actors collaborate closely with each other to produce tangible outcomes. Similarly, Neptune developers at times adapted their routines to collaborate more closely for specific development challenges, such as sharing github repositories and scheduling more frequent meetings for the highly interdependent AI predictor and ECDIS components (paper 4).

Regarding *coordination capabilities*, both networks operated with relatively flat hierarchies, allowing members a high degree of autonomy in organizing and managing their interactions. Although there were formally assigned network leaders, their role was often described as primarily "keeping the machine well-oiled" and facilitating activities in the background rather than managing top-down. This approach was partly due to the diverse range of technologies involved, which made it challenging for network leaders to fully grasp every technical detail. As a result, they relied on individual actors to determine themselves with what other network members to collaborate closely and what knowledge to exchange. A general challenge in both networks was sharing highly specialized knowledge from one domain to another. Most members in either network had little knowledge in the domains of the other network members, and also did not have the time, resources, or motivation to fully understand the specific technical details of what others were doing. Instead, actors focused on sharing just enough information to help others understand basic component capabilities and what was required from others to make multiple components work together. On a technical level, this included sharing information such as interoperability requirements, what technical resources were needed from other actors (e.g., data sets) or negotiating responsibilities for error messages. While in OceanAI, such discussions often were of a hypothetical basis and focused on brainstorming how the innovation outcome should look like, for instance discussing how complex datasets should be to justify the use of AI (paper 1), discussions tended to focus more on concrete development of technical interfaces (paper 4).

Additionally, all papers show instances of how network members utilized boundary objects to facilitate the translation of complex knowledge across different domains. This included both relatively simple tools like drawings or prototypes, and more complex software-based tools where developers leveraged the flexibility that digital components afforded to illustrate complex functionalities or allow others to experiment with different configurations. For instance, data scientists in OceanAI used simple visualization apps to allow non-technical experts to visualize how different AI algorithms created different predictions of invasive species spread (paper 1), whereas Neptune employed advanced simulation software that allowed other developers to try out different various design parameters when integrating their components (paper 2 & 4).

Finally, in terms of *socialization capabilities*, it was important in both networks to agree on shared goals and build trust amongst network members since most had not collaborated previously and there was much initial uncertainty regarding each other's expectations, work styles, and the potential challenges they might face. Several papers touch upon how different aspects of the networks' visions helped collaborative efforts. Most prominently, paper 3 illustrates how OceanAI's vision changed several times to adapt to unforeseen development challenges. A certain degree of rhetorical ambiguity helped align diverse member motivations towards a unified goal while also not constraining possible ideas and encouraging experimentation. Neptune's goals were overall more clearly defined than OceanAI's, but nonetheless were broad enough to allow developers implement ideas for slightly different purposes. For example, the AI predictor was intended both to assist current maritime navigators and to build capabilities for future autonomous ships. This flexibility meant that different developers could focus on different system functions according to their interests, such as working on GNSS transponders with far higher accuracy than current navigators require or developing new ECDIS functionalities that would be more relevant to human operators than autonomous systems (paper 2).

Moreover, it became generally accepted in both networks that certain individuals with necessary expertise would step up to help other actors within the network address specific challenges. This was helpful to build a culture of mutual support and shared responsibility. For instance, throughout OceanAI's innovation process, a specific data scientist repeatedly took the lead in evaluating technical decisions and bridging gaps between other data scientists and marine experts (paper 1). Similarly, within Neptune, ECDIS developers often focused not only on their own tasks but also applied their experience from the maritime domain to point out potential issues and offer guidance to other members (paper 4).

Table 6 – Key concepts in appended papers

Concept	**OceanAI (Papers 1 & 3)**	**Neptune (Papers 2 & 4)**
Innovation Strategy	Radical: broad exploration of various technology components and possible architectural configurations	Architectural: integration of clearly defined, pre-existing components into novel architecture
Component Knowledge	Network members have general component knowledge about broad range of components related to their domain expertise	Network members have detailed component knowledge about their respective components
Systems Capabilities	Adapt organizational structure and task distribution to changing architectural configurations (P3) Explore component limitations and comparable architectural configurations (P3)	Adapt organizational structure to facilitate tighter collaboration when needed (P4) Codify component bottlenecks and comparable architectural configurations from other industries (P4)
Coordination Capabilities	Employ simple boundary objects to translate complex knowledge across epistemological domains (P1)	Employ technically advanced boundary objects to facilitate detailed decisions on component integration (P2 & P4)
Socialization Capabilities	Promote both ambiguous and concise visions to encourage experimentation and pivot when necessary (P3) Encourage informal leadership by actors with boundary-spanning expertise who can evaluate usefulness of key components (P1)	Promote system's utility for both short- and long-term navigational needs to allow overengineering (P2) Encourage informal leadership of domain experts who can detect technical issues through "gut feeling"(P4)
Architectural Knowledge	Frequently refined as network members learn about component capabilities and explore potential combinatorial configurations (P1 & P3)	Frequently refined as network members specify component interaction and adapt generic components to maritime conditions (P2 & P4)
Value Creation Opportunities	Malleability of digital components serendipitously creates new value opportunities (P3)	Implement new component-level functionalities and publish component technology as open-source to derive value creation beyond project's scope (P4)

5 DISCUSSION

This chapter discusses the findings of the papers in relation to the two research questions and implications for research and practice.

5.1 Understanding Architectural Knowledge in Digital Innovation

IS research has highlighted a distinct difference between IT innovation and digital innovation. IT innovation traditionally describes the application of new IT in well-bounded organizational settings, often to improve process or operational efficiency (Yoo 2010, Swanson 1994). Digital innovation encompasses a much broader scope of enabling transformative product, service, business-model, and process innovation (Nambisan 2017). Like other "Digital X" phenomena like digital transformation, strategy, or infrastructure, the malleability of digital technology introduces qualitative differences and new complexities to sociotechnical processes (Baiyere et al., 2020; Fichman et al., 2014; Nambisan et al., 2017). However, extant definitions of architectural knowledge do not account for this complexity. As noted in section 2.2.1, the conceptual rooting stems from physical product innovation where components are arranged in a nested hierarchy of inclusion (Henderson & Clark, 1990). And while some IS scholars have applied the concept and demonstrated its usefulness in the context of digital innovation (Hylving & Schultze, 2020; Kindermann et al., 2022), they do not go further in accounting for how architectural knowledge in digital innovation might differ compared to physical or IT innovation. Thus, this section addresses RQ1: *How should architectural knowledge in the context of digital innovation be defined given the malleability of digital components?*

Generally, a good definition should be rich, accurate, parsimonious, generalizable across organizational settings, and provide grounds to stimulate further research (Weick, 1979). The fact that the concept of architectural knowledge has been used across organizational settings and research disciplines speaks to its usefulness. However, concept definitions benefit from being revised when significant technological advancements or shifts in organizational norms and practices arise (Podsakoff et al., 2016). Ambiguities in a conceptual definition may become apparent when researchers try to operationalize a concept for a phenomenon that should be a measure of the concept but struggle to do so (Jaccard & Jacoby, 2020). This can help examine in what area extant conceptual definitions are deficient and evaluate whether potential shortcomings can be attributed to its original source context or 'conceptual stretching', i.e., subsequent operationalizations that have substantially relaxed conceptual attributes (Podsakoff et al., 2016; Welch et al., 2016). Podsakoff et al. (2016) suggest a process to develop or refine conceptual definitions: identify potential attributes of the concept by a representative set of definitions, organize potential attributes by theme, and develop and refine a new concept definition. Case studies can serve as one approach to help refine theoretical concepts (Yin, 2018).

Two representative definitions of architectural knowledge are provided by Baldwin & Clark (2006) and Andersson et al. (2008). While Henderson & Clark (1990) coined the concept, they only defined it as "knowledge about the ways in which the components are integrated and linked together into a coherent whole" (p. 11) and focused more in their paper on using the concept to explain the need for organizational rejuvenation to maintain such knowledge. As shown in Table 3, most empirical studies do not stray from that view. Baldwin & Clark (2006), drawing on Baldwin & Clark (2000) and Crawley et al. (2004), define architectural knowledge as knowledge of

"(1) how the system performs its functions (the function-to-component mapping);

(2) how the components are linked together (the interfaces between components); and

(3) the behavior of the system, both planned and unplanned, in different environments." (p. 5).

Andersson et al. (2008), drawing on action research in an innovation network developing a ubiquitous computing environment (UCE), define three dimensions of architectural knowledge in the context of IT innovation[6]:

"*Technology capability awareness* refers to actors' perception of the base service capability of a specific component IT base. The awareness of technological capability is governed by prior experiences pertaining to core technologies of the IT base.

Use context sensitivity refers to the understanding of work contexts in which a specific component IT base is typically deployed. This sensitivity may also encapsulate an understanding of the fact that multiple use contexts of IT innovations may exist.

Business model understanding refers to the appreciation of business opportunities afforded by applications of a component IT base" (p. 35).

Three themes can be identified from these definitions: technology, context, and value impact (Table 7). The technology dimension is not surprising, although the definitions differ in focus. Andersson et al. focus on declarative component knowledge (technology capability awareness), whereas Baldwin & Clark focus on mapping functions to components and creating suitable interfaces. The latter reflects the design logic of the inclusionary hierarchy where the overall product architecture has to be sufficiently known *a priori* and remain relatively stable before functions can be assigned to specific components (Clark, 1985; Sanchez & Mahoney, 1996).

In the context dimension, Andersson et al. describe declarative knowledge of the boundary conditions of the intended use context, whereas Baldwin & Clark describe predictive knowledge of how

[6] One might argue that Andersson et al. (2008) use the term 'IT innovation' rather than 'digital innovation' because the latter term only gained popularity in IS literature in the 2010s. However, their conceptualization of architectural knowledge is consistent with how later researchers have described 'traditional IT innovation' (using IT to improve existing products and processes) to distinguish from the newer phenomenon 'digital innovation' (using digital technology to enable or transform business models, processes, products, and services in new ways) (cf. Baiyere et al., 2020; Fichman et al., 2014; Pittenger et al., 2022; Tilson et al., 2010).

a system architecture will behave under unintended circumstances to understand the system's limitations.

The value dimension is only explicitly acknowledged by Andersson et al. and focuses on technological affordances to enhance business models. Baldwin & Clark do not mention value, but other authors have noted that the main value from modularity in inclusionary hierarchies stems from enabling variations in degree within the scope of a single design hierarchy (Schilling, 2000; Yoo et al., 2010).

In the following, I propose three dimensions of architectural knowledge in digital innovation: *component-interaction awareness*, *architecture-context alignment*, and *dynamic value recognition*. These aim to refine the conceptual definition to account for the implications of digital technology, such as product-agnosticism, contingently obligatory coupling, and generativity. They do not contradict prior definitions, but rather add nuance. Similar to how digital innovation is the "the carrying out of new combinations of digital and physical components" (Yoo et al., 2010, p. 725), architectural knowledge in digital innovation is the amalgamation of tacit design knowledge for the characteristics of both digital and physical technologies. In practical terms, if innovators possess this knowledge, they are likely to succeed in assembling different components into a coherent, useful, and value-adding digital product architecture.

Table 7 – Architectural knowledge in physical innovation, IT innovation and digital innovation

Dimensions of architectural knowledge	**Physical innovation**	**IT innovation**	**Digital innovation**	**Implications of digital technology**
Technological dimension	Function-component mapping, interface design	Technology capability awareness What can a component do?	Component interaction awareness How do multiple components interact to produce a product-specific function?	Digital components are product-agnostic; their function in an architecture is defined by relations with other components and can be procrastinated until point of use (Henfridsson et al., 2018; Yoo et al., 2010, 2012), complicating mapping functions to components *a priori*
Contextual dimension	System behavior How does a product architecture behave under different conditions?	Use context sensitivity What is the use context?	Architecture-context alignment What are architectural design implications arising from external use context conditions?	Digital technology used more ubiquitous in variety of increasingly complex and unbounded contexts (Berente et al., 2021; Yoo et al., 2012), resulting in a need to account for more environmental variety Product-agnosticism facilitates transferring components across contexts (Kallinikos et al., 2013; Nambisan et al., 2017), but pose higher demands for contextual adaptation
Value dimension	Variation accomplished within the scope of singular architectural framework	Business model understanding How does a product architecture support an organization's value propositions?	Dynamic value recognition What are current and potential alternative value paths of a product architecture and its components?	Digital components can be recombined or repurposed while in use (Antonopoulou et al., 2016; Henfridsson et al., 2018), requiring recognition of emerging recombinatorial value opportunities

Technological

As a first dimension of architectural knowledge, I suggest *component interaction awareness*, i.e., an awareness of how different components can synergistically contribute to overarching architectural goals. It focuses on understanding the role of each component within the larger system that stems from its interactions with other components. This dimension emphasizes understanding the practical application of components (the "know-how") rather than just their features (the "know-what"). This requires for instance understanding whether a component A has complementarities with component B ($h(A,B) > f(A)+g(B)$), presents bottlenecks/constraints ($A = f(B)$), or latent interdependencies where a change in A results in changes in B and vice versa ($A \leftrightarrow B$). This relational knowledge is important for creating rules for desirable interaction between components, such as through APIs.

This revised definition is useful because of the product-agnosticism of digital components that makes their relationship with other components only contingently obligatory (Henfridsson et al., 2018). Digital components exhibit relations of exteriority (De Landa, 2006), meaning their function and importance within the overall architecture are contingent upon their connections with other components. Simply knowing a component's capabilities (i.e., “technology capability awareness”) is a good start but insufficient to understand its full potential, which becomes apparent only through its integration with other components. For instance, one can understand the basic capabilities of Google Maps in isolation as a generic navigation tool; however, its functionality changes when embedded in different product architectures, such as ridesharing or crisis coordination systems. Hence, the term ‘component-interaction awareness’ better delineates the technological dimension of architectural knowledge from explicit component knowledge and emphasizes relational knowledge of how one component influences another. This helps in identifying which component interactions are desirable, particularly when components exhibit complementarity. For instance, at the beginning of OceanAI’s innovation process, members explored a wide range of components. However, the goal of that exploration was not to acquire in-depth component knowledge, but rather to envision potentially desirable component combinations (paper 3).

Just like architectural knowledge is inherently incomplete (Leo, 2020), understanding component interactions is a continuous process. Unlike physical components, the binding between form and function in digital components can be procrastinated, i.e., meaning that new interactions and capabilities can be added even when the architecture has been designed (Yoo et al., 2010). Thus, the definition of architectural functionalities does not necessarily precede component selection (Baldwin & Clark, 2006), but may emerge serendipitously. For instance, as described in paper 4, the telecommunications component in Neptune was originally only assigned to transmit predictor information between ships. As developers shared basic component knowledge about their respective components, they gained a better understanding of potential complementarities, which resulted in extending the telecom component’s functionality to also transmit GNSS data. Thus, the functionality was extended during the development process and changed the role of the telecom component within the larger architecture. This in turn meant that telecom developers had to adapt their component for different types of interaction, for instance continuous data transmission from shore-to-ship and periodical transmission from ship-to-ship. Similarly, for OceanAI (paper 3), the need to revise component interaction rules emerged following a pivot in their architectural design. Initially conceived as a decision-support system integrated within the technical infrastructure of a specific government agency, OceanAI shifted towards developing a freely accessible educational AI proof-of-concept. This shift required the exclusion of non-public data to ensure usability and shareability of the proof-of-concept across a wider range of contexts.

Contextual

As a second dimension of architectural knowledge, I suggest *architecture-context alignment*, i.e., the understanding how a digital product architecture can be embedded in the intended use context.

Generally, designing an artifact requires alignment of the artifact's inner environment, i.e., the material and organization of the artifact itself, and its outer environment, i.e., the surrounding in which it operates (Simon, 1969). This is not limited to digital technology. One milestone innovation in the 18th century, John Harrison's design of a marine chronometer sea, required accounting for the environmental influences like physical movements, moisture, or changes in temperature and air pressure. Without adapting the design to those influences, a chronometer would be suitable for domestic settings, but it would not be considered a marine chronometer.

Andersson et al. (2008) explicitly acknowledge the importance of understanding the use context. However, having only an understanding of the use context is insufficient because it is only information. Knowledge is created through assimilation of information. Hence, architectural knowledge involves a relational comprehension of both the internal and external conditions and the procedural know-how to align them accordingly. In the case of the marine chronometer, many scientists were aware of the material conditions at sea, i.e., they possessed "use context sensitivity." However, part of Harrison's achievement was to translate these conditions into specific design requirements and adapt components accordingly, for instance by building chronometer components out of wood instead of metal that expanded less under temperature changes (Sobel, 1995).

In the era of ubiquitous digital technology, the challenge of aligning architecture with its external environment is amplified. Digital products increasingly operate across diverse sociotechnical settings, extending beyond traditional organizational boundaries. As Simon (1969, p. 110) notes, "*complexity emerges from the richness of the outer environment*". As the intended use environments for digital products become more diverse and complex, architectural designs have to match that complexity (Ashby, 1956; Cybulski & Scheepers, 2021). The product-agnosticism of digital components, while facilitating their transfer across different contexts, also heightens the need to reevaluate their design logics to ensure alignment with new contexts. An example of this is Neptune's GNSS component, originally designed for automotive use, which required adjustments to suit maritime navigation contexts where lateral drift is a common phenomenon (paper 2).

Obviously, the outer environment encompasses a wide range of elements that have to be considered, such as technical aspects like existing digital infrastructures, legacy systems, and physical conditions (Cybulski & Scheepers, 2021; Rolland & Lyytinen, 2021), and social factors like user preferences, regulatory frameworks, and institutional norms (Lehmann et al., 2022; Lyytinen, 2022). My aim is not to give an extensive overview of which of these elements matter the most or least, partially because the answer would be ‘it depends.’ Instead, the key point here is that architectural knowledge should not be understood as mere understanding of outer conditions; it involves the translation of this understanding into architectural design implications. These implications can result in changes in the architecture itself, but it can also guide actions to change the outer environment to align with the architecture (Sarasvathy, 2008).

Paper 2 specifically investigates misalignments between Neptune's system architecture and the physical conditions of its operational context, including environmental factors and onboard legacy technologies. Mitigating actions included both adaptations in the inner environment (such as reducing the AI component's input data parameters due to unreliable accuracy from onboard physical sensors) and the outer environment (such as the installation of an ultra-precision GNSS reference system onboard test ships to ensure the integrity of GNSS input data, which was affected by the ship's constant motion).

Moreover, the increasing significance of sociotechnical elements in digital innovation underscores the need for greater architecture-context alignment (Sarker et al., 2019). Digital innovation is distinguished by its facilitation of new affordances through actor engagement and contextual embedding, which assigns new meanings to digital objects and varies their utilization across different contexts (Leonardi, 2011; Lyytinen, 2022). Since different agents have differing cognitive frames, multiple technical identities may be attributed to the same digital object (Faulkner and Runde 2019). This underscores the importance of considering the social aspects of digital technology in defining the boundaries of digital product architectures. While not explicitly acknowledged in the appended papers, insights from earlier versions of paper 3 (cf. Bumann, 2022) and non-appended publications (Bumann (2024) and Kandaurova & Bumann (2023)), confirm the diversity in actor perceptions of digital artifacts.

Value

As a third dimension of architectural knowledge, I suggest *dynamic value recognition*, i.e., strategic knowledge to anticipate how digital resources might be creatively combined or repurposed to unlock new opportunities for value creation. Central to this dimension is the recognition of the dynamic nature of digital innovation, where the recombinatorial potential of digital components is unconstrained by functional or temporal constraints (Faulkner & Runde, 2013). This opens up a broader spectrum of value creation possibilities, extending beyond the development of new business models. Those opportunities can emerge both during design and utilization phases of digital products (Henfridsson 2018).

Any process of technological innovation involves an early 'era of ferment', characterized by a proliferation of ideas regarding potential applications and value (Kaplan & Tripsas, 2008). Over time, these typically coagulate in a dominant design where many such assumptions are taken for granted and no substantially new value paths emerge (Anderson & Tushman, 1990; Murmann & Frenken, 2006). However, the reprogrammability and loose coupling of digital components in layered modular architectures grant innovators more flexibility and freedom from the constraints of established designs (Baskerville et al., 2020; Kallinikos et al., 2013). As Lee & Berente (2012) note, the inclusion of digital components "*in a complex system tends to stimulate additional, often unforeseen, digital applications […], thus compounding the uncertainty and unpredictability associated with potential applications*" (p. 1430). New value opportunities may emerge both from external shifts in industrial or socioeconomic landscapes (Swanson & Ramiller, 1997) or from internal variations in technology components (Sandberg et al., 2020).

In contrast to the two previous dimensions, dynamic value recognition is not necessary to achieve a functional, coherent product architecture on a technical level; however, recognizing current and future value paths is important for two reasons. First, a clear definition of intended value creation guides architectural design. A product can be technically functional, but still useless, e.g., a weather app that predicts weather accurately but displays temperatures exclusively on a Kelvin scale. Second, continuous identification and capitalization of emergent value opportunities is necessary in order to leverage the generative potential of digital technologies (Thomas & Tee, 2022). Without this proactive approach, there is a risk that the product's relevance and utility will decay due to exogenous events like market competition or evolving user needs. New value opportunities are not restricted to business models as suggested by Andersson et al. (2008), but may extend to societal benefits, enhanced user experiences, or creation of new knowledge (Lundqvist & Williams Middleton, 2010). For instance, OceanAI's recognition of the broader utility of an aggregated marine dataset was partially motivated by the societal shift from the covid-19 pandemic which created an opportunity to engage housebound citizens in crowdsourcing activities (paper 3). Similarly, ECDIS developers in Neptune implementing a new functionality in their ECDIS derived from integration tests exemplifies the recognition of new value opportunities on a component level that extended beyond the original project scope (paper 4).

Thus, dynamic value recognition encompasses strategic knowledge of both how a digital component contributes value within its current architectural context and of its broader, value-adding affordances that can be aligned with new opportunities.

Taken together, these three dimensions can be synthesized in a revised definition: *architectural knowledge in digital innovation is knowledge of how digital and physical components synergistically contribute to overarching architectural goals within specific use contexts to create current and future* *value opportunities*. This revised definition emphasizes relational and strategic knowledge to account for the product-agnostic and generative nature of layered modular architecture.

5.2 Generating Architectural Knowledge in Digital Innovation Networks

So far, I have outlined a revised definition of architectural knowledge in the context of digital innovation. This definition applies in any organizational context of digital innovation, even if it only involves a single person. In this section, I address RQ2, i.e., how architectural knowledge is generated in digital innovation networks with different innovation strategies.

As noted in section 2.2.2, my conceptual logic considers architectural knowledge generation as a process of integrating diverse component knowledge bases through enacting combinative capabilities. Any innovation network requires combinative capabilities, but their specific enactment depends on the network's innovation strategy (e.g., architectural, radical innovation) as the network must overcome differing degrees of uncertainty.

For the purpose of understanding knowledge generation in digital innovation networks, the concept of combinative capabilities (Kogut & Zander, 1992) and their classification as systems, coordination, and socialization capabilities (1999) still hold up. They offer a broad, timeless, and fairly generic lens, and my research has not found anything that would substantially contradict these or identify substantial gaps. The question to what extent IS research should develop new theories or use existing ones is subject to ongoing debates (Grover & Lyytinen, 2023b; Holmström, 2018). I aim for a middle path (Swedish: "*lagom*") in attending the cumulative tradition by building on prior theories, while also addressing specific implications of digital technology (Baiyere et al., 2023).

Therefore, in the following, I will outline six *microfoundations* for combinative capabilities (cf. Teece, 2007) in digital innovation networks, i.e., distinct processes, routines, skills, and decision rules, that constitute a network's ability to generate architectural knowledge (Table 8). These microfoundations do not challenge but rather expand the vocabulary of combinative capabilities to specifically address the creation and evolution of architectural knowledge in digital innovation networks. They are designed to capture all three dimensions of architectural knowledge outlined in 5.1, although naturally, some microfoundations are more likely to contribute to some knowledge dimensions than others. For instance, *collaborative interface design* and *dual horizon value vision* are especially useful for innovation networks to enhance *component-interaction awareness* and *dynamic value recognition*, respectively. Finally, these microfoundations are "necessarily incomplete, inchoate, and somewhat opaque and/or their implementation must be rather difficult" (Teece, 2007, p. 1320). Otherwise, the novelty and value derived from innovation efforts would be diluted from the straightforward communication and application of these capability concepts.

Table 8 – Microfoundations of combinative capabilities in digital innovation networks

Combinative Capability	Microfoundation	Description	Implications of digital technology	Architectural Innovation	Radical Innovation
System Capabilities	Codification of extant architectural knowledge	accumulate existing architectural knowledge from within/outside network (e.g. standards, members' prior experiences, similar designs from other contexts) and codify in design documents	product-agnosticism of dig. tech. facilitates transferrability of extant architectural knowledge	codify well-known component interactions like "hard bottlenecks" between components	translate existing architectural blueprints where applicable
	Task structures adaptation for architectural evolution	periodically redraw, relax, or tighten task structures to respond to new knowledge needs resulting from design changes	digital product boundaries and meaning are fluid and perpetually incomplete	facilitate temporary skunkwork groups to accommodate smaller design changes	re-assess network composition and member roles to accommodate large design changes
Coordination Capabilities	Collaborative interface design	negotiate and develop technical interfaces to reduce cross-domain knowledge acquisition	dig. interfaces do not have to be specified before innovation process	joint creation of standardized interfaces to shield component complexity and guide component adaptation	joint creation of interim interfaces to reduce uncertainty and explore desirable complementarities
	Boundary-spanning practices	employ prototypes, simulations, or real-life tests to translate complex component knowledge across different design hierarchies in layered architecture	layered nature of dig. tech. requires knowledge translation across components with differing design hierarchies	integration decisions, align design logics	explain component functionality and underlying design logics
Socialization Capabilities	Dual horizon value vision	create vision narrow enough to guide collective action yet broad enough to leverage generativity	value multiplicity of dig. tech. facilitates recombination-in-use	define short- and long-term value creation paths	create "sufficiently ambiguous" architectural vision to facilitate pivoting architectural design
	Integration-expertise empowerment	recognize and elevate status of network members with specific integration-relevant skills and expertise	high knowledge diversity in digital innovation networks complicates assigning systems integrator *a priori*	elevate members who can provide narrow guidance towards sucessful integration (*how* to integrate)	elevate members who can provide broad guidance towards general feasibility (*if* to integrate)

Systems Capabilities

Codification of extant architectural knowledge. While the generation of new architectural knowledge is central to digital innovation, there is always at least a bit of existing architectural knowledge that can be applied to a new innovation endeavor. This is particularly useful in early stages to reduce uncertainty. Extant knowledge can be accumulated from both within and outside the network (Henderson & Cockburn, 1994), for instance by drawing on prior technical product architectures by network members or industry-specific standards (Andersson et al., 2008). Thus, networks need capabilities to identify and codify extant architectural knowledge in a manner that is accessible and interpretable. Resulting documents act as a frame of reference and limit the intensity and scope of later combination of component knowledge (Weick, 1979). Nonaka (1994) refers to this codification as "combination," a process that transforms explicit knowledge into new explicit knowledge. The product-agnosticism of digital technologies offers a broader scope of available knowledge sources that could be potentially translated to a new innovation context. For instance, architectural blueprints for automotive fuel consumption analysis software could provide at least some guidance for developing similar software for ships, despite vastly different physical conditions. However, this also carries some risks, as context-specific architectural knowledge might not be easily transferable as it initially seems.

In the context of architectural innovation, emphasis is placed on codifying well-known component interactions and identifying critical bottlenecks that could impede functionality. For instance, many of Neptune’s early activities focused on developers sharing basic technical specifications of their components (e.g., data formats, transmission rates), and how these components had been previously embedded in earlier architectures (e.g., designs of GNSS components embedded in automotive product architectures).

For radical innovation, where selection of key components is more ambiguous, architectural blueprints from other contexts can be useful to guide early ideation. For instance, OceanAI’s early idea to create an AI prediction tool to predict marine invasive species spread was partially inspired by similar tools in forestry to track invasive bark beetles. However, this also illustrated the challenge of translating architectural designs, as ocean data quality collected from multiple European institutions was less consistent than in the nationalized forestry data ecosystem.

Task structure adaptation for architectural evolution. As time progresses, architectural design is likely to evolve and deviate from initially envisioned designs. This requires networks to remain flexible and adapt their structures to periodically re-align with emerging needs to access and share knowledge. The principle that organizational structures should ‘mirror’ design structures to facilitate efficient division of labor is a key tenet in modularity literature (Baldwin & Clark, 2000; Conway, 1968). Empirical evidence has generally found support for this mirroring hypothesis (Brusoni et al., 2023); however, it also found that the complexity introduced by the layered nature of digital products tends to obscure clear task boundaries, complicating the establishment of rigid task structures (Colfer &

Baldwin, 2016; Lee & Berente, 2012). This is particularly pronounced when the product has to reconcile opposing logics from inclusionary and layered component architectures (Hylving & Schultze, 2020). Additionally, due to generativity, the design of digital products is inherently incomplete (Garud et al., 2008). Therefore, networks need capabilities to periodically redraw, relax, or tighten task structures to respond to new knowledge needs.

Paper 3 illustrates the dynamic trajectory in radical innovation, where large changes in the architectural vision resulted in similar large changes in organizational structures and processes. Here, substantial modifications to the product vision resulted in corresponding shifts in organizational structures and processes. For instance, decisions to eliminate or specify technical features—such as the development of custom APIs or the integration of sensor data from commercial ships—required a reassignment of roles among actors who were initially responsible for those tasks. This also led to a concentrated effort by a smaller subset of actors who were then tasked with developing a more clearly defined feature.

In architectural innovations, design changes are still likely but on a smaller scale compared to radical innovation and thus require less extensive adaptation of task structures. For instance, as described in paper 4, the integration of additional components or addressing minor technical challenges prompted the formation of temporary skunkworks groups within the network for more intensive knowledge exchange.

Coordination Capabilities

Collaborative Interface Design. No innovation network has unlimited resources, and thus knowledge recombination processes need to make a tradeoff between knowledge depth and breadth. The primary driver for collaboration across organizational boundaries is often the *access* to diverse knowledge rather than the *acquisition* (Grunwald & Kieser, 2007). Therefore, coordination capabilities should focus on the generation of new knowledge and value opportunities by leveraging members' respective component knowledge, rather than assimilating each other's knowledge. Grant & Baden-Fuller (2004) illustrate this dynamic with Pavarotti's 1998 collaboration with the Spice Girls that was "for the purposes of combining their different styles and capabilities in a music album, not about Pavarotti learning how to be a girl band" (p. 65). This requires combinative capabilities that are efficient in sharing just enough knowledge needed to generate new knowledge, and storing knowledge in artifacts instead of network members' memories (Grunwald & Kieser, 2007).

In technological innovation, such efficiency can be enabled by creating technical interfaces between components that hide complexity (Baldwin & Clark, 2000). This abstraction reduces the cognitive load on developers, allowing them to focus on advancing their component's functionality without the need to understand the internal complexities of other components it interacts with. This reduces the need for sharing specialized component knowledge and facilitates independent component modification (Sanchez & Mahoney, 1996). An interface has no objectively correct design; it must be negotiated among developers to establish interaction rules that are agreeable to all parties involved (Eaton et al., 2015). Poorly designed interfaces may result in excessive work load for one party or unduly restrict component functionality (Gawer, 2021). While interfaces in an inclusionary hierarchy have to be determined *ex ante* (Langlois, 2002), they can be created and adapted *hic et nunc* in layered modular architectures (Ghazawneh & Henfridsson, 2013). Therefore, networks should facilitate collaborative efforts where developers can determine suitable interaction rules that reduce the need for cross-domain knowledge acquisition. The resulting technological interfaces serve both as a border and a bridge; they delineate the boundaries of individual component responsibilities while specifying the nature of linkage they facilitate. While interface design still requires the exchange of declarative know-what component knowledge, this is only a means to an end. The objective here is not to cultivate domain-specific expertise among all actors but to establish a consensus on interaction parameters conducive to an efficient division of labor (Murmann & Frenken, 2006), similar to a butcher and a chef determining supply chain specifics to ensure optimal product quality and responsiveness to workflow changes.

Such efforts are especially important in architectural innovation where the main challenge lies in creating new linkages between existing components. This can be helped by outlining more abstract network-of-pattern design language (Henfridsson et al., 2014) that outlines broad problem-solution patterns and provides developers flexibility in negotiating the technical implementation through interfaces. For instance, one of Neptune's initial steps was outlining broad functional requirements that described functional component interactions (e.g., "predictor receives and validates GNSS data"). This approach afforded developers the flexibility to collaboratively refine technical integration specifics at a later stage, focusing initially on identifying the necessary knowledge exchange for effective technical coordination. As these requirements were solidified and mutually agreed upon, developers gained insulation from modifications in other components, enhancing certainty regarding the requisite adaptations for their components (paper 4).

In radical innovation that involves a higher degree of uncertainty, joint interface development is useful to reduce such uncertainty. Chuma (2006) describes this as "interim modularity," referring to the temporary interfaces established in the trial-and-error or prototyping phases of product development. This approach enables developers to collaboratively unveil the "inherent interdependencies" within the nascent product architecture. The goal is thus not to develop definitive interfaces but to explore hypothetical linkages between components that create 'component-interaction awareness' and inform which configurations should be pursued further. For instance, OceanAI's early commitment to incorporating a predictive AI model facilitated the exploration of complementary components which in turn informed feasibility and detect potential hindrances (paper 3).

Boundary-spanning Practices. Boundary-spanning practices are well-recognized as key enabler for integrating diverse knowledge. They help to convey complex, tacit knowledge across knowledge domains which is inherently difficult (Barrett & Oborn, 2010; Dougherty, 1992). Thus, they are important in any organizational arrangement with heterogeneous knowledge bases. A notable implication of digital technology is its layered modular nature, which, in contrast to the singular design hierarchy seen in physical, inclusionary hierarchies, allows for the coupling of components across different design hierarchies (Yoo et al., 2010).. For example, all components in an inclusionary hierarchy, such as a car's braking or engine system, belong to a unified design hierarchy and must adhere to specific criteria derived from the system’s (vehicle) overall functionality (Clark, 1985). Here, boundary-spanning practices aim to bridge varying abstraction levels within this singular design hierarchy.

Conversely, in layered modular architectures, boundary-spanning practices must facilitate the flow of knowledge across different functional domains, conveying the distinct design hierarchies and complexities of each layer. For instance, a car’s digital information module is only loosely coupled with the car’s physical architecture and follows its own distinct design hierarchy (Hylving & Schultze, 2020). Digital innovation networks, therefore, require boundary-spanning practices that translate component knowledge across layers into actionable design decisions. Such practices might encompass visualizations, simulations, and real-life testing.

In architectural innovation, where components are already selected, these practices focus on conveying tacit knowledge stemming from the different design hierarchies to detect incongruences when integrating components with different underlying design logics. For instance, Neptune’s sea trials were useful not only in evaluating component functionality within a maritime setting but also in promoting knowledge exchange among developers from diverse specializations. Such interactions enabled, for instance, telecommunications developers to understand the iterative design approach of the predictor component, which differed from their own sequential methodologies (paper 4). Additionally, these trials uncovered how the automotive-based design logic of the GNSS component affected its performance in marine applications, helping ECDIS developers in addressing compatibility issues (paper 2).

In radical innovation, where there is a broader search for understanding component functionalities, boundary-spanning practices become more important for explaining component functionalities and design rationales. For instance, as described in Paper 1, AI visualization techniques were employed to demystify the basic functionality and underlying logic of a predictive AI model for network members lacking a background in data science. This clarified the model's capabilities and helped external stakeholders ascertain whether the predictive AI system aligned with their expectations.

Socialization Capabilities

Dual horizon value vision. Creating and maintaining a clear vision of the innovation objective is important for innovation networks to reduce uncertainty, align differing expectations, and create a shared sense of purpose amongst network members (Hurmelinna-Laukkanen et al., 2022). However, the generative potential of digital technology, the capacity to produce an unbounded set of recombinatorial opportunities that may only emerge serendipitously (Lehmann et al., 2022), results in a tension between vision clarity and ambiguity. The crux of this tension is crafting a vision that is simultaneously precise enough to direct collaborative efforts and broad enough to embrace emergent value opportunities emerging from the recombination of technological and procedural elements within a layered modular architecture [7].

To navigate this tension, it is useful for innovation networks to formulate both short and long-term goals in their vision. Short-term goals provide clear, actionable directives that facilitate the immediate integration of component knowledge into coherent architectural frameworks. Long-term goals offer a vision expansive enough to explore future technological landscapes and potential recombinations. For instance, Spotify's initial focus on simply providing music "legal but free" has evolved into a platform with extensive integration capabilities, illustrating the evolution from immediate operational goals to broader strategic objectives (Eriksson et al., 2019). Thus, a well-crafted vision serves as both a compass and a map: it provides direction for short-term goals while allowing serendipitous discovery of the open-ended value landscape (Henfridsson et al., 2018) without getting lost.

Innovation networks pursuing radical innovation may particularly struggle with visions that are either excessively ambiguous or overly focused on ambitious, potentially unfeasible long-term goals, which can lead to confusion and or frustration due to the lack of immediate achievements (Aarikka-Stenroos et al., 2017). The theoretical framework in paper 3 describes how this can be mitigated by periodically refining the vision towards more tangible outcomes and maintain forward momentum, the results of which can spark recognition of new value paths.

In architectural innovation, where possible value paths are somewhat predetermined by the chosen components, the scope for entirely novel developments might be narrower, yet it's important to remain sensitive to future trends and digital shifts in socio-technical landscapes. This ensures innovations are not only relevant today but can also adapt with emerging opportunities. This can be accomplished by designing interfaces in a way that maintains openness for evolving or indistinct long-term objectives, allowing adaptation by network members or third parties. For example, efforts by Neptune’s developers to enhance component utility and interoperability, such as engaging in industry standards development or open-sourcing code, illustrated proactive measures to ensure components remained relevant and adaptable for future innovations (paper 4).

Integration-expertise Empowerment. The modular and layered nature of digital technology facilitates collaboration across diverse knowledge bases, resulting in increasingly heterogeneous digital innovation networks characterized by decentralized control mechanisms (Lyytinen et al., 2016; Yoo et

[7] This tension is further elaborated upon in paper 3.

al., 2012). In such environments, traditional centralized coordination approaches, such as those relying on a single network orchestrator (Dhanaraj & Parkhe, 2006) or a systems integrator (Brusoni et al., 2001), become challenging to implement effectively. Although formal leadership roles exist within most interorganizational collaborations, their capacity to directly steer the innovation process diminishes in these settings. Given high knowledge diversity, identifying a central systems integrator *a priori* is often impractical. Generally, it is not uncommon that in organizations with flat hierarchies, certain actors organically assume a stronger informal role. However, as part of a network's socialization capabilities, there should be a culture of recognizing and elevating the role of certain actors who possess distinct skills and integration-expertise that aid the architectural assembly. In paper 4, I draw on Brusoni et al. (2001) description of systems integrators as those who "know more than they make" to describe this bottom-up dynamic as "those who know more, become systems integrators". These 'emergent systems integrators' possess tacit knowledge and the ability to apply network-of-pattern thinking (Henfridsson et al., 2018) that helps other network members to make design decisions.

In architectural innovation, where components are already selected, such integration-expertise helps others understand *how* to integrate different components. For instance, maritime domain experts in Neptune applied their 'gut instinct' to detect and diagnose various technical bugs that were difficult to find with technical tools alone, like detecting faulty predictor outputs displayed on the ECDIS (paper 2) and guiding error search for transmission outages (paper 4). In radical innovation, integration-expertise helps with the broader search and guide others in what potential components are feasible and desirable, i.e., *what* to integrate. For instance, data scientists in OceanAI who had acquired basic understanding of the marine context informed decisions whether certain datasets had sufficient quality (paper 1).

A Theoretical Framework for Architectural Knowledge Generation in Digital Innovation Networks

I synthesize the above in a theoretical framework (Figure 6) that explains how architectural knowledge in digital innovation networks is generated through combining the diverse component knowledge of network members through the network's combinative capabilities, the specific enactment of which is guided by the network's innovation strategy.

The basic conceptual logic is consistent with the framework presented in section 2.2.2. New additions include:

- a more nuanced and holistic definition of architectural knowledge that encapsulates what knowledge dimensions are needed to create a coherent, context-specific, value-adding digital product architecture.
- microfoundations of a network's combinative capabilities that facilitate the combination of diverse component knowledge, that account for the specific implications of digital technology in the innovation process

    - Systems capabilities involve procedures that facilitate codification and application of extant architectural knowledge and the adaptation of organizational task structures to evolving design needs.
    - Coordination capabilities involve collaborative processes that facilitate development of technical interfaces that reduce the need for inter-actor knowledge transfer and boundary-spanning practices that translate complex component knowledge across functional domains.
    - Socialization capabilities involve cultural norms and informal processes that support the pursuit of short- and long-term objectives and informal leadership by individuals with integrative expertise.
- acknowledgement of use context conditions, the knowledge of which is combined with component knowledge to derive 'context-architecture alignment' knowledge. Subsequent design implications either result in the adaptation of architectural design or the adaptation of use context conditions.
- value creation opportunities that can both arise from architectural knowledge and component knowledge, in line with the fact that the coupling of digital components in a layered modular architecture are loosely coupled and can be used stand-alone to channel new value paths. For instance, for the product architecture of a car's driver information module, new value opportunities may emerge on the architectural level, e.g., adding new functionalities, or derived from the component level, e.g., leveraging collected fuel consumption data to develop an entirely separate predictive maintenance system.

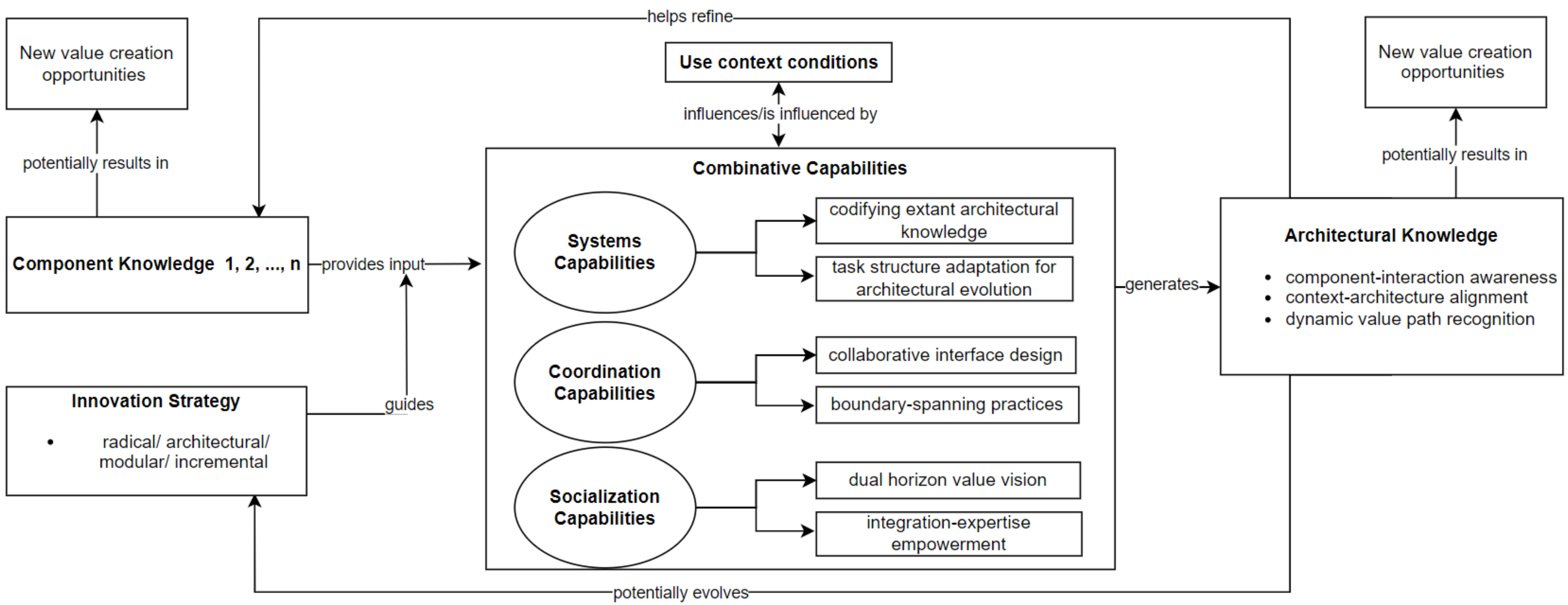

Figure 6 – An extended theoretical framework for architectural knowledge generation in digital innovation networks

5.3 Implications for Research and Practice

The findings of this thesis have implications for both theory and practitioners. First, related to the literature on modularity and digital innovation, the proposed definition of architectural knowledge provides a comprehensive lens on its role within the context of digital innovation. Although the concept of architectural knowledge is inherently relevant to product innovation at large, it has been underexplored in IS literature. This revised definition aims to address this gap. Previous definitions have largely framed architectural knowledge in terms of declarative and procedural knowledge, focusing on the integration of immutable, product-specific components within a nested product hierarchy. In contrast, I highlight the importance of *relational* knowledge and *strategic* knowledge to account for higher technological complexity (Simon, 1962) in digital innovation that complicates traditional design approaches, such as *a priori* function-component mapping (Ulrich, 1995). Relational knowledge is needed to understand how malleable, product-agnostic components, characterized by relations of exteriority (De Landa, 2006), are assigned specific functions through their interactions with other components in an architecture, and how adjustments must be made to align them with the use context or vice versa. This focus on relational knowledge aligns with previous IS research that has explored the interplay between general-purpose digital technology and its embedding in specific applications, for instance, dynamic problem-solution pairing (Nambisan et al., 2017), cognitive network-of-patterns frames (Henfridsson et al., 2014), or virtual and contextual embedding (Lyytinen, 2022). S*trategic* knowledge is needed for identifying emerging opportunities for innovative recombinations to exploit the generative potential of digital product architectures. This allows innovators to sustain and renew value creation by using components beyond their original design intent (Henfridsson et al., 2018). In sum, my proposed revised definition offers a different lens that builds on core concepts in the modularity literature and connects it to the context of digital innovation.

Second, related to the literature on digital innovation networks, my proposed theoretical framework (Figure 6) provides a sufficiently holistic lens to explain the generation of architectural knowledge and induced dynamics in digital innovation networks. While prior literature has repeatedly acknowledged the organic and garbage-can-like nature of such networks (cf. Lyytinen et al., 2016; Nambisan et al., 2017), it has rarely investigated their specific dynamics and evolution. This framework helps fill this gap by viewing digital innovation as a continuous process of combining diverse component knowledge that results in new architectural knowledge, emerging value opportunities on both component- and architectural levels and, over time, in adaptations to a network's innovation strategy. Knowledge combination is enabled by the network's combinative capabilities.

The identified microfoundations of combinative capabilities provide a better understanding of how and why organizational actors take actions that result in newly generated architectural knowledge in such networks. Taken individually, none of these microfoundations presents entirely new concepts. For instance, the importance of ambidextrously pursuing short- and long-term goals, boundary-spanning practices, system integrators, or the possibility of creating new value paths from individual components have all been individually acknowledged in prior literature and are not exclusive to digital innovation (cf. Zahra et al., 2020). However, Baiyere et al. (2023) note it is important that IS researchers are "*well-steeped in the existing tradition to understand how any emerging theoretical perspective goes beyond existing knowledge*" (p. 68)[8]. It is my assertion that the only qualitative difference in digital innovation lies in the difference between digital and physical material and the resulting different architectural configurations in an inclusionary hierarchy and a layered modular architecture (Hylving & Schultze, 2020; Yoo et al., 2012). In other words, the layered and generative nature of digital technologies creates fundamentally different product categories, or *differences in kind* (Yoo et al., 2010).

However, the knowledge dynamics underlying digital innovation are characterized by quantitative *differences in degree*. Any innovation process is inherently complex, uncertain, iterative, non-linear, and requires integration of various knowledge bases. This is true for both digital and non-digital innovation[9]. However, the malleability of digital components amplifies or adds nuances in knowledge dynamics. In this thesis, I have outlined how these nuances play out specifically. They demonstrate that combinative capabilities in digital innovation networks need to facilitate knowledge combination across more disparate component knowledge domains, facilitate higher paces of architectural knowledge refinement due to the emergence of desirable component interactions, and enable increased design flexibility. Differentiating between different innovation strategies further illustrates how the specific application of combinative capabilities is dictated by whether the network's focus is on exploration and mitigating uncertainty or on exploitation and streamlining integration.

At a broader level, the framework can be understood as a commentary on the prevalent assumptions of technological determinism in the digital innovation literature. In his seminal paper, Bailey (1986) notes that technology offers an *occasion* for structuring, not a guarantee. This perspective challenges more deterministic views of technology's role in organizations by emphasizing that the effects of new technologies on organizations are not predetermined but rather are shaped by the interactions between the technology and the organizational context into which it is introduced. Similarly, the layered nature of digital technology offers *opportunities* for "a virtually infinite number of potentially valuable recombinations" (Brynjolfsson & McAfee, 2014, p. 77) of individual digital components. However,

[8] The quoted paper is a response to Grover & Lyytinen (2023b) who called for more novelty and variance in theorizing IS phenomena. Grover & Lyytinen (2023a) later responded to Baiyere et al. (2023) to clarify their position, stating they encourage establishing creative connections with reference theories preceding digital phenomena.

[9] At the time of writing, instances of digital technologies fundamentally altering knowledge creation processes can only be found in science-fiction movies like 'The Matrix' (1999), where new knowledge can be received through direct downloads in a person's brain.

these technological characteristics alone do not ensure recombinatorial innovation and generativity. It requires sociotechnical processes, such as the generation and continuous refinement of a shared understanding of the technical architecture, to identify and exploit these opportunities. Taken together, the proposed framework illustrates how this occurs.

Third, related to the literature on organizational design, papers 1 & 3 and certain elements of the theoretical framework provide insights on the correlation between technological and organizational structures in digital innovation networks. The mirror hypothesis suggests that the technical architecture of a product or system will or should mirror the organizational structure of the organization that develops it (Baldwin & Clark, 2000; Conway, 1968). However, under certain circumstances, organizations might benefit from engaging in partial mirroring (i.e., drawing knowledge boundaries broader than operational boundaries) or mirror breaking (i.e., intentionally dissolving this structural isomorphism) (Colfer & Baldwin, 2016). The implications of digital technology on the mirror hypothesis are relatively underexplored (Brusoni et al., 2023). However, some have suggested that the trend towards collaborative network structures and the substitution of organizational ties through digital means present exceptions to the mirror hypothesis (Baldwin, forthc.; Colfer & Baldwin, 2016). In particular, the images of 'anarchy' and 'garbage-can' ascribed to digital innovation networks (Lyytinen et al., 2016; Nambisan et al., 2017) imply randomness and little formal structure.

The theoretical framework proposed in this thesis (Figure 6) and the findings of paper 3 offer a more nuanced understanding of the structural correlation in such networks. High knowledge heterogeneity and distributed control result in fluid organizational and technological structures, but this does not result in the absence of structural correlation. Instead, these networks can be described as a *flexible mirror*, where organizational structures are stable for periods but periodically adapt to align with evolving technological structures. Innovation networks are characterized by subgroups of actors collaborating, with the innovation strategy—radical or architectural—shaping the breadth and specificity of these subgroups. Collaboration within and among these subgroups mirrors the technical architecture they develop, including intra-component and interface work. Additionally, certain key individuals assume the role of systems integrators, thereby enabling partial mirroring. What distinguishes digital innovation networks from traditional forms is the dynamic nature of the innovation process, which prevents predetermined architectural knowledge or organizational structures and thus requires more frequent adjustments to stay aligned with evolving technological structures. In paper 3, this process is described as a cycle of divergence and convergence, where organizational structures maintain a degree of stability but are adapted broadened or tightened in response to changes in the architectural vision. Thus, equating digital innovation networks to anarchic systems or "garbage can organizations" oversimplifies their nature.

Implications for Practice

For organizations engaged in digital innovation networks, the different elements in the theoretical framework can serve as practical guidelines. The three dimensions of architectural knowledge can help answer 'what should we think about during the innovation process? What should we know at the end?' The emphasis on the adaptable nature of digital technologies can facilitate the identification of latent interdependencies among components and between components and their use contexts and can spur creativity in searching for new value opportunities. Moreover, the framework's microfoundations of combinative capabilities offer strategic directions for developing and refining network governance and collaboration structures. The inclusion of a cyclical perspective within the framework underscores the importance for network capabilities to be dynamic and adjusted in tandem with the evolving innovation strategy, for instance when networks transition from phases of broad exploration to focusing on a few core components.

Second, for funding agencies supporting publicly sponsored digital innovation networks, the insights from this thesis can provide guidance in supporting such networks. For example, when overseeing multiple innovation networks that share objectives but operate in varied contexts, funding agencies may initiate cross-network collaboration activities to enable the sharing of extant architectural knowledge across contexts. Additionally, in the event of significant design changes, agencies may assist networks in identifying and partnering with complementary organizations possessing the requisite component knowledge to accommodate these changes. Furthermore, when crafting funding calls for new networks, funding agencies can benefit from considering the required combinative capabilities to increase success chances. For instance, they might deliberate on whether to promote architectural or radical innovation, emphasize the inclusion of network members with a capacity for integrative expertise, or articulate preferred balances between immediate and long-term objectives. This approach ensures that funding specifications not only align with strategic innovation goals but also support the development of networks equipped to handle the complexities of digital innovation.

5.4 Limitations & Future Research

Limitations inherent to case study research apply to this thesis (Flick, 2009). A small sample size of two case studies limits generalizability (Yin, 2018). The empirical settings are subject to contextual conditions that were not explicitly accounted for in this thesis, for instance cultural norms found in Northern Europe influencing collaboration practices. Additionally, theoretical generalization is limited by the application specific theories (Lee & Baskerville, 2003). I have explained my rationale for applying an architectural view on the outcomes of digital innovation and a knowledge-based view on the process of digital innovation. However, other viable alternatives exist, for instance a service-dominant logic or actor-network theory.

There are further limitations that can provide avenues for further research. This thesis compares only architectural and radical innovation strategies in the two investigated case studies. As noted in section 2.1.3, it is more likely for networks to pursue architectural or radical innovation, because the access to diverse knowledge in networks outweighs the heightened transaction costs of crossing organizational boundaries in these types of innovations. In contrast, it is generally more desirable to pursue incremental or modular innovation in-house. That said, there may be instances of modular or incremental innovations occurring in interorganizational systems with heterogeneous actors that are tightly connected and subject to laws or agreed-upon standards. For instance, maritime ports, airports, or energy infrastructures are organizational systems of loosely coupled yet interdependent actors. Developing and implementing individual components into a larger existing technical infrastructure shared by these actors, for instance just-in-time software solutions or real-time cargo monitoring systems in a port, would exemplify modular innovation in an interorganizational network. According to Henderson & Clark (1990), this would require little architectural knowledge. However, insights from a non-appended paper on implementation of low-code AI software in firms (Kandaurova & Bumann, 2023) suggest otherwise, as extensive architectural adaptations in technical legacy infrastructure and interfaces were required. Investigating incremental or modular innovation in innovation networks could illuminate how these strategies influence the generation of architectural knowledge and assess to what extent Henderson & Clark's (1990) classification of innovation strategies remains relevant in the context of layered modular architectures, given the blurring of digital product boundaries (Yoo et al., 2010).

Additionally, the empirical observations focused on digital innovation networks during early stages of development where commercial deployment of developed products was not in scope. Prior research has highlighted the heightened challenges in meaning-making during deployment stages of digital product innovation (Wang et al., 2022). It would have been interesting if Neptune or OceanAI had deployed their systems to operating practitioners to observe how end users make sense of new digital tools, and the influence of such contextual embedding (Lyytinen, 2022) in shaping architectural knowledge. Hence, future studies may study digital innovation networks in more mature stages or formed to specifically deploy new digital technologies to end users. The proposed theoretical framework can be a useful tool for such studies.

Finally, this thesis outlines the combinative capabilities required for generating architectural knowledge but offers limited guidance on developing such capabilities, aside from recommending this thesis as a resource. Future research could enhance the practical application and understanding of these concepts.

6 CONCLUSION

Today's world is not in lack of complex problems, and while it is not certain we will be ever able to solve them, it is arguably more likely that we will if organizations from different areas of expertise collaborate and if they leverage the potential of digital technologies to find innovative solutions. Hence, it is important that actors in such collaborative arrangements effectively share and generate knowledge to succeed. This thesis has explored how this process unfolds. Beyond offering a more nuanced understanding of architectural knowledge in the context of digital innovation, this thesis finds that the capabilities required for innovation networks to generate such knowledge are fundamentally similar to those in non-digital innovation. However, these capabilities must accommodate the integration of knowledge across more disparate domains, support faster refinement of architectural knowledge, and enable greater design flexibility.

Innovation is inherently complex - it requires knowledge processes to understand, codify, and realize recombinatorial opportunities. While digital technology presents new challenges and opportunities, it does not simplify this complexity but instead transforms it. Through this thesis, I hope to have provided a better understanding of what this complexity entails and how it can be managed in the context of digital innovation networks.

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