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Leveraging the Interplay of Digital and Sustainability Transformation: An Empirical Study of Twin Transformation in Corporate Practice

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Abstract

As organizations increasingly face the simultaneous challenges of digital transformation and sustainability transformation, the concept of twin transformation has gained growing attention. Prior research suggests that digital transformation and sustainability transformation are mutually reinforcing. However, empirical evidence on organizational level remains limited, particularly with regard to reciprocal relationships and underlying organizational mechanisms. This study addresses this gap by empirically examining the interplay between the two transformations and by analyzing the role of enabling and guiding capabilities within the twin transformation context. Building on a maturity models and a capability framework, a conceptual model is developed and tested using survey data from German firms engaged in both transformations. The hypotheses build on theory are examined using linear regression analyses, complemented by exploratory analyses on the role of artificial intelligence and perceived value of twin transformation.

The results provide strong support for a positive and reciprocal relationship between digital transformation and sustainability transformation, with both equally influencing each other ($\beta = .603$, $p < .001$). Enabling capabilities are strongly associated with digital transformation maturity($\beta = .629$, $p < .001$) and significantly advance sustainability transformation maturity($\beta = .650$, $p < .001$). Guiding capabilities are strongly shaped by sustainability transformation maturity ($\beta = .697$, $p < .001$) and relate back to digital transformation with a weaker but significant effect ($\beta = .567$, $p = .002$), potentially suggesting an influence on the orientation rather than the overall maturity of digital transformation. Exploratory findings further indicate that twin transformation is primarily associated with economic value creation and that artificial intelligence contributes through broad organizational integration rather through specific technologies.

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List of Abbreviations

AI .... *Artificial intelligence*
DT .... *Digital transformation*
DTM .... *Digital transformation maturity*
ESG .... *Environmental, social and governance*
IoT .... *Internet-of-Things*
IT .... information technology
NLP .... *Natural Language Processing*
ST .... *Sustainability transformation*
STM .... *Sustainability transformation maturity*
TBL .... *Triple Bottom Line*
TT .... *Twin transformation*

1 Introduction

Digitalization and sustainability are widely recognized as two dominant megatrends shaping the twenty-first century (Apata, 2024; Irajifar et al., 2023). In particular, sustainability transformation (ST) has gained increasing prominence in response to major societal challenges such as environmental degradation, biodiversity loss and growing social inequalities (Latino, 2025). Since the Brundtland Reports from 1987 (United Nations Brundtland Commission) introduced the principle of meeting present needs without compromising the ability of future generations to meet their own needs, sustainability has become firmly embedded in global policy agendas (Burinskienė & Nalivaikė, 2024) and corporate strategies (Sari et al., 2021). Increasingly, sustainability is no longer perceived as a compliance requirement or reputational concern, but as a driver of organizational resilience (Wijethilake & Lama, 2019) and long term value creation (Chau et al., 2025; Newman & Noy, 2023). In parallel, digital transformation (DT) represents an ongoing process that has been influencing organizations for decades. Driven by continuous technological advancements, DT has progressively reshaped organizational structures, processes and business models (E. Gökalp & Martinez, 2021). As digital technologies continue to evolve at an accelerating pace, organizations are required to engage in sustained adaption while coping with increasing complexity and uncertainty. Consequently, firms are confronted with the dual challenge of advancing ST while simultaneously managing an already ongoing DT (Graf-Drasch et al., 2023).

To address these growing digital and sustainability demands, organizations are increasingly required to pursue both transformation in an integrated manner (Graf-Drasch et al., 2023). Prior research refers to this joint pursuit as “twin transformation” (TT), emphasizing the coordinated and mutually reinforcing advancement of DT and ST. Rather than being addressed independently, digital and sustainability related initiatives are understood as interconnected, with DT enabling ST objectives and ST guiding DT efforts (Christmann et al., 2024; Graf-Drasch et al., 2023). By integrating both transformations, TT is expected to unlock synergies and added values that cannot be realized when DT und ST are pursued in isolation (Auweiler et al., 2025).

Research on TT, however, is still at an early stage. Existing studies predominantly examine DT and ST separately or focus on one transformation at the expense of the other. In particular, prior research has mainly investigated how DT contributes to sustainability related outcomes (Birkel & Müller, 2021; Sepasgozar, 2021). By contrast, considerably less attention has been paid to how ST may influence or guide DT. Moreover, much of the existing literature is conceptual or qualitive in nature. As a result, a comprehensive understanding of TT that captures the reciprocal relationship between DT and ST remains limited. In particular, firm level empirical research that systematically examines both directions of influence is still rare. Although prior literature emphasizes the importance of organizational capabilities in the context of TT (Breiter et al., 2024), it remains unclear how enabling and guiding capabilities shape the interaction between DT and ST. This gap constrains both theoretical progress and practical guidance for organizations seeking to integrate DT and ST in a coherent manner.

Against this backdrop, the primary aim of this study is to empirically examine the reciprocal relationship between DT and ST at the firm level. Accordingly, the study addresses the following research question:

How do digital transformation and sustainability transformation reciprocally influence each other and what role do enabling and guiding capabilities play in shaping these relationships within the context of twin transformation.

In addition to this research question, the study pursues two complementary exploratory objectives. First, the study explores the role of artificial intelligence (AI) as an enabling technology in the context of TT. While prior research has highlighted the role of digital technologies in enabling ST, existing contributions differ substantially with regard to specific technologies (Ong et al., 2025; Shahin et al., 2024) and application areas (Chen et al., 2024; Maibaum et al., 2024; Schöggl et al., 2023). By adopting a broad and practice oriented perspective on AI, the study aims to provide a contemporary assessment that remains concrete without limiting on specific use cases. Second, it examines the value potentials of TT form corporate perspectives, thereby building on existing literature that has primarily relied on qualitative interview based studies (Auweiler et al., 2025).

To answer the research question, this study adopts a quantitative research design based on a firm-level survey of organizations engaged in DT and ST. Building on the theoretical background and prior literature, a set of theory driven hypotheses is developed. These hypotheses are empirically tested using linear regression analyses. DT and ST are operationalized using a maturity based perspective, complemented by measures capturing enabling and guiding capabilities. The exploratory objectives related to value potentials and the role of AI are addressed through descriptive analyses of multiple choice items, complementing the core regression based examination. However, the main contribution of this study lies in providing an initial firm-level empirical assessment of the reciprocal interplay between DT and ST and in clarifying the role of enabling and guiding capabilities as underlying organizational mechanisms.

Finally, this study is structured as follows. Chapter 2 provides the theoretical background by outlining foundational concepts of organizational transformation, capabilities and maturity models. It then examines DT and ST in more detail, before integration both perspectives within the concept of TT and reviewing the existing literature. Building on this theoretical background, the chapter further derives a set of theory driven hypotheses that capture the reciprocal relationship between DT and ST. Chapter 3 outlines the research design and methodology, including data collection, measurement of constructs and the analytical approach. The empirical results are presented in Chapter 4, covering both hypothesis testing and exploratory analyses related to value potentials and the role of AI in context of TT. Chapter 5 discusses the findings in light of prior literature and derives theoretical contributions as well as translates key insights into managerial implications. Chapter 6 concludes the thesis by summarizing the main results , acknowledging limitations and proposing opportunities for future research.

2 Theoretical Background

This chapter establishes the theoretical background of the study by outlining core concepts of organizational transformations as well as maturity models, which serve as a theoretical basis for the measurement and operationalization of these constructs examined in this study. It further examines DT and ST first as distinct constructs, including specific capabilities for transformation and maturity models discussed in literature. Building on these foundation, the concept of TT is introduced. Subsequently, theory-driven hypotheses are developed, followed by a review of the literature on AI and value creation in the context of TT.

2.1 Foundations of Organizational Transformation

This section introduces organizational transformation as a fundamental change, that affects all organizational levels and highlights organizational capabilities, particular dynamic capabilities, as key mechanism for managing transformational change. These foundation provide the basis for the subsequent chapters on DT and ST.

2.1.1 Understanding Transformation in Organizations

In the organizational context transformation refers to a fundamental reorientation across the organization that goes beyond incremental change and affects core structures, processes and underlying logics of the firm (Greenwood & Hinings, 1996; Nadler & Tushman, 1989; Romanelli & Tushman, 1994). Nadler and Tushman (1989) conceptualize transformation as a strategic reorientation through which organizations redefine how they operate and compete. Building on this distinction, Romanelli and Tushman (1994) describe organizational transformation as a discontinuous shift that interrupts periods of relative stability and entails deep structural and strategic changes. Greenwood and Hinings (1996) emphasize that such transformations are shaped by broader contextual conditions and may be shaped by pressures arising from the organizational environment. As organizations operate in these dynamic environments, the ability to manage transformational demands represents an ongoing challenge that requires continuous adaptation (Tushman et al., 1986; Weick & Quinn, 1999). Successfully managing such transformation therefore requires organizations to revise their strategies and develop internal capabilities that support effective responses to environmental change (Pearce & Robbins, 2008).

2.1.2 Capabilities and Dynamic Capabilities

According to O'Reilly and Tushman (2008), capabilities reflect how organizations combine and utilize its resources and expertise in order to carry out tasks that create and deliver value to the customers. Similarly, Amit and Schoemaker (1993) describe capabilities as the organizational ability to combine and apply available assets and processes to achieve their objectives.

In literature a fundamental distinction is made between operational and dynamic capabilities (Pavlou & El Sawy, 2011). Operational capabilities refer to the routines and processes that ensure efficiency and stability in day-to-day business operations (Teece et al., 1997; Winter, 2003). According to Steiniger et al. (2022) operational capabilities allow firms to produce, sell and maintain existing products for current customer segments. Therefore such operational capabilities, are also referred to as "zero-level" capabilities (Winter, 2003). In contrast. dynamic capabilities refer to the skills and processes that allow a company to adjust and renew its resources when the environment changes (Teece et al., 1997).

Following Teece (2007), dynamic capabilities can be divided into three interrelated dimensions: Sensing, Seizing and Transforming. Sensing is the ability to recognize and understand opportunities and threats. Seizing means using resources to turn these opportunities into value through investments and new business models. Transforming involves continuously renewing the organization by adjusting and combining its resources (Teece et al., 1997). Together, these dynamic capabilities determine how effectively organizations can respond to change and remain competitive over time. They are essential for managing transformation processes, as they enable companies to continuously adapt their structures, processes and resources in dynamic environments . Hence, developing dynamic capabilities is crucial for implementing and advancing both the DT and the ST as they both reflect a company's ability to adapt and innovate in response to technological and environmental changes (Breiter et al., 2024).

2.2 Maturity and Maturity Models

The concept of maturity and maturity models has been discussed for over fifty years, originating with the early work of Gibson and Nolan (1974) and Crosby (1979). The term maturity refers to the extent to which an organization, process, system or object has evolved and reached a predefined level of sophistication within a particular domain (Becker et al., 2009; Mettler, 2011). A maturity model provides a structured framework to assess and guide this evolutionary progress. It enables organizations to evaluate their current state, identify gaps and define concrete steps for continuous improvement (Becker et al., 2009). Maturity models typically consist of a sequence of distinct stages representing characteristic or desired levels of development (Röglinger & Pöppelbuß, 2011). These stages describe the transition from an initial, often ad hoc state to a fully optimized and institutionalized level of maturity (Becker et al., 2009; de Bruin et al., 2005). According to Lasrado et al. (2015) maturity models can usually be described as structured frameworks in which maturity levels are arranged on one axis and the corresponding capabilities on the other, typically organized within specific dimensions.

Despite their wide application, critics argue that such models may oversimplify complex realities (de Bruin et al., 2005) , lack theoretical grounding (Gollhardt et al., 2020) and suggest linear development paths that do not reflect the dynamic nature of transformation (Breiter et al., 2024). However, this work draws on various maturity models as a conceptual foundation to enable an empirically measurable comparison between companies and to assess their respective maturity levels within the context of DT and ST.

2.3 Digital Transformation

DT represents both risks and opportunities for organizations. Companies that fail to adapt risk losing their competitiveness, whereas those that embrace DT can unlock new business models and sources of value creation (Hortovanyi et al., 2023). Accordingly, the necessity of engaging with DT is widely acknowledged in literature (Verhoef et al., 2021). Accordingly, the following chapters elaborate on the conceptual foundations of DT, introduce digital transformation maturity (DTM) as a basis for operationalizing DT and synthesize key DT capabilities discussed in literature.

2.3.1 Conceptual Foundations of Digital Transformation

The concept of DT has been widely discussed in recent years, yet scholars still disagree on its precise meaning. Several authors emphasize different aspects, leading to a variety of definitions in the literature. Some scholars like Hanelt et al. (2021) and Liu et al. (Liu et al., 2011) view DT primarily as organizational change induced by digital technologies .Others place greater emphasis on process improvements, such as efficiency gains or enhanced operations as reflected in Vials (2019) definition of DT as "a process that aims to improve an entity by triggering significant changes to its properties through combinations of information, computing, communication and connectivity technologies" (p.188). In contrast, Fitzgerald et al. (2014) adopt a more technology centered perspective highlighting the enabling function of digital innovations, ranging from communication platforms and mobile tools to data driven analytics and sensor based technologies. Finally Rogers (2016) argues that DT should be understood primarily as a matter of strategy rather than technology.

Despite their different emphases, the various definitions share the view that DT goes beyond mere technological development This broader understanding is further illustrated in the distinction made by Vial (2019) between information technology (IT) enabled transformation and DT. Drawing on Bharadwaj et al.(2013), Vial (2019) positions DT as a progression beyond IT-enabled transformation. Bharadwaj et al.(2013) originally writing in the context of digital business strategy, identify four central themes that provide a conceptual foundation for future research: the scope, scale and speed of digital business strategy, as well as the sources of value creation and capture. Although their work does not explicitly address DT, these themes can be applied to the DT discourse, as done by Vial (2019). He particular builds on the first three, emphasizing that digital technologies broaden the scope of change, increase its scale by affecting entire industries and accelerate its speed compared to traditional IT projects.

DT also has been described as part of a three stage trajectory of technological change (Verhoef et al., 2021). The first stage is digitalization, which refers to the conversion of analog information into digital formats. The second stage is digitization, where digital technologies are used to optimize and reorganize existing processes. The third stage is DT, understood as a holistic reconfiguration in which the core business model of a company can be reshaped (Verhoef et al., 2021). In contrast to IT-enabled transformation, which largely corresponds to the first two stages, this stage is far more comprehensive and characterized by strategic and disruptive effects that go well beyond operational process improvements (Verhoef et al., 2021).

Building on the commonalities across the various definitions and the conceptual developments leading to DT, this work follows the understanding of DT as a holistic transformation that goes beyond efficiency gains and entails a profound reorientation on how organizations operate and create value.

2.3.2 Digital Maturity Models

First Nerima et al. (2021) describe digital maturity as the degree of digitalization achieved through the integration of digital processes into an organization's structure. Zaoui and Souissi (2022) expand this view by framing it as an indicator of how far a company has advanced on its DT journey and which steps remain to progress further. Goumeh and Barforoush (2021) builds on and intensifies this understanding by extending it beyond technological adoption to include managerial and organizational aspects such as changes in products, services, processes, culture and skills. In line with the perspective outlined in the prior chapter, this work follows Gourmeh and Barforoush's (2021) broader conceptualization, as DT is understood to go beyond technology and involve comprehensive organizational change.

To evaluate and guide this progress, researchers have developed digital maturity models which function as structured frameworks for assessing an organizations level reached of DT (Soares et al., 2021). Such models typically consist of defined criteria and assessment methods that help determine the current and desired maturity levels, often accompanied by improvement measures (Mettler, 2010). Measuring digital maturity remains challenging due to the multidimensional nature of DT (Zaoui & Souissi, 2022), yet digital maturity models offer a practical approach to diagnose digital readiness, classify capabilities and benchmark performance (Aguiar et al., 2019; Santos & Martinho, 2020).

A large variety of maturity models in the topic of IS have been developed in recent years (Thordsen et al., 2020), addressing domains such as IT Management (Becker et al., 2009) and business process management (de Bruin et al., 2005) or specific branches like health (Doctor et al., 2023) or banking (Goumeh & Barforoush, 2021). As transformation challenges differ across industries and organizational contexts, maturity assessments are often tailored to specific sectors.

One example for the industry 4.0 context is the model by Schumacher et al. (2016), which was developed for manufacturing companies and structures digital maturity across nine dimensions: Strategy, Leadership, Customers, Products, Operations, Culture, People, Governance and Technology. The model introduces six maturity levels which are Computerization, Connectivity, Visibility, Transparency, Predictive Capacity and Adaptability, although these levels are not described narratively (Schumacher et al., 2016). A different model is offered by Rossmann (2018), who developed a cross-industry capability based model and identifies eight central capability dimensions. In his approach, digital maturity is assessed through the extent of capability development. However, he does not specify discrete maturity stages, nor does he predefine which capability configurations correspond to a particular level such as "beginner" or "advanced" (Rossmann, 2018). Another model is provided by Kirmizi and Kocaoglu (2022), whose model is based on a design science development process and compromises six dimensions: Strategy and Governance, Organization and Corporate Culture, Smartness, Employee, Processes and Customer, as well as ten subdimensions and 39 capability items. This model also defines five maturity levels which are Awareness, Pilot, Engagement, Supply Chain Integration and Optimization. The Awareness level reflects an early phase in which organizations begin to familiarize themselves with DT and develop basic understanding of its relevance while the Optimization level marks the most advanced phase, where digitalization is firmly established and companies continuously refine their digital practices and integrate new digital solutions into existing processes (Kırmızı & Kocaoglu, 2022). These levels help to position an organization's digital maturity along the defined dimensions and illustrate the progression between the different levels.

Despite the absence of a standardized approach and the wide variety of existing maturity models, recurring themes can be observed across the different frameworks. Dimensions such as culture, customer orientation, leadership, process, strategy and technology consistently appear in many models, regardless of industry focus or methodological design, as demonstrated in

Authors	Year	Customer & Value	Data & Analytics	Governance	Leadership	Operation & Processes	Organization & Culture	Product & Services	Strategy	Technology
Schumacher et al.	2016	x		x	x	x	x	x	x	x
Colli et al.	2018	x		x			x			x
Aguiar et al.	2019	x	x		x	x	x			
Rossmann et al.	2019	x	x	x	x	x	x		x	x
Gollhardt et al.	2020	x		x		x	x		x	
Santos & Martinho	2020					x	x	x	x	
Deja et al.	2021						x			
Ehrensperger et al.	2021		x	x		x	x	x		x
Gökalp & Martinez	2021					x	x		x	x
Goumeh & Barforoushi	2021	x		x		x			x	x
Nemira & Ralyté	2021		x		x	x	x		x	x
Zitoun et al.	2021		x				x			x
Amaral & Peças	2021				x		x	x		x
da Costa et al.	2022			x	x	x	x	x	x	x
Gökalp et al.	2022		x				x		x	x
Kırmızı & Kocaoglu	2022	x				x	x		x	x
Zaoui & Souissi	2022	x					x		x	x
Doctor et al.	2023					x	x			x
Hortovanyi et al.	2023	x						x	x	x
Nebati et al.	2023	x			x	x	x		x	x

Table 1: Digital Maturity Dimensions Across Existing Models
Source: Own illustration

Table 1, which illustrates the most common dimensions identified across several digital maturity models. While the naming of dimensions may differ across models, their substantive meaning fits consistently within these dimensions. These shared dimensions indicate a common understanding of the elements that shape DT respectively digital maturity and therefore serve as a suitable conceptual basis for this thesis.

2.3.3 Digital Transformation Capabilities

DT capabilities are frequently operationalized in maturity research through structured survey assessment, as seen for example in Kirmizi and Kocaoglu (2022) as well as Rossmann (2018). These items are rated on Likert scales to determine the degree to which specific capabilities are present within an organization (Deja et al., 2021; Latino, 2025). In most maturity models, these items are structured into broader dimensions and subdimensions to capture the multidimensional nature of digital maturity. As illustrated in Table 1, the literature consistently highlights a similar set of dimensions when assessing an organization's level of digital maturity. Across these different models and empirical studies, dimensions related to strategy, technology, operations and processes as well as organization and culture, are mentioned most frequently and can therefore be understood as core dimensions. The following paragraphs therefore outline the core capabilities associated with each of these dimensions, summarizing the recurring themes across existing research.

Within the Strategy dimension, maturity assessments typically begin by examining whether the organization has established a digital strategy at all (Gollhardt et al., 2020). Scholars also emphasize the importance of a clearly communicated strategy that is transparent to employees and embedded into the overarching corporate strategy (Hortovanyi et al., 2023; Kırmızı & Kocaoglu, 2022). Beyond the existence and integration of strategic intentions, companies require the capabilities to steer the digital strategy respectively the digital transformation through measurable and clear objectives (Kırmızı & Kocaoglu, 2022) and defined performance indicators (Santos & Martinho, 2020). Furthermore, this dimension captures the strategic approach to innovation and emerging technologies (Hortovanyi et al., 2023; Santos & Martinho, 2020). Overall, the Strategy dimensions encompasses organizational capabilities that align DT with long-term strategic direction.

The Technology dimension compromises the capabilities required to provide and manage digital technologies and technical infrastructures. One reoccurring focus in literature is the ability to establish and maintain a modern IT infrastructure, including cloud environments and interoperable systems (Ehrensperger et al., 2023; Zitoun et al., 2021). Another essential technological capability is about IT security and privacy protection. Several Studies underline that organizations must be able to manage cybersecurity threats, ensure comp with data protection regulations and protect IT systems (Doctor et al., 2023; Nebati et al., 2023). A further crucial set of technological capabilities relates to the use of emerging technologies. Research points to the optimization of production processes using AI (Santos & Martinho, 2020) or the automation of repetitive task with the help of AI (Kırmızı & Kocaoglu, 2022). Besides, research highlights Internet-of-Things (IoT) enabled real-time data availability (Nebati et al., 2023) and the increasing relevance of cloud integration for ensuring scalability and organizational flexibility, both of which are commonly assessed when evaluating an organization's engagement with emerging technologies (Amaral & Peças, 2021; Ehrensperger et al., 2023). In addition, several maturity models refer to the organization's ability in the dimension Technology to automate business processes more broadly, signaling that automation represents an important technological foundation for DT (Rossmann, 2018).

The Operations and Processes dimension focuses on the processual implementation of DT and therefore likely overlaps with the technological dimension, because many process related capabilities rely on digital technologies. Studies commonly assess how far operational processes are digitalized and whether capabilities for process automation exist (Doctor et al., 2023; E. Gökalp & Martinez, 2021). Another recurring capability relates to process integration and coordination. This includes cross-functional cooperation within the organization as well as vertical and horizontal processes, meaning that processes are digitally connected both across internal business functions and along the supply chain with external partners (E. Gökalp & Martinez, 2021; Kırmızı & Kocaoglu, 2022). The degree to which process run end to end and are interconnected is repeatedly identified as a key prerequisite for digital maturity. Moreover, process agility is a key operational capability, as the ability to adapt processes quickly is essential for translating transformation efforts into operational performance (Kırmızı & Kocaoglu, 2022; Santos & Martinho, 2020).

The Organization and Culture dimension relates to the human and cultural foundations of DT. Across maturity assessments, a frequently examined capability is whether employees are provided with opportunities to develop their digital skills and whether appropriate training programs exist to support competence development (Doctor et al., 2023; Gollhardt et al., 2020; Rossmann, 2018). Another element refers to a general culture of learning that encourages experimentation and accepts mistakes as a part of the innovation process (E. Gökalp & Martinez, 2021; Kırmızı & Kocaoglu, 2022). Furthermore, organizational culture includes structural and behavioral aspects such as a agile working environment with lean hierarchies and rapid decision-making (Aguiar et al., 2019; Nebati et al., 2023). Many studies additionally highlight cultural readiness for change, referring to employees' willingness to accept DT and actively participate in it (Amaral & Peças, 2021; E. Gökalp & Martinez, 2021). Lastly several contributions underline that innovation oriented cultural capabilities, including the ability to develop, test and implement digital ideas, form an important part of the cultural dimensions of DTM (Santos & Martinho, 2020; Schumacher et al., 2016).

2.4 Sustainability Transformation

Despite political fluctuations and occasional regulatory rollbacks, sustainability remains highly relevant for customers, investors and capital markets in general as well as other stakeholders (Auweiler et al., 2025; Wijethilake & Lama, 2019). This sustained relevance requires organizations to move beyond isolated sustainability initiatives and address sustainability through a structured transformation across the organization. Against this background, the following chapters outline the conceptual foundations of ST, review sustainability transformation maturity (STM) and summarize key ST capabilities discussed in literature.

2.4.1 Conceptual Foundations of Sustainability Transformation

Compared to DT, the academic discourse on ST is still less extensive. This imbalance is also reflected in bibliometric evidence i.e. in Burinskiene and Nalivaike (2024) who's results show that publications focusing on DT outnumber those addressing ST by a factor of five. Despite this gap, ST has gained increasing attention among researchers and practitioners in recent years (Peters & Simaens, 2020). Organizations increasingly recognize that global issues such as resource pressure, environmental harm and social inequality require substantial shifts toward more sustainable ways of operating (Adams et al., 2016). At the same time, expectations from employees, customers and policymakers continue to rise, therefore companies must realign their strategies to remain competitive and fit for a future in which sustainability plays a central role (Graf-Drasch et al., 2023).

Before exploring the concept of ST in more detail, it is essential to clarify the broader concept of corporate sustainability. Contemporary understandings of corporate sustainability go beyond the initial emphasis on minimizing environmental harm. They are commonly grounded in Elkington's formulation of the Triple Bottom Line (TBL), which integrates economic, environmental and social sustainability (Elkington, 1998). The economic pillar relates to the long-term viability of the organization, the environmental pillar focuses on reducing ecological impacts and the social pillar concerns the wellbeing of people directly affected by organization's activities, including fair working conditions, responsible supply chains and broader societal wellbeing often described as societal capital (Dyllick & Hockerts, 2002).

Building on this foundation, ST describes a comprehensive organizational change that reorients structures, practices and culture toward sustainability goals. The literature highlights that this process is multidimensional (Dao et al., 2011; Dyllick & Muff, 2016) and therefore it is comparable in scope to DT. According to Graf-Drasch et al. (2023), ST refers to an organizational shift aimed at enhancing environmental and social performance in line with the TBL. This implies that the organization contributes to human well-being while operating within ecological boundaries (Graf-Drasch et al., 2023). In contrast, Christmann et al. (2024) adopt a broader perspective, describing ST as a multilayered organizational change shaped by environmental, social, regulatory, governmental and individual influences and thus extending beyond the TBL. In this thesis the perspective suggested by Christmann et al. (2024) is adopted, since it acknowledges the interplay between diverse levels and actors that shape an organization's transition toward corporate sustainability.

Contemporary debates increasingly frame sustainability not only as a moral obligation but as a strategic necessity, since integrating sustainability into organizational processes can mitigate risks assigned with for example resource scarcity and climate risks and also enhance long-term financial performance (Chau et al., 2025; Newman & Noy, 2023; Zhang et al., 2020). From this perspective, ST is both ethically desirable and economically rational. Furthermore, it can also stimulate organizational innovation for instance through business models that combine commercial viability with environmental and social value creation, often driven by technological advances, shifting customer expectations or regulatory developments (Fabrizi et al., 2024; Geissdoerfer et al., 2018).

2.4.2 Sustainability Maturity Models

The concept of sustainability maturity is rarely clearly defined in literature, yet Sari et al. (2021) refer to sustainability maturity as the extent to which sustainability related processes and practices are defined, managed, measured and improved, indicating an organization's progress toward becoming a mature sustainable organization. While Sari et al. (2021) focus on the degree of process formalization and continuous improvement, Vásquez et al. (Vásquez et al., 2021) add a complementary perspective by framing sustainability maturity models as tools that measure organizational progress along the three dimensions of the TBL. Sustainability maturity models therefore represent multistage conceptual frameworks that describe structured patterns in the development of sustainability related capabilities, specify indicators for each maturity level and enable to self asses their current sustainability maturity and identify pathways for

Author	Year	Focus of maturity model	Dimensions	Maturity levels
Okongwu et al.	2013	Supply chain sustainability	Organisation; Strategy and Policies; Stakeholders; Performance measurement; Sustainability standards; Economic issues; Report structure; Supply chain design; Employee managment; Supplier relationship management; Customer relationship management; Environment	4 levels: initial; intermediate; advanced; world class
Edgeman & Williams	2014	Self-assessment anaytics for sustainability, resilience and robustness	Strategy and Governance; Process Implementation, Translation and Execution; Financial and Marketplace Performance; Sustainability Performance; Human Ecology and Capital Performance; SEI and General Innovation, Design and Continuous Improvement Performance	Five levels: Very Low Maturity, Low Maturity, Moderate Maturity, High Maturity, Very High Maturity
Barletta et al.	2020	Manufacturing	Manufacturing processes; Materials; Assets; Data driven decision support; Information systems; Organisational competences	Four levels: Unprepared; Novice; Almost ready, but static; Ready continuous improver
Sari et al.	2020	Corporate sustainability	CS driver (external); CS driver (internal); CS strategy; CS action; CS performance	3 levels: initial stage; managed stage; defined stage
Pigosso & McAloone	2021	Circular Economy within manufacturing companies	Organisation; Strategy & Business Model Innovation; Product & Service Innovation; Manufacturing & Value Chain; Technology & Data; Use, Support & Maintenance; Takeback & End-of-Life Strategies; Policy & Market	Five levels: Understanding the potential, Planning pilot implementation, Piloting initiatives, Planning scale up, Scaling up initiatives
Vásquez et al.	2021	SME	Environmental knowledge management; Environmental practices and strategies; Mmgt. systems	Four levels
Uhrenholt et al.	2022	Circular Economy	Value Creation; Governance; People and Skills; Supply Chain and Partnership; Operations and Technology; Product and Material	Six levels: None; Basic; Explorative; Systematic; Integrative; Regenerative
Sohns et al.	2023	Green business process management	Green attitude; Green strategy; Green governance; Green modeling; Green monitoring; Green optimization	Four levels
Sajadieh & Noh	2024	Manufacturing	Employee; Customer; Citizen; Environment; Society; Economy; Internal Disruption; External Disruption	Four levels: Beginner; Piloted; Developed; Outstanding
Cuevas-Lopez-de-Baro et al.	2025	Industry 5.0	vision and strategy; resource allocation innovation; communication; technological readiness; data and analytics; resource efficiency; circular economy; renewable energy; eco-friendly materials; green supply chain; human-machine collaboration; skill development and training; safety and ergonomics; work-life balance; personalization of work experience; ethical considerations; cybersecurity; adaptive technologies; redundancy and flexibility; data and analytics; supply chain resilience; remote operations	6 levels: Not Initiated; Exploration Phase; Partial Implementation; Advanced Implementation; Fully Integrated; Industry Benchmark
Latino	2025	Industry 5.0 in manufacturing SMEs	People and culture; Awareness on I5.0 production; Organizational strategy; Value chain and processes; Smart manufacturing technology; Technology based products and services; Industry 4.0 Technologies	Five Levels

Table 2: Sustainability Maturity Dimensions and Maturity Levels
Source: Own illustration

improvement (Sari et al., 2021).

Similar to the literature on digital maturity models, research on sustainability maturity has produced many models tailored to different contexts. Vásquez et al. (2021) emphasizes that these models vary strongly in scope and purpose, as they target different organizational environments. Examples include models focusing on manufacturing companies (Barletta et al., 2021; Sajadieh & Noh, 2024), models addressing sustainability maturity within supply chains (Okongwu et al., 2013) or models concentrating on business process management (Sohns et al., 2023). However, compared to digital maturity models, sustainability maturity models are considerably more diverse and less coherent, which can be observed in Table 2. There is less convergence in the terminology used to describe for example maturity dimensions and the structure of maturity levels varies widely across studies. Although underlying items often reveal conceptual overlaps, the naming and clustering shows substantial variation across models. The range of perspectives shown in Table 2 therefore underscores that sustainability maturity lacks a universally shared structure, reinforcing the argument that consolidation across models is challenging and that recurring themes rather than distinct model structures should guide the conceptual foundation of sustainability maturity models applied in this study.

2.4.3 Sustainability Transformation Capabilities

To ensure conceptual comparability with the dimensions used for DT, the capabilities examined in the context of ST are largely aligned with the same overarching structure. This consistent with the broader maturity model literature, as sustainability related dimensions frequently intersect with those of DT due to their organization wide transformative nature. Studies such as that of Uhrenholt et al. (2022) underscore this overlap as they use dimensions like Value creation, Governance or People and Skills (see Table 2). A key adjustment, however, concerns the replacement of the Technology dimension with a Governance and Risk dimension, which reflects the particular relevance for organizational sustainability.

Within the ST Strategy dimension, the literature commonly assess a range of organizational capabilities that reflect how strategically sustainability is positioned within the company. Typical assessment items examine for example, whether sustainability is integrated into the overall corporate strategy or treated as a strategic component of long-term organizational development (Pigosso & McAloone, 2021; Vásquez et al., 2021). Another frequently captured aspect concerns the capability to make targeted sustainability investments, indicating the extent to which organizations allocate resources to support sustainability initiatives (Pigosso & McAloone, 2021). Furthermore, maturity models evaluate the strategic role of sustainability in enabling innovation, including the emergence of new business opportunities of sustainability-driven business models (Edgeman & A. Williams, 2014; Pigosso & McAloone, 2021; Sohns et al., 2023).

The Governance and Risk dimension in the sustainability maturity model is commonly described through capabilities that enable organizations to manage sustainability obligations in a consistent and accountable manner. A first area frequently highlighted in the literature concerns the systematic identification and assessment of sustainability risks, including the ability to detect vulnerabilities within supply chains and to incorporate these insights into ongoing risk management routines (Cuevas-Lopez-de-Baro et al., 2025). A second recurring theme relates to regulatory alignment, where governance capabilities are reflected in the organization's capacity to understand, interpret and operationalize for example relevant environmental requirements at national and international levels (Pigosso & McAloone, 2021; Vásquez et al., 2021). A third theme focuses on sustainable supply chain practices, emphasizing whether environmental and social criteria shape supplier selection and whether suppliers demonstrably comply with sustainability related expectations (Vásquez et al., 2021). Depending on the focus of the respective maturity model, some studies also include highly specific governance items, including detailed environmental control procedures such as the verification of proper hazardous waste disposal as assessed by Vásquez et al. (2021).

Operational sustainability is frequently reflected in the concrete practices and systems that shape daily production and process execution. One aspect often examined in maturity assessments is whether organizations have already implemented environmental practices that guide routine operational activities and support the reduction of resource use or emissions (Vásquez et al., 2021). In their operational items, Vásquez et al. (2021) illustrate this through concrete measures such as the reuse of office materials, which serves as an example of how environmental considerations can be embedded into everyday procedures. Assessments also pay attention to the presence of a structured environmental management system, which enables organizations to monitor operational performance, establish standards and coordinate improvement measures across units (Vásquez et al., 2021). In addition, studies like Pigosso and McAloone's (2021) consider the capability to address the end-of-life stage of products, for example through remanufacturing or recycling initiatives that recover value and reduce waste streams.

Organization and Culture related aspect of sustainability are for example reflected in the extent to which employees possess the knowledge, cultural orientation and learning conditions required to support ST (Barletta et al., 2021; Cuevas-Lopez-de-Baro et al., 2025; Sari et al., 2021). For instance, Barletta et al. (2021) illustrate through an item capturing employees' environmental knowledge and the regular provision of environmental training, which together indicate whether sustainability related competencies are systematically developed within the workforce. In addition, the literature points to the role of leadership in shaping shared sustainability norms. In those items the commitment of leaders to realize the vision and integrate sustainability into the company's strategy is assessed (Sari et al., 2021). Finally, assessments consider whether organizations create conditions that encourage learning and innovation, such as by supporting employees in proposing sustainability related ideas or engaging in circular economy training (Cuevas-Lopez-de-Baro et al., 2025).

2.5 Twin Transformation

Building on the preceding chapters of DT and ST, this section focuses on TT as an integrated perspective emphasizing their reciprocal interdependence. It aims to provide the theoretical basis for examining this interplay empirically. The chapter first reviews related work on TT, then derives theory-driven hypotheses from it and subsequently addresses the current literature on the roles of AI as enabling technology for ST and value creation of TT.

2.5.1 Related Work on Twin Transformation

Over recent years, both academic literature and practitioners have increasingly examined how digitalization and sustainability relate to one another (Barth et al., 2023). Contributions have been largely focusing on the potential of digital technologies to enable sustainability emphasizing digital solutions that support the achievement of environmental and social goals (Birkel & Müller, 2021; Kranz et al., 2015; Sepasgozar, 2021). More recent work however, points to the fact that sustainability can also influence and shape DT processes, suggesting a bidirectional relationship between the two domains (Barth et al., 2023). Following Christmann et al. (2024), the complexity of contemporary transformation processes requires integrated approaches that avoid fragmented or conflicting organizational efforts.

Against this backdrop, the idea of a bidirectional interdependence has gained traction and scholars have increasingly described this intertwined perspective as TT or twin transition, while some also refer to this concept as dual transformation i.e. del Socorro Encinas-Grijalva et al. (2024). In this study TT is defined as the strategic interlinkage of DT with ST within an organization.

It encompasses the use of digital technologies to advance sustainability objectives as well as the integration of sustainability principles across areas of DT. Through this reciprocal embedding, synergies and additional value emerge that go beyond the effect of each transformation in isolation (Auweiler et al., 2025; Christmann et al., 2024; Graf-Drasch et al., 2023). Although contributions such as Ortega-Gras et al. (2021) explicitly reference the concept, they adopt a unidirectional view in which digital technologies serve primarily as enablers of sustainability. This illustrates a broader pattern in the field. The multivocal literature review by Shajari and David (2025) underlines this as they show that although many studies address the concept of TT, most do not examine the link between them. Instead a substantial proportion only acknowledges a connection in one direction – how DT influences ST. Ultimately, only 24 of 161 analyzed studies, explicitly recognized the mutual interplay between DT and ST (Shajari & David, 2025).

Existing research has examined various aspects of TT in considerable detail, as summarized in Table 3. The literature is dominated by conceptual contributions, many of which develop frameworks or theoretical models, such as the capability based "Butterfly Model" by Christmann et al. (2024). Likewise, several literature-based studies for example the systematic review by Hammerschmidt et al. (2025) summarize the existing research landscape on TT. In contrast, empirical studies on TT remain scarce. To the best of the authors' knowledge, the work by del

Author	**Year**	**Contribution**	**Study type**
Zimmer & Järveläin	2022	Concept of a digital–sustainable co-transformation	Conceptual
Graf-Drasch et al.	2023	Multi-level model of digital–sustainability interplay across various organizational layers	Conceptual
Breiter et al.	2024	Capability maturity model for twin transformation	Conceptual
Christmann et al.	2024	Capability-based "Twin Transformation Butterfly" framework	Conceptual
Auweiler et al.	2025	ESG based value framework for twin transformation	Conceptual
Tabares et al.	2025	Twin transition implementation framework for industrial organizations	Conceptual
del Socorro Encinas-Grijalva et al.	2024	Dual transformation readiness assessment of SME in Latin America	Empirical
Ortega-Gras et al.	2021	Desk research on I4.0 as circular economy enabler	Literature-based
Burinskiene & Nalivaike	2024	Bibliometric analysis of twin transformation in EU SMEs	Literature-based
Hammerschmidt et al.	2025	Systematic literature review on twin transformation	Literature-based
Ologeanu-Taddei et al.	2025	Analyzing relationship between digital transformation and corporate sustainability	Literature-based
Sharjari & David	2025	Multivocal literature review on twin transition	Literature-based

Table 3: Literature Overview on Twin Transformation
Source: Own illustration

Socorro Encinas-Grijalva (2024) is the only empirical investigation in this domain.

However, their study focuses primarily on assessing the readiness of SMEs in Latin America for TT and does not analyze the bidirectional interplay between DT and ST. Instead, the authors adopt diagnostic perspective by operationalizing DT and ST through a set of identical organizational dimensions, including Strategy, Culture, Organization and Technical capabilities. The empirical analysis relies on descriptive statistics and correlation analyses to examine the degree of alignment between these dimensions (Del Socorro Encinas-Grijalva et al., 2024).

2.5.2 Hypotheses Development

Building on the identified research gap, this study focuses on the mutual influence between DT and ST. Although the notion of TT is conceptually grounded in the idea of reciprocal interdependence, existing research on TT offers almost no empirical analyses that test this relationship directly. This lack of evidence leaves a central assumption of the TT unexamined. The following section therefore derives hypotheses to examine these relationships empirically.

As previously outlined, the theoretical foundation of the TT rests on two core mechanisms depicted in Figure 1. First, DT is assumed to enable ST. Second, ST is expected to guide respectively redesign DT (Christmann et al., 2024; Graf-Drasch et al., 2023).

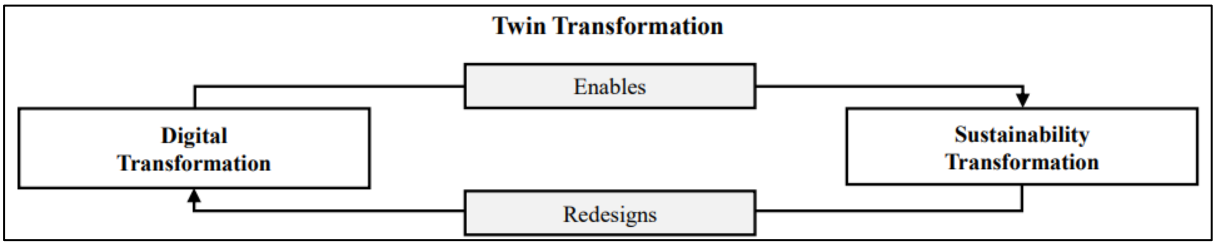


Figure 1: Theoretical Framework Underlying the Twin Transformation
Source: Graf-Drasch et al., 2023, p.6

These reciprocal mechanisms imply that both transformations streams influence one another rather than progressing independently. A central empirical question therefore concerns whether organizations that exhibit a higher degree of DT also show a more advanced ST, which can be directly examined through the following hypothesis:

H1: *Digital transformation positively affects sustainability transformation.*

In contrast, the reverse relationship is theoretically grounded in the notion of redesign. Redesign refers to a qualitative reorientation of DT, as ST shifts its underlying purpose, priorities and direction beyond purely economic value creation (Graf-Drasch et al., 2023). Although redesign does not imply a simple intensification of DT, such reorientation typically necessitates the adoption of new digital tools and infrastructures. This includes, for instance, increasing transparency regarding data practices (Ghobakhloo et al., 2021), using digital systems to analyze environmental performance (Vergara & Ferruz Agudo, 2021) and advancing the transition toward low-carbon digital infrastructures (Birkel et al., 2019). To empirically capture this effect, the qualitative reorientation is approximated through the measurable maturity of DT. Following the theoretical argument that redesign ultimately manifests in a higher level of DTM, the effect is therefore modelled as positive relationship. Based on this reasoning, the following hypothesis is derived.

H2*: Sustainability transformation positively affects digital transformation.*

To understand more precisely how DT contributes to ST, it is necessary to include a mechanism that explains this connection. While the previous hypotheses examine whether such a relations ship exist at all, the next step is to explore why and through what DT may support ST. For this purpose, enabling capabilities are introduced as a mediating construct. They describe the technological and organizational capabilities that allow an organization to use digital technologies in a way that support sustainability objectives. In the existing literature, these capabilities are operationalized through a range of digitally enabled functions. For instance Ghobakhloo (2020) and Auweiler et al. (2025) conceptualize enabling capabilities, among other things, as the ability to leverage digital monitoring and connected systems to better track resource consumption and environmental impacts. Other studies like Christmann et al. (2024) emphasize analytical approaches based on data that allow organizations to model environmental scenarios and inform sustainability oriented decision-making. Further contributions show how AI can uncover patterns relevant to sustainability within large or unstructured datasets, thereby supporting more targeted improvement measures (Miranda et al., 2022; Padmanabhan et al., 2022). In addition, enabling capabilities are also reflected in digitally integrated processes and connected production systems that enhance operational efficiency and facilitate circular practices (Graf-Drasch et al., 2023).

Based on this understanding, companies that achieved a higher level of DTM are expected to possess stronger enabling capabilities, as excelling in DT typically involves substantial investments in digital infrastructure, data systems and process improvements (Hortovanyi et al., 2023), which form the technological basis of these enabling capabilities. At the same time, these enabling capabilities are assumed to improve ST because they provide the digital foundation needed to implement sustainability related improvements (Al-Husain et al., 2025). This leads to the following hypotheses:

H3: *Digital transformation positively affects enabling capabilities.*

H4: *Enabling capabilities positively affects sustainability transformation.*

While hypotheses three and four examine how DT contributes to ST through enabling capabilities, this perspective captures only one direction of TT. To examine the reverse direction and understand how ST guides the redesign of DT, guiding capabilities are introduced as an additional construct. Guiding capabilities in this study refer to the organizational ability to align digital development with environmental and social ambitions, ensuring that digital initiatives are shaped by priorities related to sustainability. In the literature, this construct is reflected in the practices that embed sustainability considerations into digital design and investment choices. Christmann et al. (2024) emphasizes for example the ability to include sustainability aspects in the development of digital products, processes and services and show that organizations with guiding capabilities may incorporate sustainability criteria when assessing digital technologies. Together with findings by Auweiler et al. (2025), this points to a shift towards directing digital resources to environmentally efficient solutions, such as cleaner cloud infrastructures or energy saving digital systems in general. Moreover, guiding capabilities also include activities that foster sustainability awareness and digital competences within the workforce. For example, companies may expand their digital training programs to include content on emerging technologies, enabling employes to develop skills that support long-term sustainability objectives (Margherita & Braccini, 2021).

Building on this understanding, organizations that have progressed further in their ST are expected to exhibit stronger guiding capabilities. As sustainability objectives become more firmly embedded in corporate strategy, organizations face pressure to also align digital design, technology choices and capability development with environmental and social goals. Advancing sustainability therefore creates the necessity to evaluate and steer digital initiatives through a lens oriented toward sustainability, which in turn fosters the development of guiding capabilities. At the same time, these guiding capabilities are expected to influence DT itself. By reshaping the criteria through which digital options are assessed and by redirecting digital investment priorities, guiding capabilities function as a mechanism that initiates qualitative redesign processes within DT. As discussed earlier, such redesign does not merely intensify existing digital activities but typically requires the adoption of new digital tools, infrastructures or technologies. Consequently, the reorientation triggered by guiding capabilities can manifest in higher levels of DTM. Based on this reasoning, the following hypotheses are derived:

H5: Sustainability transformation positively affects guiding capabilities.

H6: Guiding capabilities positively affects digital transformation.

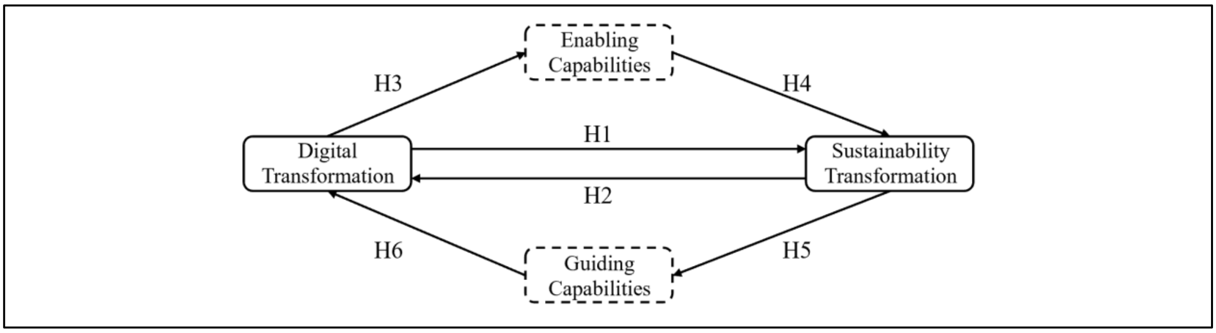


Figure 2: Conceptual Framework
Source: Own illustration

Drawing on the theoretical arguments developed in this chapter, a conceptual framework was constructed to illustrate the proposed relationships between DT, ST and the two capability constructs (see Figure 2). The framework integrates both directions of TT and positions enabling and guiding capabilities as key mechanisms though which digital and sustainability mutually influence each other. Together these relationships form the basis for the six hypotheses tested in this study.

2.5.3 The Role of Artificial Intelligence in Sustainability Transformation

AI has gained increasing relevance for organizations and has become an integral component of DT initiatives (Kavak & Rusu, 2025). Beyond efficiency and performance oriented applications, AI is increasingly discussed in the context of sustainable development, as it supports organizations in addressing environmental and social challenges while maintain economic viability (Kar et al., 2022). Advances in data availability, computational power and algorithmic capabilities have expanded the potential of AI applications in sustainability related contexts (Costa et al., 2025; Pugliese et al., 2021).

AI does not represent a single technology but rather a continuously evolving set of advanced computational capabilities (McCorduck, 2004). Within sustainability contexts, different AI technologies enable transformation through distinct mechanisms and application areas. For example, Schöggl et al. (2023) examine the role of digital technologies in the circular economy and highlight how machine learning and predictive analytics support ST through applications such as predictive maintenance, resulting in for example improved energy efficiency, enhanced demand planning and reduced emissions. Natural language processing contributes by processing and structuring large volumes of sustainability related textual information, thereby supporting sustainability reporting and text analysis related to environmental, social and governance (ESG) (Maibaum et al., 2024; Ranawaka et al., 2024). Shahin et al. (2024) show that computer vision enables automated monitoring and control of physical processes, for instance in waste sorting, resulting in waste reduction: In addition, Chen et al. (2024) demonstrate how optimization algorithms support the coordination of complex logistics and supply chain networks by improving resource allocation and transportation efficiency. Focusing on manufacturing environments, Kamble et al. (2022) highlight the simulation based approaches and digital twins represent the operational environments of a plant using collected data, enabling organizations to evaluate alternative actions and improve efficiency and sustainability outcomes. Finally, generative AI complements these applications by supporting scenario generation (Xu & Lin, 2025). Taken together, these examples illustrate the wide range of AI technologies applied in sustainability contexts and underline the diversity of application areas, ranging from energy efficiency management and waste management in manufacturing contexts to supply chain management and sustainability reporting.

However, the effectiveness of AI as an enabler of ST is contingent upon several critical preconditions. In particular, reliable data availability, high data quality and the integration and sharing opportunities of data across organizational units are essential, as fragmented, inconsistent or unstructured data can significantly constrain the performance and reliability of AI technologies (Kavak & Rusu, 2025).

Despite its significant potential, the use of AI in sustainability contexts is also associated with emerging risks that may limit its effectiveness if not adequately addressed. Insufficient organizational competencies can hinder the responsible development, deployment and interpretation of AI based systems (Mikalef & Gupta, 2021). In addition, compliance related challenges arise form evolving regulatory requirements (Aldoseri et al., 2024)), which leads to higher data protection obligations. Moreover, the operation of AI systems itself may entail increased energy consumption, which can partially offset sustainability gains if efficiency and environmental impacts are not carefully managed (Lee et al., 2025). Nevertheless, when appropriately governed and embedded within organizational processes, AI represents a powerful lever in different application fields for organizations seeking to advance ST.

2.5.4 Value Creation in Twin Transformation

As briefly outlined in Chapter 2.5.1, the literature suggests that the value potential of TT exceeds the value enabled by DT and ST in isolation (Christmann et al., 2024; Lockl et al., 2025). While this integrative perspective is gaining increasing attention, a substantial body of prior research has focused on how DT and ST individually contribute to organizational value (Bocken et al., 2019; Corona et al., 2019; Karimi & Walter, 2015; Svahn et al., 2017).

Following Pitelis (2009), in this study, value is understood as the perceived worth of an organization's activities, products, services and underlying capabilities for its beneficiaries, such as customer or other market participants. This value may exist as an anticipated potential or become realized through market exchange, at which point value can be captured by the firm. Whether such value translated into measurable outcomes depends on contextual conditions, including market dynamics, competitive intensity and evolving customer expectations (Shollo et al., 2022).

In this context, Vial (2019) for example synthesizes prior research by highlighting DTs' multifaced effects on organizations. Existing studies show that DT enhances innovativeness, as digital technologies enable new forms of product and service development and support organizational experimentation (Svahn et al., 2017). DT is further associated with improved financial performance, reflecting efficiency gains and new revenue opportunities enabled by digital initiatives (Karimi & Walter, 2015). Moreover, research links DT to firm growth, particularly by facilitating capability and market expansion through digital channels (Yao et al., 2023). Finally, Neumeier et al. (2017) emphasize the role of DT in creating competitive advantages, for instance by enabling differentiated value propositions and more agile organizational structures. While these studies emphasize the economic and organizational value of DT, another stream of research has for over a decade examined the environmental value of digital technologies under the label of Green IS. Green IS research examines how information systems support sustainability by for example reducing resource consumption, improving energy efficiency and enabling more sustainable business practices (Ixmeier et al., 2024).

Similar to DT, ST affects organizations holistically. Accordingly, both transformation processes exhibit substantial overlap in the types of organizational value they generate. In line with the TBL perspective, sustainability oriented changes have been shown to enable value creation across economic, environmental and social dimensions. Form an economic perspective, prior studies associate ST with improved financial performance, cost efficiencies, enhanced long-term competitiveness, as well as new revenue opportunities arising from sustainable products and services (Bocken et al., 2019; Xie et al., 2019). Environmental value emerges through for example reduced resource consumption, lower emissions and improved energy efficiency resulting from more sustainable processes and products (Corona et al., 2019; Zakari et al., 2022). Beyond economic and environmental effects, sustainability oriented changes also generate value for instance by strengthening stakeholder relationships and improving working conditions (Glavas, 2016; Schönborn et al., 2019).

However, while value of DT and ST has been widely examined individually, TT remains a comparatively new research field and insights to its value creation are still predominantly conceptual. Auweiler et al. (2025) to the best of the authors knowledge is the only contribution that analyzes TT value in detail. Auweiler et al. (2025) conceptualize the value of TT by developing an integrative framework that links strategic approaches, underlying mechanisms and value levers to explain how DT and ST jointly contribute to organizational value. In total, the authors identify 45 distinct value levers, ranging from broad organizational outcomes, such as increased employee satisfaction, increased innovations, new business models and reductions in operational costs to less obvious and more specific effect, for example improvements in user-friendliness resulting from increased customer centricity through enhanced usability and customization (Auweiler et al., 2025)

3 Methodology

This chapter describes the methodological approach used to empirically examine the reciprocal relationship between DT and ST and the mechanisms through which these interactions unfold. It presents the quantitative research design, the survey and sampling strategy and the operationalization of constructs underlying the conceptual framework. Furthermore, it outlines the regression based analytical approach used to test the theory-driven hypotheses and the descriptive analyses applied to the exploratory items. The methodological choices reflect the initial character of the study and the limited availability of prior quantitative evidence in this research field.

3.1 Research Design

This study applies a quantitative research design using a structured online questionnaire. The online questionnaire was chosen, as it is provides standardized, quantitative and therefore comparable data. The structure of the conceptual framework builds on the core theories supporting TT (Christmann et al., 2024; Graf-Drasch et al., 2023). Furthermore, the conceptualization of both transformations builds on the model by del Socorro Encinas-Grijalva (2024). However, the dimensions were refined and the questions were designed by using existing literature like Rossmann (2018) and Uhrenholt (2022). The extracted information from all studies listed in Table 1 and Table 2 including measurement items, item-dimension links or dimension only resulted in 578 DT and 322 ST entries. These results were categorized, consolidated and synthesized with the most frequently mentioned dimensions and items being structurally adapted for inclusion in the questionnaire. Items measuring enabling - and guiding capabilities, TT value and AI in context of TT were primarily derived for established TT literature such as Christmann et al. (2024) and Auweiler et al. (2025). The theoretical foundation of each individual item as presented in Table 8 and Table 9 is discussed in the chapters preceding Section 2.5.2

Although the investigation follows a hypothesis-guided approach, it is exploratory in nature because empirical research on the interaction between DT and ST remains limited and the available sample size is small. According to Cohen's (1988) effect size conventions for linear regression large effects can be detected with comparatively small samples, whereas medium and small effects require larger sample sizes up to 300 observations. Since each hypothesis in this study is tested using linear regression with one predictor, the released sample of N = 27 is sufficiently powered to detect large effects but not medium or small effects. The questionnaire consisted of several sections covering firm characteristics and the four constructs of interest, each measured using a five-point Likert scale. Details on item wording, scale development and operationalization of variables are provided in Chapter 3.3. The study aims to generate initial empirical insights into the TT and the associated enabling and guiding capabilities. The empirical design is based on a cross-sectional survey that was created in LimeSurvey and distributed to organizations from multiple industries and various cities in Germany. A cross-sectional design was chosen due to practical constraints and the exploratory nature of the research.

3.2 Sample and Data Collection

The relevant population for this study is relatively small, as suitable participants must be involved either in DT, ST or preferred in both areas simultaneously, although combined responsibilities are still rare in organizational practice. For this reason, the sampling strategy followed a combination of purposive sampling, targeting individuals with relevant transformation responsibilities and convenience sampling, reflecting practical access constraints. The target group consisted primarily of sustainability managers, complemented by employees involved in digitalization initiatives. Data collection was carried out using an online questionnaire distributed via email to interested organizations as well as through personal outreach and a randomized LinkedIn search.

Survey administration took place between September 2025 and the end of November 2025. The final respondent group was formed through two recruitment streams. On the one hand, within a larger research project on TT, 21 employees from 15 out of 17 partner organizations completed the questionnaire. Multiple responses from the same company were aggregated into a single entry at the organizational level by averaging item scores, ensuring internal consistency across respondents representing the same organization. On the other hand, to expand the sample, the author contacted 45 companies though personal networks and a randomized LinkedIn search, resulting in further 13 responses. In total 28 organizational observations were collected before data quality screening was conducted. Resulting in a response rate of 53.85 percent for both recruitment streams combined.

Data quality was ensured through a pragmatic speed check based on Leiner (2019), using a speed index of 2.0, which means that respondents who completed the survey in less than half of the median response time were excluded, as such unusually fast completion times indicate a high likelihood that items were not read carefully. For the present dataset, this corresponded to a minimum completion time of approximately nine minutes. One case fell below this threshold and was excluded. The final sample size therefore compromises 27 valid firm responses, as incomplete questionnaires were automatically excluded.

Participation was voluntary, confidential and anonymous for the external recruitment stream. Project partner organizations could be identified at the firm level. No incentives were provided. All participants were informed prior to completing the questionnaire, ensuring compliance with ethical standards.

Firm information	Frequency	Percentage	Respondent information*	Frequency	Percentage
Area of value creation			**Knowledge of Twin Transformation**		
Production	19	70.37%	Yes	17	51.52%
Trade	3	11.11%	No	16	48.48 %
Services	3	11.11%	**Focus of current role**		
Public sector /Non-profit	0	0.00%	Digitalization	6	18.18%
Other	2	7.41%	Sustainability	20	60.61%
Company size			Interface role between both	7	21.21%
1–9 employees	0	0.00%			
10–49 employees	0	0.00%			
50–249 emploees	2	7.41%			
250–999 employees	6	22.22%			
>1,000 employees	19	70.37%			
Transformation priority					
Digital transformation	11	40.74%			
Sustainability transformation	3	11.11%			
Both equally important	12	44.44%			
Neiter one	1	3.70%			

Table 4: Profile of the Sample
Source: Own illustration

Table 4 summarizes the characteristics of the participating organizations and respondents. As shown, participating firms operate in the production sector and the sample is strongly dominated by large companies with more than 1,000 employees. Nearly half of the organizations report that DT and ST are equally important in their current strategic context. The distribution of respondents' roles suggests that employees working at the intersection of both transformation were either not reached or that the concept of TT is not widely established in practice, as most respondents work primarily in positions focused on sustainability. Customer regions were excluded from the Table 4, although they were assessed in the questionnaire, because multiple selections were possible for this item. Nevertheless, the DACH region was mentioned most frequently, followed by Europe outside the DACH region and worldwide markets, while North America appeared regularly and other regions were mentioned less often.

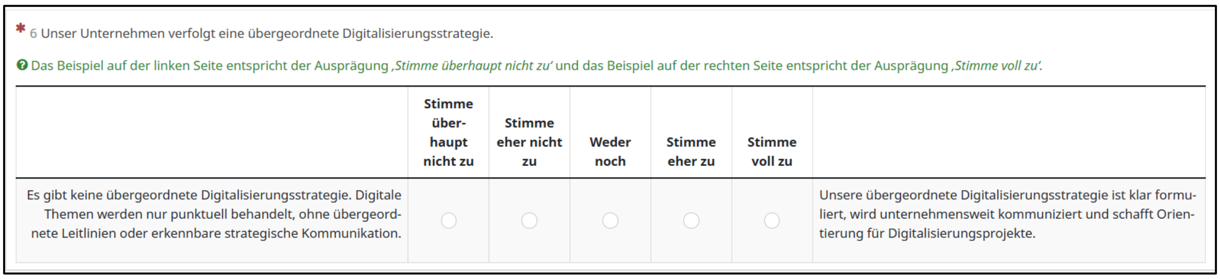
3.3 Measurement of Variables

The survey instrument consisted of 42 items and was structured to capture the four constructs underlying the theoretical framework, including DTM, STM as well as enabling and guiding capabilities. The structure of the survey is demonstrated in Table 5. The complete questionnaire is documented in the Appendix A.

Sections/ Constructs	Number items
Twin Transformation Classification and understanding	4
Digital Transformation Maturity	13
Sustainability Transformation Maturity	12
Enabling Capabilities	1 (matrix style)
Guiding Capabilities	1 (matrix style)
Value of Twin Transformation	1
Use of AI in the context of Sustainability	6
Organizational Characteristics	4

Table 5: Survey Structure
Source: Own illustration

Table 6 to Table 8 provide an overview of all items underlying this theoretical framework. Their conceptual foundations have already been discussed in Chapter 2 and are attached in the Appendix B. These constructs were complemented by additional sections assessing respondents' understanding of TT, perceived value of TT, an exploratory section on the use of AI in the context of TT and basic organizational characteristics.


* 6 Unser Unternehmen verfolgt eine übergeordnete Digitalisierungsstrategie.

Das Beispiel auf der linken Seite entspricht der Ausprägung ‚*Stimme überhaupt nicht zu*' und das Beispiel auf der rechten Seite entspricht der Ausprägung ‚*Stimme voll zu*'.

	Stimme überhaupt nicht zu	Stimme eher nicht zu	Weder noch	Stimme eher zu	Stimme voll zu	
Es gibt keine übergeordnete Digitalisierungsstrategie. Digitale Themen werden nur punktuell behandelt, ohne übergeordnete Leitlinien oder erkennbare strategische Kommunikation.	○	○	○	○	○	Unsere übergeordnete Digitalisierungsstrategie ist klar formuliert, wird unternehmensweit kommuniziert und schafft Orientierung für Digitalisierungsprojekte.

Figure 3: Example Item and Five-Point Likert Scale with Verbal Anchors
Source: Own illustration

DTM was measured using twelve items grouped into four dimensions with three items each: Strategy, Technology, Operations and Processes and Organization and Culture. All items were assessed using a five-point Likert scale ranging from "strongly disagree" to "strongly agree", with clearly defined verbal anchors at both ends of the scale to ensure a consistent interpretation of the response option across respondents. Figure 3 illustrates an example item and the corresponding response scale.

Dimension	Item Code	Item
Strategy (DTS)	DTS_1	Our company pursues an overarching digitalization strategy.
	DTS_2	Our digitalization strategy is embedded in the company's overall strategy
	DTS_3	The implementation of the digitalization strategy is steered through measurable goals.
Technology (DTT)	DTT_1a	Artificial intelligence is used systematically in our company.
	DTT_1b	Internet-of-Things is used systematically in our company.
	DTT_1c	Cloud services are used systematically in our company
	DTT_2	Our ERP system is integrated with other central systems and enables process automation.
	DTT_3	Our IT infrastructure is flexible and scalable for digitalization projects.
Operations & Processes (DTOP)	DTOP_1	Our core processes are digitalized and supported by digital tools.
	DTOP_2	Our processes enable an agile response to digital challenges.
	DTOP_3	Our operational processes are continuously optimized.
Organization & Culture (DTOC)	DTOC_1	Our culture fosters digital innovation.
	DTOC_2	Employees are systematically supported in developing digital skills and competencies.
	DTOC_3	Leaders actively drive the digital transformation.

Table 6: Digital Transformation Maturity Items
Source: Own illustration

The Strategy dimensions captures the extent to which digital ambitions and priorities are formally articulated and embedded in the organization's strategy. The Technology dimension reflects the availability and use of digital infrastructure and emerging technologies. Within this dimension, a specific subdimension (DTT_1) captures the systematic use of selected emerging technologies, measured through items DTT_1a to DTT_1c. To complement the quantitative maturity items, an additional qualitative multiple-choice question was included asking respondents which further digital technologies are used within their organization. This item served as an exploratory purpose and was not incorporated into the maturity index. The Operations and Process dimension assesses how far workflows and business processes are digitally supported. The Organization and Culture dimensions examine the degree to which employees and cultural structures enable DT.

ST was assessed analogously also using the five-point Likert scale and twelve items organized into four dimensions with three items each: Strategy, Governance and Risk, Operations and Processes and Organization and Culture. The Strategy dimension captures the strategic anchoring of sustainability within i.e. corporate decision-making. The Governance and Risk dimension reflects capabilities for managing sustainability related obligations and risks.

Dimension	Item Code	Item
Strategy (STS)	STS_1	Our company pursues a clear sustainability strategy.
	STS_2	The sustainability strategy is embedded in the company's overall strategy.
	STS_3	The implementation of the sustainability strategy is steered through measurable goals.
Governance & Risk (STGR)	STGR_1	We systematically assess sustainability related risks (e.g., supply chain risks arising from human rights violations) across all business units.
	STGR_2	Our company complies with ESG related regulatory requirements (e.g., CSRD, EU Taxonomy).
	STGR_3	We consider ESG criteria when selecting our suppliers.
Operations & Processes (STOP)	STOP_1	Our core processes (e.g., product development) incorporate sustainability aspects.
	STOP_2	Our processes enable an agile response to new sustainability requirements.
	DTOP_3	Our operational processes are continuously developed to enable resource-efficient and sustainable operations.
Organization & Culture (STOC)	STOC_1	Our culture fosters sustainable thinking and behavior.
	STOC_2	Employees are systematically supported in developing sustainability related competencies.
	STOC_3	Leaders actively drives the sustainability transformation.

Table 7: Sustainability Transformation Maturity Items
Source: Own illustration

The Operations and Processes dimension assesses the implantation of environmentally and socially responsible practices in operational processes. The Organization and Culture dimension examines employees' sustainability related competencies and cultural readiness.

Measuring DT and ST as maturity constructs is essential for hypotheses testing, as the proposed relationship requires a continuous representation of each transformation's progression. Only by capturing varying levels of maturity the directional effects between DT, ST and the two capability constructs can be meaningfully analyzed. Structuring both maturity constructs in this parallel form ensures conceptual and measurement comparability.

Enabling capabilities were measured using as single matrix question containing seven items that assess how digital technologies support sustainability related improvements. All items were assed using a five-point Likert scale ranging from "strongly disagree" without verbal anchors, as these items leave less room for different interpretations than the maturity related items. Example items include the use of IoT-based systems that monitor progress toward sustainability goals and the integration and analysis of relevant data for sustainability across organizational IT systems.

Construct	Item Code	Item
Enabling Capabilities	EC_1	We use digital technologies such as the Internet of Things to automatically capture sustainability data in real time.
	EC_2	We use digital solutions to systematically monitor progress toward sustainability targets.
	EC_3	We use digital solutions to simulate sustainability scenarios and assess their impacts in advance.
	EC_4	Our digital technologies support the analysis of sustainability data, e.g., through data preparation, pattern recognition and the derivation of actionable insights.
	EC_5	Digital technologies help us reduce resource consumption.
	EC_6	Our IT infrastructure enables the systematic integration and provision of sustainability data across different systems.
	EC_7	Our digital systems support the circular economy, e.g., through reuse, recycling and sharing.
Guiding Capabilities	GC_1	We consider sustainability aspects when using digital technologies, e.g., by taking energy consumption into account when deploying AI applications such as ChatGPT.
	GC_2	We consider sustainability aspects when investing in digital technologies, e.g., the recyclability of hardware or the energy efficiency of new software.
	GC_3	We consider sustainability aspects in the development of digital products, processes and services, e.g., through environmentally friendly design, low resource intensity during operation and sustainable product lifecycle management.
	GC_4	Sustainability aspects influence the prioritization of our digitalization projects, e.g., by favoring sustainability related digital projects over digitalization projects without a sustainability focus.
	GC_5	Our digital infrastructure is designed to be sustainable and energy-efficient, e.g., through the use of energy-efficient servers or renewable energy in data centers.
	GC_6	In digital transformation initiatives, we consider sustainability aspects, e.g., by offering measures to promote employees' health.

Table 8: Enabling and Guiding Capabilities Items
Source: Own illustration

Guiding capabilities were measured through a second matrix containing six items that assess the extent to which sustainability considerations steer digital development. Among other aspects, the items assess the extent to which sustainability aspects are taken into account when choosing digital technologies, incorporated into development of digital products and services and used as criteria for prioritizing digitalization projects.

Cronbach's α was analyzed to assess the internal consistency of these multi-item constructs (see Table 9). STM exhibits a very high Cronbach's α of 0.983, indicating a strong degree of intercorrelation among its underlying dimensions. While values above 0.90 are sometimes discussed as potentially indicating item redundancy, this level of internal consistency does not undermine the reliability of the construct in the present measurement model (Streiner, 2003). In contrast, DTM shows a lower, yet still good, internal constancy with a Cronbach's α of 0.848. While both constructs demonstrate sufficient reliability for further analysis, the difference in magnitude reflects varying degrees of intercorrelation among their respective subdimensions. The enabling and guiding capacity constructs also show very good reliability, with Cronbach's α values of 0.872 for enabling capabilities and 0.879 for guiding capabilities, indicating consistent measurement across a broader set of indicators.

Constructs	Cronbach's α	Number of Items
DTM	0.848	4
DTS	0.872	3
DTT	0.755	3
DTT_1	0.668	3
DTOP	0.784	3
DTOC	0.781	3
STM	0.983	4
STS	0.844	3
STGR	0.821	3
STOP	0.853	3
STOC	0.867	3
EC	0.872	6
GC	0.879	7

Table 9: Internal Reliability - Cronbach's α
Source: Own illustration

The only construct falling slightly below the conventional threshold of 0.70 is the Technology related subdimension (DTT_1) of DTM focusing on emerging technologies, which yields a Cronbach's α of 0.688. Given the exploratory nature of the study, the limited sample size and the small number of items capturing these heterogeneous technologies, this value is considered acceptable. Methodological literature supports the inclusion of constructs with lower reliability coefficients in exploratory research contexts, particularly when constructs are theoretically grounded and measurement models are well-specified (Hair et al., 2020).

The perceived value of TT was measured using a single item assessing the benefits organizations associated with pursuing DT and ST jointly. Several response options that reflect different forms of organizational benefit, including advantages (Tabares et al., 2025; Zimmer & Järveläinen, 2022), competitive improvements (Fan et al., 2025), efficiency gains (Auweiler et al., 2025; Tabares et al., 2025), enhancements in employee well-being (Auweiler et al., 2025), strengthened relationships with customers or suppliers increased organizational resilience (Guennoun et al., 2024; Petani et al., 2023) and contributions to long-term value creation (Auweiler et al., 2025), all of which align with value dimensions commonly discussed in literature and elaborated in Chapter 2.5.4.

Item Code	Items	Measurement
AI_USE	What types of AI are you already using in the context of sustainability?	Multiple choice
AI_REL	Please rank the following AI technologies according to their relevance to sustainability in your company	Ranking
AI_APP	In which areas of application are you currently using AI to promote sustainability?	Multiple choice
AI_CHAL	Which of the following challenges make it difficult for your company to use data for AI in the context of sustainability?	Multiple choice
AI_RISK	What risks do you perceive in your company for the use of AI for sustainability goals?	Multiple choice
AI_FUT	In which additional areas would you like to use AI specifically for sustainability goals in the future?	Multiple choice

Table 10: Exploratory Items on Use of AI in the Context of Sustainability
Source: Own illustration

The items related to the use of AI in context of sustainability (see Table 10) were selected to capture the current state, perceived relevance, application areas, challenges, risks and future potentials of AI from an organizational perspective. As empirical evidence on the concrete use of AI for ST remains limited, existing studies tend to focus either on specific fields of application, such as manufacturing environments (e.g., (Kamble et al., 2022) or on individual AI technologies, for example computer vision (e.g., (Shahin et al., 2024). Accordingly, these items were designed for exploratory purposes rather than for measuring of a latent construct. The selection of response option was grounded in prior literature on AI and sustainability, as discussed in Chapter 2.5.3, which provides the conceptual foundation for the identified AI technologies, application domains, challenges and risks.

3.4 Data Analysis

The data analysis followed a structured approach aligned with the hypotheses developed in Chapter 2.5.2 and the study's aim to provide an initial empirical assessment of TT. All analyses were conducted on firm-level data, using aggregated construct indices derived from the survey items. Prior to hypothesis testing, descriptive statistics were calculated to examine central tendencies and dispersion of the key constructs. To test the proposed relationships between DTM, STM, enabling capabilities and guiding capabilities, linear regression analyses were employed. Linear regression was chosen because the hypotheses focus on directional relationships between continuous variables and because this method allows for an assessment of both effect direction and explanatory power (Field, 2024). Given the early stage of empirical research on TT and the absence of prior studies using regression analyses to examine these relationships, the analyses focus on identifying strong associations rather than estimating complex causal models. Accordingly, more advanced multivariate models were deliberately not applied. The internal consistency of all multi-item constructs was assessed using Cronbach's alpha as a prerequisite for further analysis, with the corresponding reliability coefficients reported in the preceding measurement chapter. Items related to the perceived value of TT and the use of AI in the context of sustainability were analyzed descriptively, as these items were designed for exploratory purposes to capture under-researched phenomena and emerging patterns rather than to test hypotheses. All statistical analyses were performed using SPSS. The results of the analyses are presented in the following chapter.

4 Results

This chapter presents the empirical findings of the study. It is structured in three parts. First, descriptive analyses provide an overview of DTM and STM and the enabling and guiding capabilities across the participating firms. Second, the results of the hypothesis testing based on linear regression analyses are reported. Third, complementary descriptive results address the role of AI in context of TT and the perceived value potentials of TT, as well as comparative insights info firms that strongly enable ST through DT while allowing ST objectives to guide DT.

4.1 Descriptive Results of Model Constructs

Descriptive analyses were conducted to assess the maturity levels of DT and ST, as well as the enabling capabilities and guiding capabilities constructs, across the participating firms.

As shown in Table 11, the results indicate a moderate level of DTM, with mean values centered around the midpoint of the five-point scale (DTM =3.40). At the beginning of the survey, respondents were asked to self-assess their organization's overall level of DTM. The self-assessed DTM (DTM_self = 3.37) closely aligns with the aggregated maturity index. At the same time,

Variables	Min	Max	Mean	Std. Dev.
DTM_self	2	5	3,37	0,7280
DTM	2,03	4,5	3,40	0,6929
DTS	2	5	3,40	0,8602
DTS_1	2	5	3,44	0,8920
DTS_2	2	5	3,58	0,9480
DTS_3	1	5	3,16	1,0500
DTT	1,11	4,56	3,22	0,9187
DTT_1	1,33	5	3,09	0,8949
DTT_1a	1	5	2,96	1,1000
DTT_1b	1	5	2,85	1,1250
DTT_1c	1	5	3,45	1,2330
DTT_2	1	5	3,47	1,2250
DTT_3	1	5	3,10	1,2130
DTOP	1,67	4,67	3,43	0,8116
DTOP_1	1	5	3,44	0,9450
DTOP_2	1	5	3,05	1,1050
DTOP_3	2	5	3,81	0,8450
DTOC	2,33	5	3,53	0,7427
DTOC_1	2	5	3,57	0,7930
DTOC_2	1	5	3,62	1,0030
DTOC_3	2	5	3,40	0,8610

Table 11: Descriptive Statistics of Digital Transformation Maturity
Source: Own illustration

DTM varies substantially across firms, ranging from 2.03 to 4.50, highlighting pronounced heterogeneity within the sample. Across the examined dimensions, Organization and Culture exhibits the highest average maturity level (DTOC = 3.53), followed closely by Operations and Processes (DTOP = 3.43) and Strategy (DTS = 3.40). Overall, the differences between the dimensions are relatively small with mean values ranging from 3.22 to 3.53, indicating a broadly balanced maturity profile. Notably. DTOP_3 records the highest mean among all individual items (3.81). In contrast, the Technology dimension of DTM shows slightly lower average maturity levels (DTT = 3.22) and the highest variability, as reflected by comparatively large standard deviations across several Technology related items. Within this dimension, certain technologies are less established than others, with the systematic use of AI (DTT_1a) and IoT technologies (DTT_1b) showing comparatively lower mean values, while more foundational technologies such as cloud-based services (DTT_1c) appear to be more widely adopted. Across nearly all constructs and items, the observed wide ranges between minimum and maximum values further underscore the substantial differences in DTM between firms. As shown in Table 12, overall STM (STM = 3.62) is slightly higher than DTM (DTM = 3.40). Similar to DT, the self-assessed sustainability maturity (STM_self = 3.59) closely aligns with the aggregated sustainability maturity index. At the same time, STM exhibits substantial heterogeneity across firms, with observed values ranging from 1.83 to 5.00, which is comparable to the dispersion observed for DT.

Variables	**Min**	**Max**	**Mean**	**Std. Dev.**
STM_Self	2	5	3,59	0,8770
STM	1,83	5	3,62	0,7682
STS	1,33	5	3,93	0,9477
STS_1	2	5	4,26	0,8480
STS_2	1	5	3,72	1,1290
STS_3	1	5	3,80	1,2420
STGR	2	5	3,69	0,8780
STGR_1	2	5	3,81	0,9720
STGR_2	2	5	3,90	1,0100
STGR_3	1	5	3,36	1,0840
STOP	1,67	5	3,52	0,8109
STOP_1	1	5	3,45	0,9460
STOP_2	2	5	3,43	0,9380
STOP_3	2	5	3,69	0,8830
STOC	1,33	5	3,33	0,8904
STOC_1	1	5	3,56	0,9740
STOC_2	1	5	3,28	1,0500
STOC_3	1	5	3,17	0,9810

Table 12: Descriptive Statistics of Sustainability Transformation Maturity
Source: Own illustration

Across the sustainability constructs, ST Strategy emerges as the most mature dimension (STS = 3.93), exceeding both overall maturity and the corresponding DT Strategy dimension maturity (DTS = 3.40). This pattern is also reflected at the item level, where STS_1 records the highest mean value across all sustainability items (M = 4.26). At the same time, practices related to sustainability are not uniformly developed, while showing considerable variability in the integration of sustainability into the overall business strategy and in the use of measurable sustainability goals, as indicated by the relatively high standard deviation of STS_3 (SD = 1.24). When comparing the sustainability dimensions with each other, Governance and Risk related aspects rank second in terms of average maturity (STGR = 3.69), while showing moderate overall variability and a relatively higher dispersion in selected items such as STGR_3 (SD = 1.08). Operational sustainability processes follow next (STOP = 3.52), with STOP_3 (M = 3.96) standing out as the most advanced item within this dimension. In contrast, sustainability related organizational culture exhibits the lowest average maturity level among the sustainability constructs (STOC = 3.33). This stands in clear contrast to DT, where organizational culture represents the most mature dimension (DTOC = 3.53). At the same time, sustainability related, organizational culture shows comparatively high variability, with STOC_2 (SD = 1.05) and STOC_3 (M= 3.17) indicating uneven cultural embedding of sustainability practices across firms and representing the lowest mean value across all sustainability items.

Variables	**Min**	**Max**	**Mean**	**Std. Dev.**
EC	1	4,86	2,92	0,8928
EC_1	1	5	2,77	1,3500
EC_2	1	5	3,50	1,1270
EC_3	1	5	2,44	1,2400
EC_4	1	5	2,88	1,1590
EC_5	1	5	3,67	0,9900
EC_6	1	5	2,83	1,2250
EC_7	1	5	2,39	1,1880

Table 13: Descriptive Statistics of Enabling Capabilities
Source: Own illustration

To complement the descriptive results on DTM and STM, the enabling capabilities construct was examined. Table 13 summarizes the descriptive statistics for enabling capabilities across the participating firms. Overall, enabling a moderate average level, with mean value of 2.92 and a standard deviation of 0.89. The index values range from 1.00 to 4.86, indicating a wide dispersion of firm level scores within the sample. At the item level, mean values vary considerably, spanning from 2.39 for digital support of circular economy practices (EC_7) to 3.67 for the use of digital technologies to reduce resource consumption (EC_5). Relatively higher means values are also observed for the systematic monitoring of progress towards sustainability targets through digital solutions (EC_2). In contrast, lower means values are reported for the simulation of sustainability scenarios (EC_3). Several items display comparatively high standard deviations, reflecting substantial in responses across firms. In particular, EC_1, which refers to use of IoT technologies for real-time sustainability data collection, shows the highest dispersion (SD = 1.35), alongside notable variability in scenario simulation (EC_3; SD = 1.24) and the integration of sustainability data across IT systems (EC_6; SD = 1.23).

As reported in Table 14, guiding capabilities display a slightly lower overall mean value (GC = 2.81) compared to enabling capabilities, while showing a similar level of dispersion across firms (SD = 0.87), Firm-level index values range from 1.00 to 4.17, indicating notable variation in the extent to which sustainability considerations are embedded in digital decision-making processes. At the item level, the highest mean values are observed for the consideration of sustainability aspects in the development of digital products, processes and services (GC_3; M = 3.19), as well as for the design of sustainable and energy efficient digital infrastructure (GC_5; M = 3.09). In contrast, sustainability considerations related to the use of digital technologies, such as accounting for energy consumption when developing digital applications (GC_1), exhibit the lowest average level (M = 2.30). The remaining items cluster around the midpoint of the scale including sustainability considerations in digital investment decisions (GC_2), project prioritization (GC_4) and DT initiatives with a focus on employee well-being (GC_6). Similar to enabling capabilities, relatively high standard deviations across most guiding capability items, particular GC_4 (SD = 1.15), GC_5 (SD = 1.14) and GC_6 (SD = 1.16), point to substantial heterogeneity in how these practices are implemented across organizations.

	Min	**Max**	**Mean**	**Std. Dev.**
GC	1	4,17	2,81	0,8670
GC_1	1	4	2,30	1,0940
GC_2	1	5	2,75	1,0120
GC_3	1	5	3,19	1,0300
GC_4	1	4	2,58	1,1500
GC_5	1	5	3,09	1,1350
GC_6	1	4	2,95	1,1600

Table 14: Descriptive Statistics of Guiding Capabilities
Source: Own Illustration

4.2 Hypothesis Testing

To evaluate the proposed hypotheses, bivariate linear regression analysis were conducted. Table 15 provides an overview of the regression results. A positive and statistically significant relationship is observed between DTM and STM. Higher levels of DT are therefore associated with higher levels of sustainability (β=.60, p <.001), explaining approximately one third of variance in STM (adjusted R^2 = .34). This finding is consistent with the expectation formulated in hypotheses 1. Examining the reverse relationship yields an identical pattern. STM is positively associated with DTM (β=.60, p <.001, adjusted R^2 = .34), indicating the same magnitude of association. This result is in line with Hypothesis 2. Taken together, both hypothesized directions of the relationship are empirically supported.

Hypothe-sis	**Standardized Coefficient (β)**	**p-value**	**Adjusted R²**	**Interpretation**
H1	0.603	< .001	0.338	Significant positive relationship
H2	0.603	< .001	0.338	Significant positive relationship
H3	0.629	< .001	0.371	Significant positive relationship
H4	0.650	< .001	0.399	Significant positive relationship
H5	0.697	< .001	0.466	Strong significant positive relation-ship
H6	0.567	.002	0.294	Significant positive relationship

Table 15: Results of the Linear Regression Analyses and Hypothesis Interpretation
Source: Own illustration

While Table 15 presents the detailed regression results for each hypothesis, Figure 4 integrates the conceptual framework with the main empirical findings and provides a consolidated overview of the constructs and relationships.

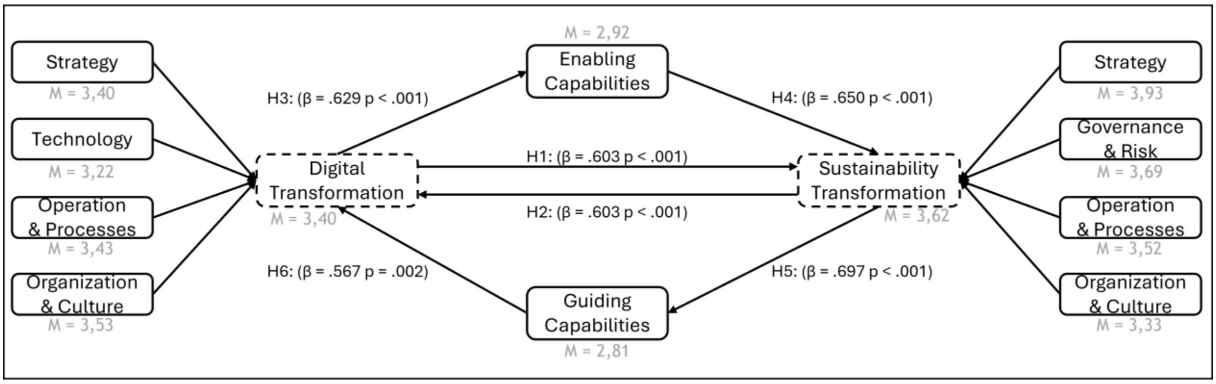


Figure 4: Conceptual Framework with Construct means and empirical regression results
Source: Own illustration

Figure 5 illustrates the relationship between DTM and STM. The scatterplot shows a clear positive linear association, which is consistent with the regression results reported above. Although some heterogeneity across firms is visible, the overall pattern suggests a stable relationship rather than an effect driven by a few extreme cases.

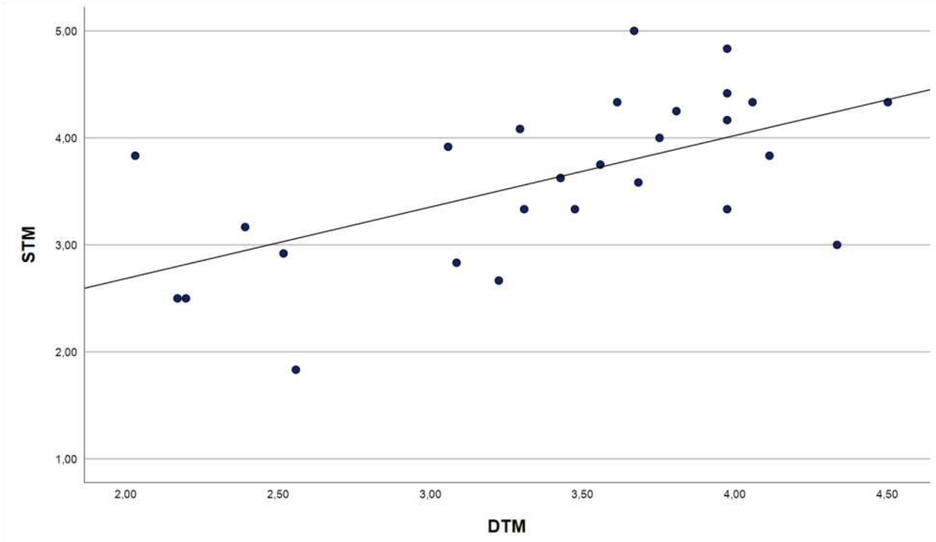


Figure 5: Scatterplot of Digital Transformation Maturity and Sustainability Transformation Maturity
Source: Own illustration

Enabling capabilities are, in turn, positively related to STM (β=.65, $p <.001$), with the model explaining approximately 40% of the variance in STM (adjusted $R^2 = .40$). The regression results indicate therefore that hypotheses 3 and 4 are empirically supported.

A similar pattern emerges with regard to guiding capabilities. STM is positively and significantly associated with guiding capabilities (β=.70, $p <.001$), accounting for nearly health of the variance in the guiding index (adjusted $R^2 = .47$), in line with Hypothesis 5. Guiding capabilities are also positively related to DTM (β=.57, $p =.002$, adjusted $R^2 = .29$). Although the explained variance is lower than previous model, the association is statistically significant and consistent with Hypothesis 6. Thus both hypothesized relationships involving guiding capabilities are empirically supported.

4.3 Exploratory Results

This chapter presents the results on the final two substantive sections of the survey. These sections were included primarily due to their high practical relevance and aim to provide additional insights into the role of AI as enabler within TT, as well as the perceived value potentials associated with the interplay of DT and ST.

4.3.1 Artificial Intelligence as an Enabling Technology in Twin Transformation

Following the hypothesis-driven regression analyses, this section presents the results on the use of AI in the sustainability context. Given the rapid development of AI and the increasing attention to its potential role in supporting sustainability related activities (Yu et al., 2025), the survey additionally captured the current status quo and perceived application areas of AI within the surveyed organizations.

First respondents were asked to indicate which types of AI technologies are currently used in their organization to support sustainability related activities. The results in Figure 6 show that Natural Language Processing (NLP) for example applied to tasks including sustainability reporting or ESG specific text analysis and Generative AI, used for example to support scenario development and generate design suggestions, are the most frequently reported technologies, selected by 14 and 13 out of 27 companies. In contrast, more specialized or technically advanced solutions are less frequently reported. AI based simulations and digital twins, which are mainly applied in production contexts to model and simulate production facilities, as well as multi-agent systems, applied to the control and coordination of energy system, are each selected by six companies, representing the lowest usage frequencies among the listed technologies. It should be noted that four companies indicated that AI is not used or that respondents were not aware of its use in the sustainability context.

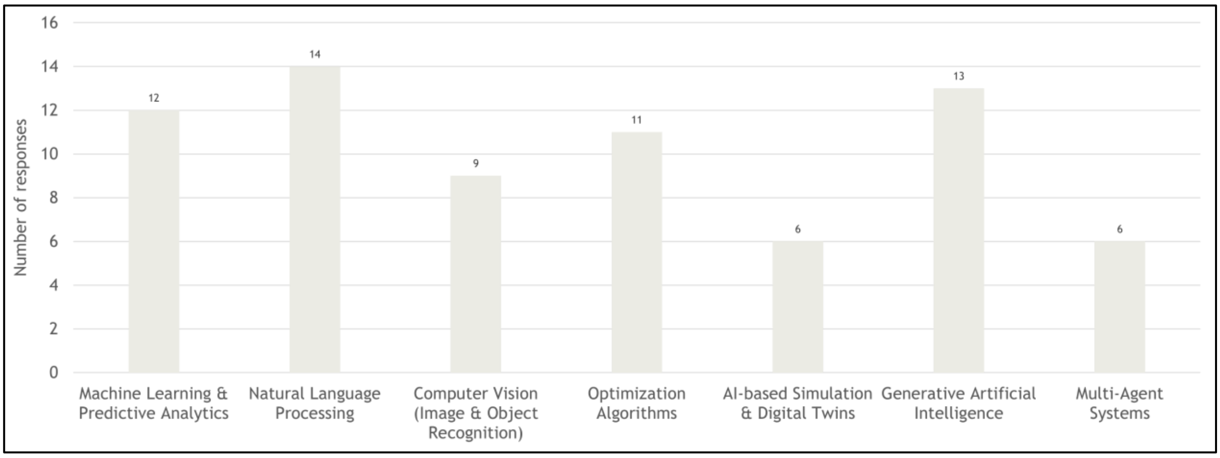


Figure 6: Graphical Overview of the Descriptive Results of the Item AI_USE
Source: Own illustration

To further differentiate between the reported technologies, respondents were asked to rank the relevance of the listed AI applications for sustainability. The resulting rank values represent average positions, with lower values indicating higher perceived relevance. A comparison of current use of AI technologies and their perceived relevance for sustainability shows a largely consistent pattern, as technologies that are already used are also generally ranked as more relevant by and for the surveyed companies. NLP is both the most frequently used technology and the highest-ranked in terms of relevance (average rank 3.18). Optimization algorithms (average rank 3.44), applied for example in routing optimization and energy consumption optimization, and machine learning and predictive analytics (average rank 3.49), used for applications such as predictive maintenance, also exhibit high usage and high relevance. However, some differences can be identified. Generative AI is widely used but positioned in the middle of relevance ranking (average rank 3.81). Image and object recognition shows moderate usage but a comparatively lower relevance ranking (average rank 4.47). AI based simulations and digital twins as well as multi-agent systems are each used by six companies and occupy the lowest relevance position (average rank 4.82). However, ranking results show a relatively narrow distribution, with average rank values ranging from 3.18 to 4.82, indicating that the assessed technologies are perceived as comparatively close in relevance and ranked differently across firms.

In addition to the types of AI technologies currently in use, respondents were also asked to choose the application areas in which these technologies are applied in the sustainability context. Again the same four companies reported no use of AI and therefore did not provide responses to this question. With regard to concrete application areas, sustainability reporting stands out as the most frequently mentioned use case, reported by 15 companies. Energy efficiency improvements and supply chain and logistics optimization are also among the more frequently selected areas, each cited by ten to 11 companies, as shown in Figure 7.

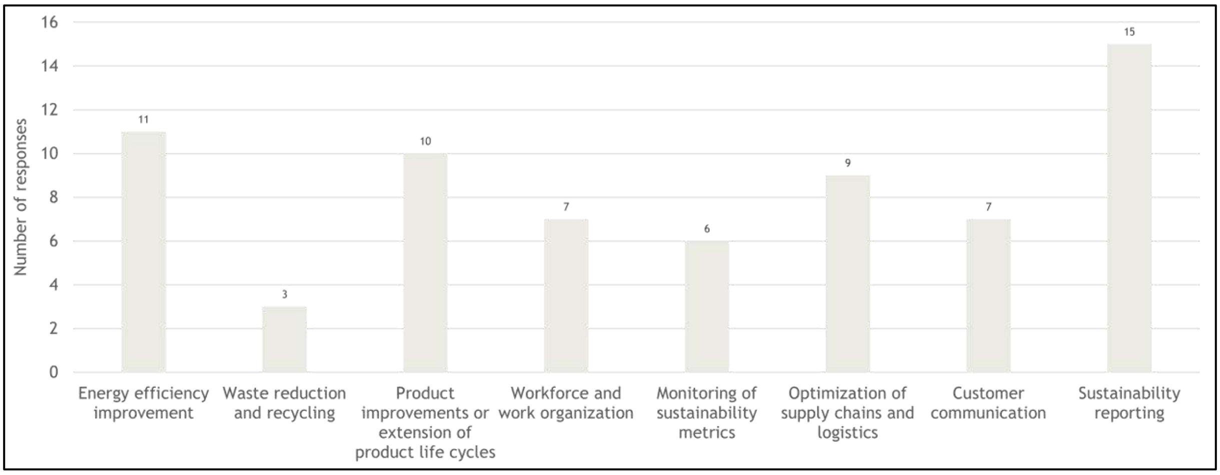


Figure 7: Graphical Overview of the Descriptive Results of the Item AI_APP
Source: Own illustration

Other application areas, such as customer communication, personnel and work organization and monitoring of sustainability indicators show lower but still notable frequencies. Waste reduction and recycling represents the least frequently reported application area, mentioned by only 3 companies.

The survey further captured challenges related to data that limit the use of AI in the sustainability context, as outlined in Chapter 2.5.3.Regarding this item, two respondents indicated that they lacked sufficient knowledge to provide an assessment for their company and therefore did not respond. Among the remaining 25 companies, six respondents, equal to 24%, reported that all five listed data related challenges apply to their organization. The results presented in Figure 8 show that insufficient data collection (e.g. infrequent data capture or missing sensors) and insufficient data quality (e.g. heterogeneous levels of granularity or lack of standardization) are the most frequently reported challenges, each mentioned by 22 companies, corresponding to 88% of the responding firms. These represent the highest frequencies within this set of challenges. Closely following, insufficient data availability, for example due to complex IT landscapes or decentralized data storage, is reported by 20 firms. Challenges related to data distribution (e.g., limited automation or manual data transfers) and data processing (e.g., a lack of suitable digital tools) are mentioned less frequently, with 15 and 13 responses respectively. Nevertheless, these challenges still affect more than half of the responding companies, indicating that they remain relevant obstacles for a substantial share of organizations.

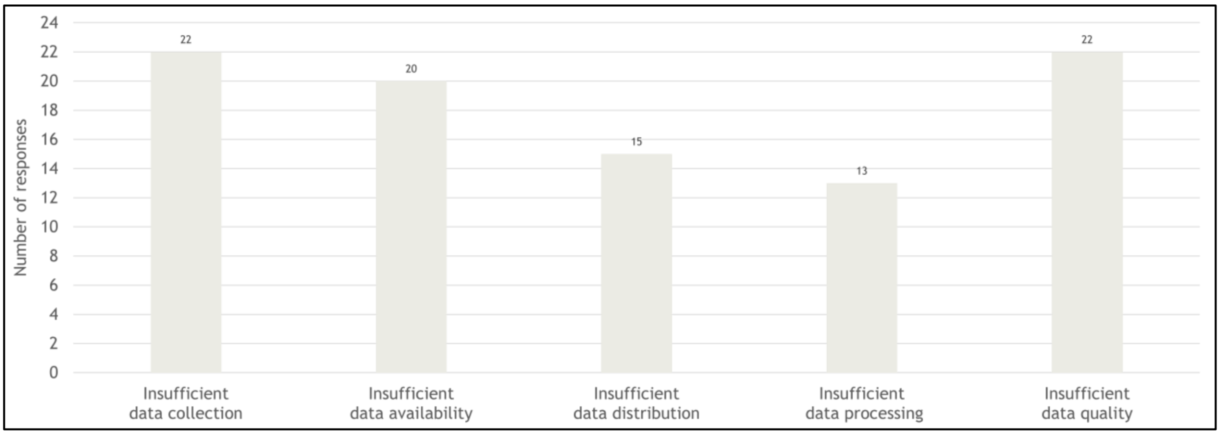


Figure 8: Graphical Overview of the Descriptive Results of the Item AI_CHAL
Source: Own illustration

With regard to the perceived risks associated with the use of AI, the survey captured respondents' assessments across a predefined set of potential risk categories. One respondents indicated insufficient knowledge to assess the remaining respondents. Only one company reported that it perceives no risks associated with the use of AI in the sustainability context, while 25 out of 26 companies identified at least one risk. At the same time, none of the respondents selected all listed risk categories, indicating a differentiated assessment rather than a uniform perception of risk. As illustrated in Figure 9, the results allow for a clear distinction between frequently reported and less frequently reported risks. Data protection concerns emerge as the most commonly mentioned issue, reported by 19 companies, corresponding to 73,08%, followed closely by missing internal competencies, cited by 18 companies. Regulatory uncertainties are reported by 14 companies, while compliance risks are mentioned by 13 companies. Other risk categories are selected less frequently. Low management acceptance, high energy costs and dependencies on service providers are each reported by five companies. Decreasing work quality is mentioned by three companies, while ethical represent the least frequently reported risk, cited by two companies (7,69%).

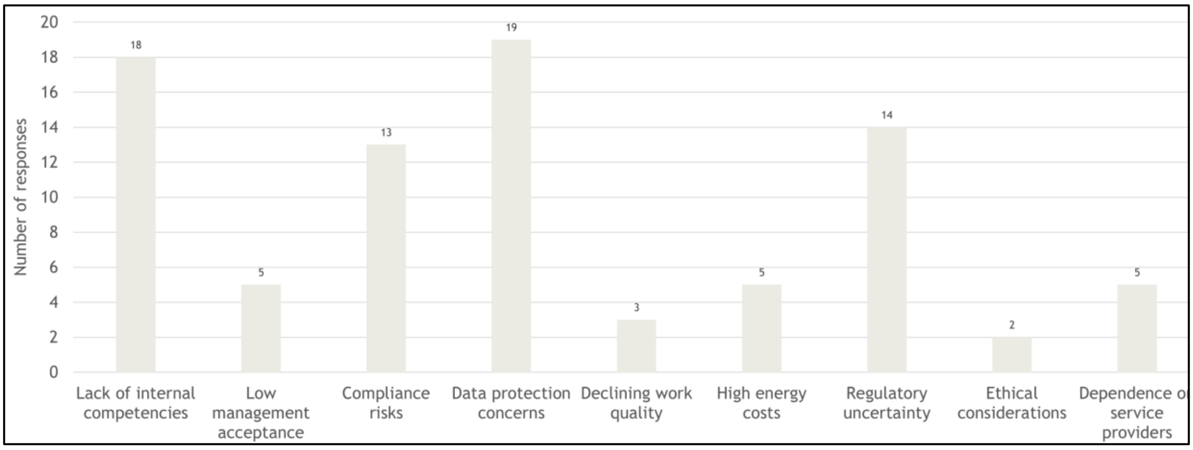


Figure 9: Graphical Overview of the Descriptive Results of the Item AI_Risk
Source: Own illustration

Finally, respondents were asked to indicate additional areas in which they would like to use AI in the future to support sustainability goals. Again, one of 27 respondents indicated insufficient knowledge to asses this question and therefore did not provide a response. Consequently, this case was excluded from the analysis. The results depicted in Figure 10 show that future AI applications are expected across a broad range of sustainability related domains. Internal process improvement, like the automation of routine tasks, represent the most frequently mentioned future application area, reported by 23 companies (88,46%). Automated sustainability reporting, for example with regard to regulatory requirements such as CSRD, follows closely and is cited by 20 companies (76,92%), placing it among the most prominent future use cases. At the lower end of the distribution, circular economy applications, such as recycling, reuse or waste management, are mentioned by 11 companies, while social sustainability, including aspects such as diversity and inclusion, represents the least frequently selected future application area, reported by 5 companies (19,23%).

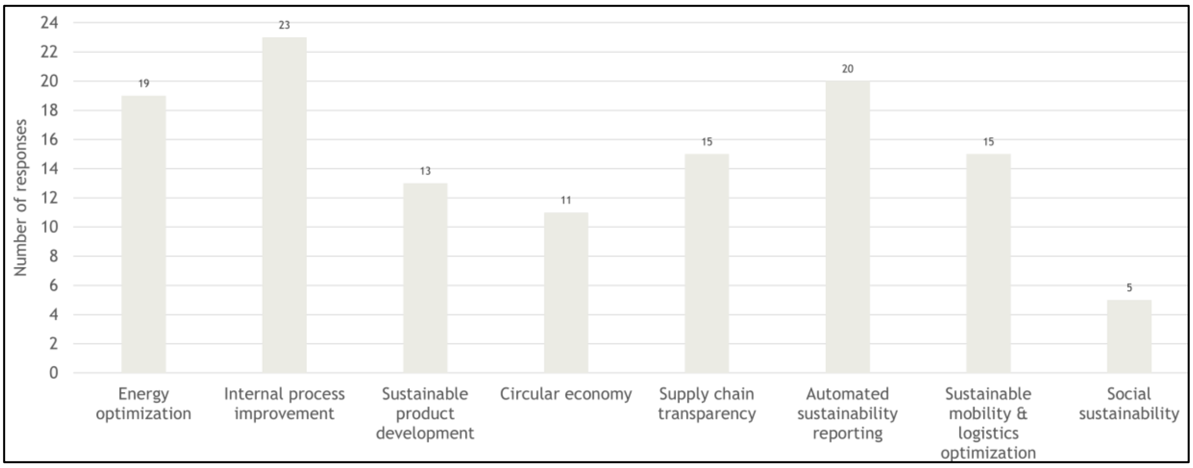


Figure 10: Graphical Overview of the Descriptive Results of the Item AI_FUT
Source: Own illustration

4.3.2 Perceived Value Potentials of Twin Transformation

As mentioned in Chapter 2.5.4, prior research has extensively discussed the value creation potential of DT and ST, largely based on qualitive studies and conceptual work (Auweiler et al., 2025). However, empirical evidence remains limited with regard to how organizations themselves assess the specific areas in which value arises from the interplay between DT and ST across firms. In the survey respondents were therefore asked to indicate the perceived effects of the interplay between DT and ST in their organization. The question was designed as a multiple-choice item to capture the areas in which companies perceive value creation resulting from TT approach.

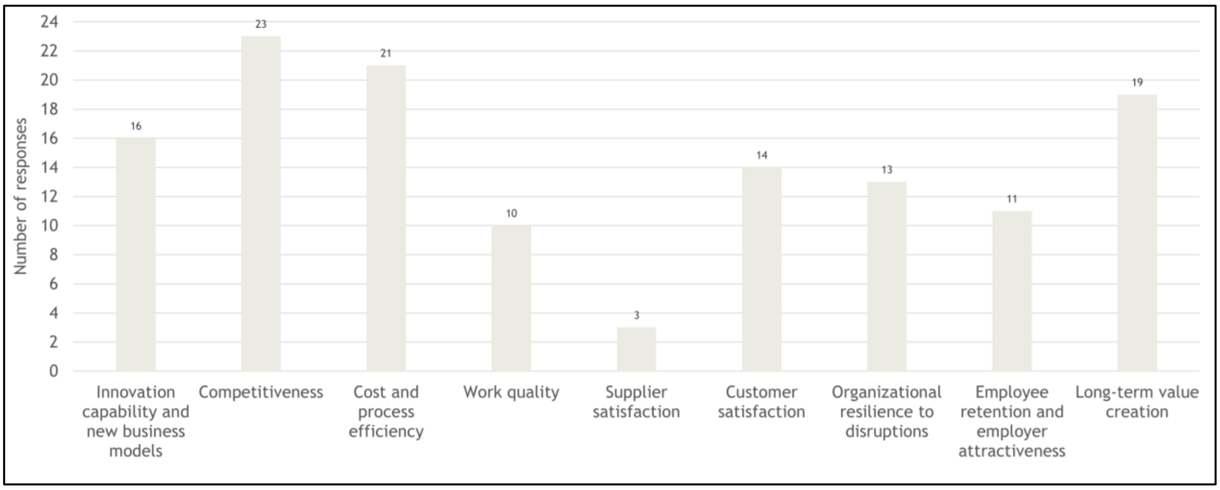


Figure 11: Graphical Overview of the Descriptive Results of Twin Transformation Value Dimensions
Source: Own *illustration:*

Figure 11 summarizes the frequency with which the different value of the interplay between

DT and ST were reported. Overall, effects referring to an increase in competitiveness, higher cost and process efficiency and long-term value creation are mentioned most frequently. Among these, the effect describing an increase in competitiveness represents the most frequently selected response option with 23 of 27 responses. In contrast, the effect referring to an increase in supplier satisfaction is reported least frequently with only three responses. Notably, an increase in competitiveness is mentioned nearly eight times as often as an increases in supplier satisfaction. Other reported effects, including higher organizational resilience, increased customer satisfaction, improved work quality and greater employee retention and employer attractiveness, appear in the middle range of the distribution.

4.3.3 Comparative Insights into Twin Transformation Pioneers

Beyond the regression models, an additional descriptive comparison was conducted to examine whether firms that are classified as particularly advanced within the scope of this study differ systematically in their perceptions of value creation and the role of AI in the context of TT. For this purpose, a subgroup of firms is defined by the author and referred to as TT pioneers. This label denotes companies that show clearly above average enabling and guiding capabilities relevant to TT. Based on this classification, five firms in the sample can be assigned to this subgroup. The classification us grounded in a threshold based approach that reflects the upper range of the observed enabling and guiding capability scores, rather than a strict statistical cut-off, ensuring a meaningful and transparent differentiation appropriate for the exploratory nature of the analysis.

The descriptive comparison of the multiple-choice responses on perceived value indicate clear quantitative differences between TT pioneers and the remaining firms. On average, pioneers selected 5.6 value dimensions, compared to approximately 2.6 among the other companies. While several value items are frequently selected by pioneers, these are also present among non-pioneer firms, such that no single value dimension uniquely differentiates the groups.

TT pioneers report a broader use of AI across current application areas compared to non-pioneer firms. In particular, computer vision (image and object recognition) and AI based simulations and digital twins are reported by 44% and 50% of pioneer firms, respectively, while these application areas are selected less frequently in the overall sample. Regarding the ranking of AI application relevance, no substantial differences between pioneers and non-pioneers are observed. Average ranking positions are similar across both groups, however, ranking responses among pioneers show less dispersion, with rankings clustering more closely compared to the remaining firms. For sustainability related AI application domains, pioneers more frequently select waste reduction, customer communication and optimization of supply chains and logistics, whereas monitoring of sustainability metrics is not selected by any pioneer firm. With respect to AI challenges, no notable group differences are observed, as a wide range of challenges is reported across both groups. In terms of AI risks, pioneer firms select on average 2.8 out of 9 risk categories, compared to 3.33 among non-pioneers. Lack of internal competencies is reported by 76.19% of non-pioneer firms and 40% of pioneer firms. Finally, future AI use differs between the groups as pioneers indicate on average 6.6 out of eight potential future AI application areas, whereas non-pioneers select 4.19 on average.

5 Discussion

The discussion focuses on synthesizing the empirical findings by identifying overarching patterns, interpreting the most important findings and observed relationships. Furthermore, the results, demonstrated in the previous chapter, are embedded within established theoretical perspectives on DT, ST, TT and AI.

5.1 Interpretation of Hypothesis-Driven Results

The hypothesis-driven results are interpreted in this section. Chapter 5.1.1 examines hypotheses H1 and H2 at the transformation level, while Chapter 5.1.2 focuses on hypotheses H3 to H6, addressing enabling and guiding capabilities as underlying organizational mechanisms.

5.1.1 Reciprocal Relationship Between Digital Transformation and Sustainability Transformation

The results of the hypothesis testing reveal a strong relationship between DT and ST, indicating reciprocity and interdependence rather than a unidirectional causal logic. Accordingly, hypotheses H1 and H2 are supported. The identical effect sizes observed for both hypotheses are direct consequences of the bivariate analytical approach applied in this study, which captures a symmetric association between two constructs. While these identical coefficients were statistically expected, the two hypotheses nevertheless represent distinct theoretical perspectives, namely DT as an enabler of ST and ST redesigning DT.

This reciprocal relationship is further underlined by the comparable maturity levels of DT and ST observed across the sample. While ST exhibits a slightly higher overall maturity level (STM = 3.62) compared to DT (DTM = 3.40), both constructs are situated at a similar, moderate level of maturity. This pattern differs from the findings of del Socorro Encinas-Grijalva et al. (2024), who reported higher levels of DTM than STM in their study of 148 firms in Mexico. In the present study, the small differences between STM and DTM suggest that neither transformation clearly dominates the other, which provides a plausible explanation for the symmetric relationship identified in the regression analyses.

A closer look at the maturity dimensions reveals a differentiated but balanced picture. For the dimensions Organization and Culture as well as Operations and Processes, DT and ST Display very similar maturity levels, with neither transformation clearly outperforming the other. Differences emerge primarily in the Technology dimension of DT and the Governance and Risk dimension of ST. The comparatively higher maturity of ST can partly be attributed to stronger agreement with Governance and Risk related items, whereas the lower maturity of digital technology dimension reflects the limited and uneven adoption of emerging technologies across firms. This heterogeneity is also reflected in the relatively low Cronbach's alpha value for the corresponding Technology construct, which falls slightly below the conventional threshold, seen in Table 9. Given that the construct intentionally captures a broad set of heterogenous emerging technologies with limited conceptual overlap beyond their technological nature, this outcome was anticipated and deemed acceptable, and the items were therefore retained. A particularly notable result is the substantially higher maturity of the Strategy dimension within the ST construct compared to the Strategy dimension within the DT construct. This finding suggest that ST is more firmly embedded at the strategic level, whereas DT appears less consistently integrated into strategic frameworks. This observation aligns with del Socorro Encinas-Grijalva et al. (2024), who argue that many medium-sized firms lack integrated digital strategies, limiting their ability to fully exploit technological potential, while sustainability objectives are often already present at the strategic level but constrained by insufficient technical capabilities. The close relationship between DT and ST is also visually supported by the scatterplot represented in Figure 5. The distribution of observations show a clear positive association across low, medium and high maturity levels, indicating that the relationship is not confined to highly mature organizations. Although some outliers are visible they do not drive the overall trend. At the same time, the dispersion around the regression line illustrates that the interaction between DT and ST is not deterministic, suggesting that additional factors influence how strongly both transformations reinforce each other across firms.

Prior literature highlights that transformation maturity is shaped by a range of organizational characteristics and conditions. For example, Wu et al. (2024) identify digital data competencies and innovation capacity, among others, as key determinants of DTM. In context of TT further contextual conditions may influence the strength of relationship between DT and ST. Industry characteristics may play a role, as sustainability is often externally driven in highly regulated or resource intensive sectors (Tabares et al., 2025), prompting the targeted use of digital technologies to meet regulatory requirements or realize efficiency gains. Organizational size may also matter, as larger firms typically possess greater resources to pursue both transformations in parallel but face higher structural complexity and coordination demands, whereas smaller firms are often more agile but more resource constrained and therefore required to prioritize selectively.

While such contextual conditions may shape how strongly DT and ST reinforce each other, they were not explicitly analyzed in this study. Moreover, the results of hypotheses H1 and H2 demonstrate that the two transformations are reciprocally related but do not explain how this interaction unfolds within the organizations. To address this question, the following section therefore focuses on underlying organizational mechanism. In this study, these mechanisms are captured by enabling and guiding capabilities whose empirical results are discussed in the subsequent chapter.

5.1.2 Capabilities as an Underlying Mechanism in Twin Transformation

Overall, the results indicate moderate level of enabling capabilities, accompanied by a relatively high degree of heterogeneity across firms. This suggests that digital capabilities supporting sustainability development are generally present, yet unevenly developed and primarily advanced in areas where immediate operational benefits can be realized. In particular, higher maturity is observed for applications aimed at reducing resource consumption (EC_5) which aligns with Auweiler et al. (2025), as they identify the optimization of resource use through digital processes as a central TT strategy. George and Schillebeeckx (2022) argue that achieving ambitious sustainability targets relies on the availability of credible and timely impact data, thereby framing digital monitoring as an essential prerequisite for effective sustainability management. The comparatively high maturity observed for EC_2 supports this argument empirically, indicating that firms increasingly recognize digital monitoring as a necessary capability for tracking and steering sustainability performance. These patterns indicate that firms tend to invest in digital sustainability capabilities where short-term efficiency gains and transparency effects are most tangible.

Accordingly, enabling capabilities tend to emphasize pragmatic implementation, whereas more advanced and integrative use cases remain less developed. Capabilities related to the simulation of sustainability scenarios (EC_3) or the digital support of circular economy practices (EC_7) exhibit notably lower maturity, pointing to a rather reactive use of digital technologies in the sustainability context. With regard to EC_3, this pattern can be partly attributed to the high complexity associated with simulation based approaches. As discussed by Ferreira et al. (2025), such applications require advanced modelling capabilities and substantial organizational resources, which significantly increase implementation effort. These challenges limit the practical applicability of sustainability simulations in many firms, thereby constraining their use as anticipatory decision support tools despite their potential strategic value.

A similar pattern emerges for the guiding capabilities, whose overall mean value is also situated at a moderate level. This indicates that the redesigning mechanisms supporting the integration of DT and ST are present but not yet fully institutionalized, leaving substantial room for further development. In this regard, the comparatively low consideration of the energy consumption and potential downsides of AI applications (GC_1) is particularly noteworthy. This finding aligns with Di Chiacchio et al. (2026), who show that corporate communication on AI frequently downplays its energy intensity and negative externalities in favor of predominantly positive aspirational sustainability narratives. Taken together, these results suggest that energy related aspects of AI are not yet systematically embedded in organizational decision-making process. Similarly, the limited integration of social sustainability aspects into digital decision-making, as reflected by GC_6, is consistent with prior evidence. A recent meta-analytic review by Oduro and Haylemariam (2025) demonstrates that while social sustainability positively affects firm competitiveness, its impact is weaker than that of environmental sustainability, implying that social considerations are often deprioritized. This provides a plausible explanation for the comparatively lower maturity observed in the item GC_6.

In contrast, the comparatively high maturity of GC_3, capturing the integration of sustainability considerations into digital products, processes and services, highlights a more advanced form of strategic alignment. This finding aligns with Pietsch (2024), who conceptualizes sustainable digital product management as a strategic balancing task requiring the systematic integration of sustainability into digital decision-making. While Pietsch (2024), develops this argument conceptually, the present findings provide empirical evidence that such strategic integration is increasingly realized in practice, although still with clear potential for further advancement. A similar interpretation applies to GC_5, which exhibits one of the highest mean values among the guiding capabilities and reflects the relevance of sustainability considerations in the design of digital infrastructures, such as energy efficient servers or the use of renewable energy in data centers. At the same time, the moderate absolute level and remaining heterogeneity indicate that these practices are far from being fully established. Consistent with Verdecchia et al. (2022), competing priorities related to performance, scalability and customer satisfaction continue to constrain the systematic and comprehensive adoption of energy efficient digital infrastructures.

Finally, it is noteworthy that the overall maturity levels of enabling and guiding capabilities are very similar, despite the extensive body of literature emphasizing the potential of DT and digital technologies to support corporate sustainability development (Birkel & Müller, 2021; Kranz et al., 2015). This convergence suggests that while the technical potential of DT for sustainability is well understood conceptually, its translation into both enabling structures and strategic redesigning mechanisms remains an ongoing process across firms.

The empirical results on the remaining hypotheses provide differentiated insights into the capability based mechanism underlying TT. The findings for hypotheses H3 und H4, both of which are empirically supported, point to a sequential relationship in which enabling capabilities connect DT and ST. DT shows a strong positive effect on enabling capabilities, indicating that such capabilities develop as organizations advance in their digital maturity. As firms expand digital infrastructures and improve their data availability, they create the conditions necessary for establishing digital capabilities that can be applied in the sustainability context. This is reflected in the substantial explanatory power of the model testing H3, suggesting that enabling capabilities are closely tied to the overall progression of DT. Building on this, the results for H4 demonstrate that enabling capabilities play a decisive role in advancing ST. Once established, these capabilities allow sustainability objectives to be operationalized through digitally supported measurement, monitoring and optimization processes. The comparatively strong relationship observed for H4 indicates that ST is highly contingent on the availability of such capabilities, which act as a translation mechanism between digital potential and sustainability related outcomes. The findings for H3 and H4 point to a sequential pattern in which enabling capabilities are closely related to both DT and ST, reflecting their central role within the TT context.

Against this background, the empirical results for hypotheses H5 und H6 shed light on the reciprocal linkage between ST, guiding capabilities and DT. ST exhibits particularly strong positive effect on guiding capabilities, with H5 showing the highest explanatory power among all tested relationships ($\beta = 0.697$; $p < .001$). The results indicate that higher STM increasingly extends beyond sustainability specific activities and begins to shape decision-making across the organization. This broader influence becomes visible through guiding capabilities, which embed sustainability related considerations into the way digital initiatives are assessed and structured. In contrast, the influence of guiding capabilities on DT, as captured by H6, is weaker in magnitude ($\beta = 0.567$; $p = .002$), although the relationship remains statistically significant. This suggests that guiding capabilities reflect the growing organizational relevance of ST and its spillover into the digital domain, without translating into a strong increase in overall DTM. This pattern is consistent with the conceptual reasoning outlined in the hypothesis development chapter. As discussed, guiding capabilities primarily capture redesign and reorientation capabilities. Such capabilities do not necessarily accelerate DT but alter its direction and underlying decision logic. Accordingly, the empirical results indicate that sustainability driven guiding capabilities are associated with DT in a qualitative sense, shaping its form rather than driving higher levels of DTM.

In response to the research question, the results provide empirical support for the core assumptions of the TT concept, according to which DT and ST are not isolated transitions but mutually interrelated. The findings show that both transformations influence each other directly, confirming a reciprocal interplay at the transformation level, while the capability based results further clarify how this interplay unfolds within organizations. Enabling capabilities are closely related to both DT and ST, supporting the translation of DTM into sustainability related outcomes. Guiding capabilities in turn, are strongly shaped by ST and relate back to DT with weaker, yet significant influence, indicating that they primarily shape the orientation of DT rather than its overall maturity. Building on this, the findings empirically substantiate and extend prior capability based conceptualizations of the TT, such as those proposed by Breiter et al. (2024). While their work has mainly identified and structured capabilities relevant for TT, the present study goes one step further by empirically examining whether the implementation of these capabilities is associated with higher levels of DT and ST. The results demonstrate that the proposed capabilities are not merely conceptual constructs, but are empirically related to observable transformation outcomes, thereby strengthening the empirical foundation of TT frameworks especially focused on capabilities.

5.2 Exploratory Insights Beyond Hypothesis Model

The observed pattern of AI use in the sustainability context aligns closely with prior research on AI adoption and readiness. Existing studies emphasize that the availability, processing and analysis of data constitutes a fundamental perquisite for the implementation of AI, as organizations must first establish robust data foundations before advanced applications can be realized (Jarrahi et al., 2023; Uren & Edwards, 2023). In this regard, Uren and Edwards (2023) distinguish two primary modes of organizational AI adoption, whereby AI is either used to incrementally optimize existing processes or to enable more fundamental changes to processes and business models. Empirical evidence suggests that many organizations remain concentrated in the optimization mode, a finding that is further supported by the McKinsey State of AI 2025 report, which highlights efficiency and optimization as the dominant objectives, particularly among less digitally mature firms. At the same time, both academic (Uren & Edwards, 2023) and practitioner-oriented research (McKinsey, 2025) indicate that a substantial share of AI initiatives remains confined to experimental or pilot phases, while more advanced AI applications frequently struggle to transition into operational use. This adoption logic is reflected in the technological patterns observed in the present study. The results indicate that organizations predominantly rely on AI technologies that can be embedded into existing processes with comparatively low integration complexity. As shown in Figure 6, NLP and generative AI are the most frequently reported technologies, whereas more specialized and technically demanding solutions, such as simulations, digital twins or multi-agent systems, are used far less frequently.

Moreover, the analysis of TT pioneers suggests that transformation success is not driven by the use of fundamentally different technologies, but rather by broader and more extensive application of AI across organizational domains. This observation mirrors findings from the McKinsey report (2025) which shows that AI high performers consistently deploy AI across a wider range of business functions than their peers. The narrow dispersion of relevance rankings across AI technologies further indicates that no single technology is perceived as clearly dominant for sustainability purposes, reinforcing the view that transformation outcomes depend less on specific tools than on the capability to integrate and coordinate them effectively. Besides, the strong focus on sustainability reporting as an AI application area can be explained by its specific characteristics. As shown by Ciccola et al. (2025), sustainability reporting is highly standardized and repetitive, relies heavily on codified textual information and involves resource intensive tasks such as data entry, benchmarking and consolidation. From a business perspective, this makes sustainability reporting particularly suitable for automation using AI, as organizations can realize immediate efficiency gains while simultaneously improving the accuracy and comparability of sustainability disclosures.

In regards to future application areas, the results indicate a strong continuity in the sustainability related use of AI. The identified future use cases largely reflect application areas that are already relevant today, suggesting that organizations primarily plan to further expand and institutionalize existing AI applications rather than shift toward fundamentally new domains. This continuity may also be explained by the fact that many existing AI initiatives are still in pilot or experimental phases, implying that future efforts are expected to focus on scaling and stabilizing these projects rather than initiating entirely new application areas.

Generally, the literature identifies a wide range of factors influencing AI adoption in general. Romeo and Lacko (2025) for example structure these determinants by distinguishing between organizational factors, such as the availability of skilled workforce, environmental factors, including regulatory frameworks and technological factors. Within the technological dimension, data related aspects play a central role, particularly data availability, data quality and data security. Against this background, prior research consistently highlights insufficient data availability and poor data quality emerges as among the most frequently reported challenges (Gurjar et al., 2024; Romeo & Lacko, 2025), a pattern that is confirmed by this studies results, where both rank among the three most salient challenges. The prominence of data collection as the second most cited challenge, see Figure 8, further indicated that these issues arise at the very beginning of the data lifecycle. This suggests that challenges related to data distribution and data processing, while reported less frequently, are not less important but rather reflect downstream consequences of deficiencies in earlier stages. Overall, the results reinforce the view that maintaining robust "data quality throughout the entire data lifecycle from data collection and storage to data processing and analysis" (Gurjar et al., 2024), is a fundamental prerequisite for effective and scalable AI adoption in general as well as in the sustainability context.

The risk patterns identified in this study reflect the way AI is currently applied in sustainability related organizational practices. While the McKinsey State of AI study (2025) emphasizes that negative consequences of AI use often stem from system-immanent risks, e.g. inaccuracy and limited explainability, these aspects were not explicitly captured in the present analysis. In the present study, a central interpretation concerns the prominence of missing internal competencies. This finding suggests that organizations perceive challenges related to skills, expertise and organizational readiness as particularly relevant when applying AI in sustainability related activities, a pattern that is also frequently discussed in the AI literature (Gurjar et al., 2024). Given the rapid pace of technological development, this finding highlights the importance of continuous training and upskilling, particularly as sustainability related AI applications often require the integration of technical knowledge and domain expertise. While missing competencies highlight challenges at the employee level, leadership support emerges as an important enabling factor at the managerial level (McKinsey, 2025). Consistent with the McKinsey (2025) report which highlights that AI performers are more frequently supported by top management, none of the identified TT pioneers in this study perceive a lack of management acceptance as a relevant risk. This indicates that managerial commitment may help mitigate capability related barriers and facilitate more advanced AI use in sustainability contexts. In addition, the results of this indicate that regulatory- and governance risks are perceived as particularly salient. This may be related to the fact that sustainability development in general is strongly shaped by compliance requirements and regulatory pressures (Uhrenholt et al., 2022; Zimmer & Järveläinen, 2022). Accordingly, AI risks in this context are primarily assessed with regard to data protection, regulatory uncertainty and compliance. Ethical concerns, by contrast, despite being frequently highlighted in the literature on AI risks (Gurjar et al., 2024), appear to play a comparatively limited role according to the results on this study. One possible explanation is that AI is predominantly applied in sustainability related activities that are already normatively framed around responsibility and fairness. Ethical aspects may therefore be perceived as implicitly addressed through sustainability objectives and existing compliance mechanisms, reducing their salience as a distinct category of AI risk.

Overall, the survey results show that the perceived value of TT is predominantly economically driven. Respondents primarily associate the interplay between DT and ST with effects such as increased competitiveness, higher cost and process efficiency and long-term value creation. This indicated that TT is currently conceptualized more as an inward-oriented endeavor focused on performance than as an outward-oriented approach aimed at partnerships, supply chains or broader stakeholder ecosystems. Interestingly, innovation is rated highly by both pioneers and non-pioneers, suggesting that in the context of TT to is perceived as a broadly shared source of value rather than a differentiating advantage. This contracts with findings from McKinsey's (2025) study on AI, which show that innovation benefits are mainly emphasized by firms with a particular focus on AI. Among TT Pioneers, the high relevance attributed to work quality is especially noteworthy. Although work quality is mentioned less frequently overall, a comparatively large share of these responses stems from TT pioneers. This pattern suggests that firms at more advanced stages of TT are more likely to associate it with improvements in everyday work, indicating that they perceive value not only in economic outcomes but also in how work is experienced within the organization. This aspect is not explicitly listed as a distinct value lever in Auweiler et al.'s (2025) conceptual framework, yet it aligns with the socially oriented mechanisms related to human-centered working conditions. Overall, the findings extend the conceptual model of Auweiler et al. (2025) by adding an empirical perspective on the topic of TT value.

5.3 Managerial Implications

From a managerial perspective, the findings imply that organizations should deliberately rethink how they structure and govern transformation initiatives. When firms pursue DT and ST in parallel but in isolation, they miss out on a substantial share of the potential value and in practice, DT and ST are often driven in isolation (Crome et al., 2023). This organizational separation reflects existing structures but constrains the emergence of synergies. Managers are therefore challenged to move beyond siloed transformation logics and establish an integrated approach that connects DT and ST across organizational boundaries.

This perspective is particularly important for managerial audiences that primarily associate TT with rising costs and complexity. The findings demonstrate that the perceived value of TT is initially and predominantly economically driven. Firms primarily associate the interplay between DT and ST with increased competitiveness, higher efficiency and long-term value creation. TT therefore does not stand in opposition to economic performance but can be framed as a transformation path focused on performance that aligns sustainability objectives with core business goals. This framing is critical for building internal legitimacy and for mobilizing resources in organizations that remain skeptical toward sustainability driven initiatives.

This potential can only be realized if organizations develop the necessary capabilities. Enabling capabilities are essential because they translate DTM into tangible sustainability outcomes increasing STM by making sustainability measurable and operational in everyday processes. Without these capabilities, DT remains detached form sustainability goals. Guiding capabilities complement this role by shaping how digital initiatives are designed and evaluated. They embed sustainability criteria into digital decision-making and influence priorities, ensuring that DT follows a sustainable direction.

The role of AI further illustrates these dynamics. Progress in the use of AI within TT is driven less by technological sophistication than by organizational integration. While most firms rely on pragmatic use cases with immediate operational benefits, TT pioneers stand out by deploying AI more broadly across organizational domains and embedding it more firmly into everyday routines. At the same time, data related issues emerge as a central bottleneck across all firms, as limitations in data collection to data analysis constrain both current AI application as well as probably the adoption of other advanced technologies. For practitioners, this implies that successful TT does not require radical technological leaps. Instead, it calls for a disciplined, integrative approach that builds data foundations, develops organizational capabilities and gradually scales solutions across functions. TT success thus result from organizational integration and capability building rather than form isolated technological breakthroughs.

6 Conclusion

The concept of TT has gained increasing attention as organizations are confronted with the simultaneous challenge of advancing DT and ST. Prior literature emphasizes that these two transformations are not independent processes but are expected to reinforce each other, with DT enabling outcomes sustainability related and ST guiding the direction of digital initiatives (Breiter et al., 2024; Christmann et al., 2024). However, existing research on TT has remained largely conceptual or qualitative in nature, leaving a significant gap with regard to firm-level empirical validation, particularly concerning reciprocal relationships and underlying organizational mechanisms. Against this backdrop, the aim of this study was to provide an initial empirical assessment of TT by examining the reciprocal interplay between DT and ST and by analyzing the role of enabling and guiding capabilities as key organizational mechanisms. Building on a maturity perspective and a capability oriented framework, the study integrates insights form DT and ST and capability theory into a coherent conceptual model.

The empirical results provide clear support for the core assumptions of the TT concept. DT and ST are shown to be positively and reciprocally related, confirming that both transformations mutually influence each other at the organizational level. The capability based analyses further clarify how this interaction unfolds in practice. Enabling capabilities play a central role by translating digital maturity into sustainability related outcomes, thereby connecting DT and ST in a sequential manner. Guiding capabilities, in contrast, are strongly shaped by ST and feedback into DT, however with less impact on its overall maturity level. Indicating it may influence more its orientation and decision logic. Complementary exploratory analyses extend these findings by showing that the value of TT is primarily perceived in economic terms, such as increased competitiveness, efficiency and long-term value creation. Moreover, the role of AI technologies illustrates that transformation success depends less on the use of specific advanced technologies than on their broad organizational integration.

Overall the study strengthens the empirical foundation of TT research by demonstrating that TT is fundamentally constitutes an integrative organizational transformation rooted in capabilities, rather than a purely technological endeavor.

6.1 Limitations

This study is subject to several limitations that should be considered when interpreting the findings. The relatively small and non-randomized sample restricts statistical power and limits the generalizability of the results. While the data enable an initial empirical examination of TT dynamics, the partial recruitment through the organizational environment of a parallel study may have led to an overrepresentation of firms with higher awareness of digital or sustainability issues, constraining external validity across industries, organizational contexts and firm sizes. Additional limitations arise from the reliance on self-reported measures and single informants per organization. Such data may be affected by perceptual biases, including social desirability or overestimation of maturity levels and do not fully reflect heterogeneous internal perspectives across functional roles. Moreover, AI and perceived value related items were treated exploratively and analyzed descriptively, preventing inferential conclusions regarding causal relationships or performance outcomes.

Finally, this study represents an initial empirical step in examining TT and was intended to provide a first quantitative assessment of its core theoretical assumptions. To enable empirical testing, the phenomenon was operationalized through maturity levels and capabilities. While this structured reduction allowed for analytical tractability, it inevitably simplifies the complexity and dynamic nature of organizational transformations and may therefore be criticized as an oversimplified representation. The findings should thus be interpreted as an initial empirical validation of the conceptual foundations, motivating further research directions discussed in the following chapter.

6.2 Future Research

Future research should extend this study by employing larger and more diverse samples to strengthen statistical power and improve the generalizability of findings. Larger datasets would allow for the systematic testing of moderating effects, such as differences across industries, firm sizes or regulatory environments, which may shape how DT and ST reinforce each other. In addition, future studies could apply broader and more differentiated capability frameworks to capture a wider range of organizational mechanisms underlying TT. A more differentiated operationalization of capabilities may help to identify which specific capability configurations are particularly relevant under different contextual conditions. Understanding these contextual and organizational contingencies is essential. As transformation dynamics are unlikely to be uniform across firms. Building on the exploratory identification of TT pioneers, future studies should apply group based comparison design, to examine whether pioneers differ systematically form other firms. Such analyses could help organizations better understand which combinations of maturity levels and capabilities are associated with more advanced forms of TT and provide clearer guidance on how firms can progress toward more integrated transformation pathways. Finally, future research should move beyond exploratory assessments of AI and perceived value creation by developing quantitative measurement models. This would enable for example a more systematic examination of how different organizational capabilities contribute to specific value outcomes of TT. In particular, future studies could analyze which enabling or guiding capabilities are most influential for distinct value dimensions, thereby providing a more differentiated understanding of how value emerges from TT.

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Appendix A: Online Questionnaire

Umfrage zur Twin Transformation in Unternehmen

Willkommen zur Umfrage

Im Rahmen meiner Masterarbeit an der Universität Bayreuth untersuche ich das Zusammenspiel von digitaler Transformation und Nachhaltigkeitstransformation - der sogenannten Twin Transformation.

Ziel meiner Arbeit ist es zu verstehen, wie die beide Transformationen aufeinander einwirken und welche Dynamiken sich aus diesen Zusammenspiel ergeben - etwa wie Digitalisierung nachhaltige Prozesse fördert und wie nachhaltiges Denken die Digitalisierung widerstandsfähiger und zukunftsfähiger macht. Mit der Umfrage soll zudem ermittelt werden, welche Erfolgsfaktoren die Umsetzung begünstigen, wo Unternehmen typischerweise auf Herausforderungen oder Hemmnisse stoßen und welche praxisnahen Muster sich in unterschiedlichen Organisation erkennen lassen.

Die Umfrage richtet sich an **Personen, die in einem oder beiden Themenfeldern** - idealerweise mit Schnittstellen zum jeweils anderen - fachliche Expertise mitbringen. Da sich die Fragen sowohl auf die digitale Transformation als auch auf die Nachhaltigkeitstransformation beziehen, möchte ich Sie bitten, diese nach bestem Wissen zu beantworten - auch wenn Sie nur in einem der beiden Feldern vertiefte Kenntnisse mitbringen. Am Ende der Umfrage werden Sie gebeten eine Angabe bezüglich Ihres fachlichen Schwerpunkts zu machen.

Die Bearbeitung dauert **ca. 25 Minuten**.

Ich danke Ihnen herzlich für Ihre Unterstützung und freue mich, die Ergebnisse im Rahmen meiner Masterarbeit mit Ihnen zu teilen.

Informationen und Einverständnis zur Umfrage:

- Ihre Teilnahme ist selbstverständlich freiwillig. Sie können die Umfrage jederzeit und ohne Angabe von Gründen abbrechen.
- Die Umfrage ist anonym.
- Bei Fragen wenden Sie sich gerne jederzeit an mich (Johanna Radtke, johanna.radtke@uni-bayreuth.de) oder an meine Betreuerin Lynne Valett (lynne.valett@fim-rc.de).
- Entsprechend den Richtlinien guter wissenschaftlicher Praxis ist eine explizite Einverständniserklärung zur Teilnahme erforderlich. Mit dem Klick auf "Weiter" erklären Sie sich mit der Teilnahme an der Umfrage einverstanden.

In dieser Umfrage sind 43 Fragen enthalten.

Weiter

Grundverständnis Twin Transformation

* 1 Haben Sie bereits von dem Konzept der "Twin Transformation", d. h. der gleichzeitigen Transformation von Digitalisierung und Nachhaltigkeit in Organisationen, gehört?

Bitte wählen Sie eine der folgenden Antworten:

- Ja
- Nein

2 **Für ein einheitliches Verständnis in dieser Umfrage gilt folgende Definition der Twin Transformation:**
Die Twin Transformation bezeichnet die strategische Verknüpfung der digitalen Transformation mit der Nachhaltigkeitstransformation innerhalb einer Organisation. Sie umfasst die Nutzung digitaler Technologien zur Förderung von Nachhaltigkeitszielen sowie die Verankerung von Nachhaltigkeitsprinzipien in allen Bereichen der digitalen Transformation. Durch diese wechselseitige Durchdringung entstehen Synergien und zusätzliche Mehrwerte, die über den Effekt der Einzeltransformationen hinausgehen (Graf-Drasch et al., 2023; Christmann et al., 2024).

Twin Transformation Einordnung

Bitte beantworten Sie die nachfolgenden Fragen auf Basis Ihrer Erfahrungen und Kenntnisse im Kontext Ihres Unternehmens.

* 3 Wie würden Sie den aktuellen Stand der digitalen Transformation in Ihrem Unternehmen einschätzen?

Bitte bewerten Sie die Aussagen auf einer Skala von ‚*sehr gering*' bis ‚*sehr hoch*'. Die Beschreibungen links und rechts verdeutlichen die Extrempole.

	Sehr gering	Gering	Mittel	Hoch	Sehr hoch	
Es gibt keine nennenswerten digitalen Prozesse oder Digitalisierungsstrategien im Unternehmen. Die meisten Prozesse werden manuell durchgeführt und digitale Technologien sind kaum im Einsatz.	○	○	○	○	○	Unser Unternehmen ist vollständig digitalisiert und nutzt fortschrittliche Technologien wie KI, Cloud-Lösungen und hat in den meisten Bereichen seine Prozesse weitgehend automatisiert.

* 4 Wie würden Sie den aktuellen Stand der Nachhaltigeitstransformation in Ihrem Unternehmen einschätzen?

Bitte bewerten Sie die Aussagen auf einer Skala von ‚*sehr gering*' bis ‚*sehr hoch*'. Die Beschreibungen links und rechts verdeutlichen die Extrempole.

	Sehr gering	Gering	Mittel	Hoch	Sehr hoch	
Nachhaltigkeit spielt in unserem Unternehmen keine Rolle. Es gibt keine festgelegten Ziele oder Strategien. Entscheidungen werden unabhängig von Nachhaltigkeitsaspekten getroffen.	○	○	○	○	○	Nachhaltigkeit ist vollständig in die Unternehmensstrategie integriert, einschließlich messbarer Ziele zu Umweltaspekten (z. B. CO_2, Ressourcen, Kreislaufwirtschaft) und sozialen Aspekten (z. B. Mitarbeitendenwohl, Diversität).

* 5 Welche der beiden Transformationen hat derzeit die höhere strategische Priorität in Ihrem Unternehmen?

Bitte wählen Sie eine der folgenden Antworten:

- ○ Digitale Transformation
- ○ Nachhaltigkeitstransformation
- ○ Beide gleich hoch
- ○ Keine von beiden im Fokus

Digitale Reife

Bitte bewerten Sie die Aussagen auf einer Skala von ‚*Stimme überhaupt nicht zu*' bis ‚*Stimme voll zu*'. Die Beschreibungen links und rechts verdeutlichen die Extrempole.

* 6 Unser Unternehmen verfolgt eine übergeordnete Digitalisierungsstrategie.

Das Beispiel auf der linken Seite entspricht der Ausprägung ‚*Stimme überhaupt nicht zu*' und das Beispiel auf der rechten Seite entspricht der Ausprägung ‚*Stimme voll zu*'.

	Stimme überhaupt nicht zu	Stimme eher nicht zu	Weder noch	Stimme eher zu	Stimme voll zu	
Es gibt keine übergeordnete Digitalisierungsstrategie. Digitale Themen werden nur punktuell behandelt, ohne übergeordnete Leitlinien oder erkennbare strategische Kommunikation.	○	○	○	○	○	Unsere übergeordnete Digitalisierungsstrategie ist klar formuliert, wird unternehmensweit kommuniziert und schafft Orientierung für Digitalisierungsprojekte.

* 7 Unsere Digitalisierungsstrategie ist fest in der Gesamtstrategie des Unternehmens verankert.

Das Beispiel auf der linken Seite entspricht der Ausprägung ‚*Stimme überhaupt nicht zu*' und das Beispiel auf der rechten Seite entspricht der Ausprägung ‚*Stimme voll zu*'.

	Stimme überhaupt nicht zu	Stimme eher nicht zu	Weder noch	Stimme eher zu	Stimme voll zu	
Es gibt keine Digitalisierungsstrategie bzw. digitale Initiativen laufen unabhängig voneinander und ohne strategische Abstimmung mit der Gesamtstrategie.	○	○	○	○	○	Die Digitalisierungsstrategie ist fest in der Gesamtstrategie verankert, trägt zur übergreifenden Ausrichtung des Unternehmens bei und wird bei strategischen Entscheidungen systematisch berücksichtigt.

* 8 Die Umsetzung der Digitalisierungsstrategie wird anhand messbarer Ziele gesteuert.

Das Beispiel auf der linken Seite entspricht der Ausprägung *'Stimme überhaupt nicht zu'* und das Beispiel auf der rechten Seite entspricht der Ausprägung *'Stimme voll zu'*.

	Stimme überhaupt nicht zu	Stimme eher nicht zu	Weder noch	Stimme eher zu	Stimme voll zu	
Es gibt keine Digitalisierungsstrategie bzw. die Umsetzung von digitalen Intiativen erfolgt ohne klare Zielvorgaben, z. B. fehlen konkrete Kennzahlen, Erfolgskriterien oder ein systematisches Controlling.	○	○	○	○	○	Die Umsetzung der Digitalisierungsstrategie wird durch messbare Ziele gesteuert, z. B. mithilfe definierter KPIs, regelmäßiger Fortschrittsanalysen und klarer Verantwortlichkeiten für die Zielerreichung.

* 9 Unser Unternehmen setzt ... systematisch ein.

Das Beispiel auf der linken Seite entspricht der Ausprägung *'Stimme überhaupt nicht zu'* und das Beispiel auf der rechten Seite entspricht der Ausprägung *'Stimme voll zu'*.

	Stimme überhaupt nicht zu	Stimme eher nicht zu	Weder noch	Stimme eher zu	Stimme voll zu	
Künstliche Intelligenz wird gar nicht oder nur experimentell in eng begrenzten Anwendungsfällen eingesetzt, ohne geschäftskritische Relevanz, z. B. in Form eines isolierten Chatbot-Tests im Kundenservice.	○	○	○	○	○	Künstliche Intelligenz ist tief in Kernprozesse integriert, unterstützt Entscheidungen, wird kontinuierlich trainiert und verbessert. Ein Beispiel ist eine agentenbasierte KI, die automatisch mit dem ERP-System interagiert.
Internet-of-Things oder Sensoren werden gar nicht oder nur zur Erfassung einfacher Messwerte eingesetzt, z. B. Temperatur, Feuchtigkeit oder Laufzeiten mit lokaler Speicherung und ohne nennenswerte Vernetzung oder Auswertung.	○	○	○	○	○	Das Internet of Things ist in vielen Prozessen umfassend integriert, teilweise kombiniert mit KI, Analytics oder Machine Learning, z. B. zur Fehlerfrüherkennung und datengestützten Optimierung von Prozessen in Echtzeit.
Cloud-Dienste werden gar nicht oder nur vereinzelt genutzt, z. B. für Dateiablage oder E-Mail, während Kernsysteme weiterhin on-premise ohne Integration betrieben werden.	○	○	○	○	○	Die IT-Landschaft ist cloud-native mit skalierbarer Multi-Cloud-Architektur, automatisiertem Deployment und Datenvirtualisierung, die eine nahtlose Unterstützung der meisten Geschäftsprozesse ermöglicht.

* 10 Welche der nachfolgenden digitalen Technologien werden aktuell zudem in Ihrem Unternehmen eingesetzt?

Wählen Sie alle zutreffenden Optionen

- ☐ Keine weiteren digitalen Technologien
- ☐ Digitaler Produktpass
- ☐ Blockchain-Technologie
- ☐ Robotic Process Automation
- ☐ 3D-Druck
- ☐ Digitale Zwillinge
- ☐ Augmented Reality/ Virtual Reality
- ☐ Edge Computing
- ☐ Sonstiges: ________

* 11 Unser ERP-System ist mit anderen zentralen Unternehmenssystemen verknüpft und trägt wesentlich zur Automatisierung von Prozessen bei.

Das Beispiel auf der linken Seite entspricht der Ausprägung *'Stimme überhaupt nicht zu'* und das Beispiel auf der rechten Seite entspricht der Ausprägung *'Stimme voll zu'*.

	Stimme überhaupt nicht zu	Stimme eher nicht zu	Weder noch	Stimme eher zu	Stimme voll zu	
Es gibt kein ERP-System oder es wird als isolierte Verwaltungssoftware ohne Integration mit anderen Systemen genutzt. Viele Prozesse erfolgen daher noch manuell, ohne Schnittstellen zu CRM-, SCM-, HR- oder Produktionssystemen.	○	○	○	○	○	Das ERP-System ist als zentrale Plattform vollständig integriert, z. B. mit CRM-, SCM-, HR- und Produktionssystemen und unterstützt weitgehend automatisierte, datengetriebene Prozesse.

* 12 Unsere IT-Infrastruktur ist flexibel und skalierbar für Digitalisierungsprojekte.

Das Beispiel auf der linken Seite entspricht der Ausprägung *'Stimme überhaupt nicht zu'* und das Beispiel auf der rechten Seite entspricht der Ausprägung *'Stimme voll zu'*.

	Stimme überhaupt nicht zu	Stimme eher nicht zu	Weder noch	Stimme eher zu	Stimme voll zu	
Unsere IT-Infrastruktur ist aufgrund von veralteten Systemen, starren IT-Architekturen oder mangelnder Erweiterbarkeit bei neuen digitalen Anforderungen unflexibel und schwer skalierbar.	○	○	○	○	○	Unsere IT-Infrastruktur ist hoch flexibel und skalierbar, z. B. durch modulare Systeme, Cloud-Lösungen oder standardisierte Schnittstellen, die neue digitale Anwendungen schnell integrieren.

* 13 Unsere Kernprozesse (z.B. Produktentwicklung) sind digitalisiert und durch digitale Tools unterstützt.

Das Beispiel auf der linken Seite entspricht der Ausprägung *,Stimme überhaupt nicht zu'* und das Beispiel auf der rechten Seite entspricht der Ausprägung *,Stimme voll zu'.*

	Stimme überhaupt nicht zu	Stimme eher nicht zu	Weder noch	Stimme eher zu	Stimme voll zu	
Unsere Kernprozesse sind nicht digitalisiert und laufen größtenteils manuell, papierbasiert und ohne digitale Unterstützung.	○	○	○	○	○	Unsere Kernprozesse sind umfassend digitalisiert, laufen vollständig digital ab, erfordern keine manuellen Eingriffe und werden durch integrierte IT-Systeme gesteuert.

* 14 Unsere Prozesse ermöglichen eine agile Reaktion auf digitale Herausforderungen (z.B. neue Datenschutzanforderungen).

Das Beispiel auf der linken Seite entspricht der Ausprägung *,Stimme überhaupt nicht zu'* und das Beispiel auf der rechten Seite entspricht der Ausprägung *,Stimme voll zu'.*

	Stimme überhaupt nicht zu	Stimme eher nicht zu	Weder noch	Stimme eher zu	Stimme voll zu	
Unsere Prozesse sind starr. Änderungen sind nur langsam oder mit hohem Aufwand möglich und Reaktionen erfolgen verzögert oder gar nicht.	○	○	○	○	○	Unsere Prozesse sind agil, lassen sich schnell an neue digitale Anforderungen anpassen und ermöglichen flexible Reaktionen.

* 15 Unsere operativen Prozesse werden kontinuierlich optimiert.

Das Beispiel auf der linken Seite entspricht der Ausprägung *,Stimme überhaupt nicht zu'* und das Beispiel auf der rechten Seite entspricht der Ausprägung *,Stimme voll zu'.*

	Stimme überhaupt nicht zu	Stimme eher nicht zu	Weder noch	Stimme eher zu	Stimme voll zu	
Unsere operativen Prozesse werden kaum weiterentwickelt. Bestehende Abläufe bleiben unverändert, und Verbesserungen erfolgen nur reaktiv oder im Ausnahmefall.	○	○	○	○	○	Unsere operativen Prozesse werden systematisch weiterentwickelt, z. B. durch klar definierte Prozessverantwortlichkeiten, regelmäßige Reviews, den Einsatz aussagekräftiger Kennzahlen sowie Tools wie Process Mining, die gezielt Verbesserungspotenziale aufzeigen.

* 16 Unsere Kultur fördert digitale Innovation.

Das Beispiel auf der linken Seite entspricht der Ausprägung *,Stimme überhaupt nicht zu'* und das Beispiel auf der rechten Seite entspricht der Ausprägung *,Stimme voll zu'.*

	Stimme überhaupt nicht zu	Stimme eher nicht zu	Weder noch	Stimme eher zu	Stimme voll zu	
Unsere Kultur hemmt digitale Innovation, z. B. durch Angst vor Fehlern, mangelnde Offenheit für neue Ideen oder geringe Unterstützung.	○	○	○	○	○	Unsere Kultur fördert digitale Innovation aktiv, z. B. durch Freiräume für neue Ideen, interdisziplinären Austausch oder Unterstützung beim Testen neuer Ansätze.

Nachhaltigkeitsreife

Bitte bewerten Sie die Aussagen auf einer Skala von *Stimme überhaupt nicht zu'* bis *,Stimme voll zu'.* Die Beschreibungen links und rechts verdeutlichen die Extrempole.

* 19 Unser Unternehmen verfolgt eine klare Nachhaltigkeitsstrategie.

Das Beispiel auf der linken Seite entspricht der Ausprägung *,Stimme überhaupt nicht zu'* und das Beispiel auf der rechten Seite entspricht der Ausprägung *,Stimme voll zu'.*

	Stimme überhaupt nicht zu	Stimme eher nicht zu	Weder noch	Stimme eher zu	Stimme voll zu	
Es gibt keine klare Nachhaltigkeitsstrategie. Nachhaltigkeitsthemen werden nur punktuell behandelt, ohne übergeordnete Leitlinien oder erkennbare strategische Kommunikation.	○	○	○	○	○	Unsere Nachhaltigkeitsstrategie ist klar formuliert, dokumentiert, wird unternehmensweit kommuniziert und schafft Orientierung für Nachhaltigkeitsaktivitäten.

* 20 Unsere Nachhaltigkeitsstrategie ist fest in der Gesamtstrategie des Unternehmens verankert.

Das Beispiel auf der linken Seite entspricht der Ausprägung *‚Stimme überhaupt nicht zu'* und das Beispiel auf der rechten Seite entspricht der Ausprägung *‚Stimme voll zu'*.

	Stimme überhaupt nicht zu	Stimme eher nicht zu	Weder noch	Stimme eher zu	Stimme voll zu	
Es gibt keine Nachhaltigkeitsstrategie bzw. Nachhaltigkeitsinitiativen laufen unabhängig voneinander und ohne strategische Abstimmung mit der Gesamtstrategie.	○	○	○	○	○	Die Nachhaltigkeitsstrategie ist fest in der Gesamtstrategie verankert, trägt zur übergreifenden Ausrichtung des Unternehmens bei und wird bei strategischen Entscheidungen systematisch berücksichtigt.

* 21 Die Umsetzung der Nachhaltigkeitsstrategie wird anhand messbarer Ziele gesteuert.

Das Beispiel auf der linken Seite entspricht der Ausprägung *‚Stimme überhaupt nicht zu'* und das Beispiel auf der rechten Seite entspricht der Ausprägung *‚Stimme voll zu'*.

	Stimme überhaupt nicht zu	Stimme eher nicht zu	Weder noch	Stimme eher zu	Stimme voll zu	
Es gibt keine Nachhaltigkeitsstrategie bzw. die Umsetzung der Nachhaltigkeitsinitiativen erfolgt ohne klare Zielvorgaben, z. B. fehlen konkrete Kennzahlen, Erfolgskriterien oder ein systematisches Nachhaltigkeitscontrolling.	○	○	○	○	○	Die Umsetzung der Nachhaltigkeitsstrategie wird durch messbare Ziele gesteuert, z. B. mithilfe definierter KPIs, regelmäßiger Fortschrittsanalysen und klarer Verantwortlichkeiten für die Zielerreichung.

* 22 Wir bewerten Nachhaltigkeitsrisiken (z.B. Lieferkettenrisiken durch Menschenrechtsverletzungen) systematisch über alle Geschäftsbereiche hinweg.

Das Beispiel auf der linken Seite entspricht der Ausprägung *‚Stimme überhaupt nicht zu'* und das Beispiel auf der rechten Seite entspricht der Ausprägung *‚Stimme voll zu'*.

	Stimme überhaupt nicht zu	Stimme eher nicht zu	Weder noch	Stimme eher zu	Stimme voll zu	
Nachhaltigkeitsrisiken werden nicht systematisch bewertet, d.h. sie werden nur vereinzelt berücksichtigt, auf einzelne Bereiche beschränkt oder reaktiv behandelt.	○	○	○	○	○	Nachhaltigkeitsrisiken werden systematisch erfasst, z. B. durch regelmäßige ESG-Risikoanalysen und die Anwendung standardisierter Bewertungsmethoden.

* 23 Unser Unternehmen erfüllt ESG-bezogene regulatorische Anforderungen (z.B. CSRD, EU-Taxonomie).

Das Beispiel auf der linken Seite entspricht der Ausprägung *‚Stimme überhaupt nicht zu'* und das Beispiel auf der rechten Seite entspricht der Ausprägung *‚Stimme voll zu'*.

	Stimme überhaupt nicht zu	Stimme eher nicht zu	Weder noch	Stimme eher zu	Stimme voll zu	
ESG-Vorgaben werden nur minimal erfüllt, z. B. werden Pflichten gerade so eingehalten, Umsetzungen erfolgen spät oder ohne strategischen Anspruch.	○	○	○	○	○	ESG-Anforderungen werden deutlich übertroffen, z. B. durch frühzeitige Umsetzung, interne Standards über gesetzliche Vorgaben hinaus oder aktive Weiterentwicklung ESG-relevanter Praktiken.

* 24 Bei der Auswahl unserer Lieferanten berücksichtigen wir ESG-Kriterien.

Das Beispiel auf der linken Seite entspricht der Ausprägung *‚Stimme überhaupt nicht zu'* und das Beispiel auf der rechten Seite entspricht der Ausprägung *‚Stimme voll zu'*.

	Stimme überhaupt nicht zu	Stimme eher nicht zu	Weder noch	Stimme eher zu	Stimme voll zu	
Lieferanten werden ohne ESG-Kriterien ausgewählt. Entscheidungsgrundlagen sind z. B. Preis, Lieferzeit oder bestehende Geschäftsbeziehungen. Nachhaltigkeitsaspekte spielen keine Rolle.	○	○	○	○	○	ESG-Kriterien sind fest im Auswahlprozess verankert, z. B. durch regelmäßige Überprüfung und Bewertung, konkrete Anforderungen an Arbeitsbedingungen, Umweltmanagement oder Zertifizierungen.

* 25 Unsere Kernprozesse (z. B. Produktentwicklung) berücksichtigen Nachhaltigkeitsaspekte.

Das Beispiel auf der linken Seite entspricht der Ausprägung *‚Stimme überhaupt nicht zu'* und das Beispiel auf der rechten Seite entspricht der Ausprägung *‚Stimme voll zu'*.

	Stimme überhaupt nicht zu	Stimme eher nicht zu	Weder noch	Stimme eher zu	Stimme voll zu	
Nachhaltigkeitsaspekte werden in den Kernprozessen nicht berücksichtigt, z. B. fehlen ökologische oder soziale Kriterien bei Planung, Beschaffung, Produktion oder Vertrieb.	○	○	○	○	○	Nachhaltigkeitsaspekte sind systematisch und bereichsübergreifend in alle Kernprozesse integriert, z. B. ökologische Effizienz in der Produktion, soziale Standards in der Lieferkette oder nachhaltige Verpackung im Vertrieb.

* 26 Unsere Prozesse ermöglichen eine agile Reaktion auf neue Nachhaltigkeitsanforderungen.

Das Beispiel auf der linken Seite entspricht der Ausprägung *'Stimme überhaupt nicht zu'* und das Beispiel auf der rechten Seite entspricht der Ausprägung *'Stimme voll zu'*.

	Stimme überhaupt nicht zu	Stimme eher nicht zu	Weder noch	Stimme eher zu	Stimme voll zu	
Unsere Prozesse reagieren nur träge auf neue Nachhaltigkeitsanforderungen. Sie werden lediglich angepasst, wenn dies zur Erfüllung regulatorischer Vorgaben wie z. B. CSRD, Lieferkettengesetz oder CO_2-Vorgaben zwingend notwendig ist.	○	○	○	○	○	Unsere Prozesse sind flexibel und antizipieren neue Nachhaltigkeitsanforderungen, indem sie frühzeitig auf Vorgaben wie CSRD, Lieferkettengesetz oder CO_2-Grenzwerte ausgerichtet werden.

* 27 Unsere operativen Prozesse werden kontinuierlich weiterentwickelt, um ressourcenschonende und nachhaltige Abläufe zu ermöglichen.

Das Beispiel auf der linken Seite entspricht der Ausprägung *'Stimme überhaupt nicht zu'* und das Beispiel auf der rechten Seite entspricht der Ausprägung *'Stimme voll zu'*.

	Stimme überhaupt nicht zu	Stimme eher nicht zu	Weder noch	Stimme eher zu	Stimme voll zu	
Unsere operativen Prozesse werden im Hinblick auf Nachhaltigkeit nicht weiterentwickelt, z. B. bleiben Ressourcenschonung, CO_2-Reduktion oder Abfallvermeidung unberücksichtigt.	○	○	○	○	○	Unsere operativen Prozesse werden gezielt unter Nachhaltigkeitsaspekten optimiert, z. B. anhand klarer Kriterien wie Ressourceneffizienz oder CO_2-Reduktion als integraler Bestandteil der Prozessverbesserung.

* 28 Unsere Kultur fördert nachhaltiges Denken und Handeln.

Das Beispiel auf der linken Seite entspricht der Ausprägung *'Stimme überhaupt nicht zu'* und das Beispiel auf der rechten Seite entspricht der Ausprägung *'Stimme voll zu'*.

	Stimme überhaupt nicht zu	Stimme eher nicht zu	Weder noch	Stimme eher zu	Stimme voll zu	
Nachhaltigkeit ist nicht Teil unserer Unternehmenskultur, z. B. spielen im Alltag ökologische oder soziale Aspekte keine Rolle und werden eher als externe Pflicht verstanden.	○	○	○	○	○	Unsere Kultur fördert nachhaltiges Denken und Handeln aktiv, z. B. fließen ökologische und soziale Aspekte aktiv in Entscheidungen ein, nachhaltige Ideen werden gefördert und kontinuierliche Verbesserung wird unterstützt.

* 29 Mitarbeitende werden gezielt beim Aufbau von Nachhaltigkeitskompetenzen unterstützt.

Das Beispiel auf der linken Seite entspricht der Ausprägung *'Stimme überhaupt nicht zu'* und das Beispiel auf der rechten Seite entspricht der Ausprägung *'Stimme voll zu'*.

	Stimme überhaupt nicht zu	Stimme eher nicht zu	Weder noch	Stimme eher zu	Stimme voll zu	
Nachhaltigkeitskompetenzen werden nicht gefördert. Es gibt weder Schulungsangebote noch einen strukturierten Austausch zu Nachhaltigkeitsthemen.	○	○	○	○	○	Nachhaltigkeitskompetenzen werden gezielt gefördert, z. B. durch Trainings, Lernformate oder Programme zur Entwicklung von ökologischen, sozialen und zukunftsgerichteten Fähigkeiten.

* 30 Führungskräfte treiben die Nachhaltigkeitstransformation aktiv voran.

Das Beispiel auf der linken Seite entspricht der Ausprägung *'Stimme überhaupt nicht zu'* und das Beispiel auf der rechten Seite entspricht der Ausprägung *'Stimme voll zu'*.

	Stimme überhaupt nicht zu	Stimme eher nicht zu	Weder noch	Stimme eher zu	Stimme voll zu	
Führungskräfte bremsen die Nachhaltigkeitstransformation, indem Nachhaltigkeitsaspekte in Entscheidungen weniger Beachtung finden oder kurzfristige Gewinnziele stärker im Vordergrund stehen.	○	○	○	○	○	Führungskräfte treiben die Nachhaltigkeitstransformation aktiv voran, indem sie klare Ziele setzen, Mitarbeitende motivieren und Nachhaltigkeit konsequent in Entscheidungen berücksichtigen.

Digitale Transformation ermöglicht Nachhaltigkeitstransformation

* 31 Inwiefern ermöglicht die digitale Transformation die Nachhaltigkeitstransformation?

	Stimme überhaupt nicht zu	Stimme eher nicht zu	Neutral	Stimme eher zu	Stimme voll zu
Wir setzen digitale Technologien wie das Internet of Things ein, um Nachhaltigkeitsdaten automatisch und in Echtzeit zu erfassen.					
Wir nutzen digitale Lösungen, um den Fortschritt bei Nachhaltigkeitszielen systematisch zu überwachen.					
Wir nutzen digitale Lösungen, um Nachhaltigkeitsszenarien zu simulieren und Auswirkungen vorab zu bewerten.					
Unsere digitalen Technologien unterstützen die Analyse von Nachhaltigkeitsdaten, z. B. durch Datenaufbereitung, Mustererkennung und die Ableitung von Handlungsoptionen.					
Digitale Technologien helfen uns, den Ressourcenverbrauch zu reduzieren.					
Unsere IT-Infrastruktur ermöglicht die systematische Integration und Bereitstellung von Nachhaltigkeitsdaten über verschiedene Systeme hinweg.					
Unsere digitalen Systeme unterstützen die Kreislaufwirtschaft, z. B. in Wiederverwendung, Recycling, Sharing.					

Nachhaltigkeitstransformation steuert digitale Transformation

* 32 Inwiefern steuert die Nachhaltigkeitstransformation die digitale Transformation?

	Stimme überhaupt nicht zu	Stimme eher nicht zu	Neutral	Stimme eher zu	Stimme voll zu
Wir berücksichtigen Nachhaltigkeitsaspekte bei der Nutzung digitaler Technologien, z. B. durch die Berücksichtigung des Energieverbrauchs beim Einsatz von KI-Anwendungen wie ChatGPT.					
Wir berücksichtigen Nachhaltigkeitsaspekte bei Investitionen in digitale Technologien, z. B. die Kreislauffähigkeit von Hardware oder die Energieintensität neuer Software.					
Wir berücksichtigen Nachhaltigkeitsaspekte bei der Entwicklung digitaler Produkte, Prozesse und Services, z. B. durch umweltfreundliche Gestaltung, geringe Ressourcenintensität im Betrieb und nachhaltiges Produktlebenszyklus-Management.					
Nachhaltigkeitsaspekte beeinflussen die Priorisierung unserer Digitalisierungsprojekte, z. B durch die bevorzugte Umsetzung nachhaltigkeitsrelevanter Digitalisierungsprojekte (z. B. Einführung ESG-Datensysteme) gegenüber Digitalisierungsprojekten ohne Nachhaltigkeitsbezug.					
Unsere digitale Infrastruktur wird nachhaltig und energieeffizient ausgebaut, z. B. durch den Einsatz energieoptimierter Server oder die Nutzung erneuerbarer Energien in Rechenzentren.					
Bei digitalen Veränderungen berücksichtigen wir Nachhaltigkeitsaspekte, z.B. durch Angebote zur Förderung der Gesundheit der Mitarbeitenden.					

Mehrwert durch die Twin Transformation

* 33 Das Zusammenspiel von digitaler Transformation und Nachhaltigkeitstransformation in unserem Unternehmen...

Wählen Sie alle zutreffenden Optionen

- ☐ ...stärkt unsere Innovationskraft und ermöglicht die Entwicklung neuer Geschäftsmodelle.
- ☐ ...erhöht unsere Wettbewerbsfähigkeit.
- ☐ ...trägt zur Kosteneffizienz bzw. Prozesseffizienz bei.
- ☐ ...trägt zur Steigerung der Arbeitsqualität bei.
- ☐ ...steigert die Zufriedenheit unserer Lieferanten.
- ☐ ...steigert die Zufriedenheit unserer Kunden.
- ☐ ...macht unser Unternehmen widerstandsfähiger gegenüber externen Disruptionen.
- ☐ ...fördert die Mitarbeiterbindung und steigert unsere Arbeitgeberattraktivität.
- ☐ ...trägt zur langfristigen Wertsteigerung des Unternehmens bei.

Exkurs: Einsatz von künstlicher Intelligenz

Angesichts der rasanten Entwicklung im Bereich Künstlicher Intelligenz möchte ich nachfolgend gerne noch den Status-quo und die Einsatzmöglichkeiten von KI im Kontext der Nachhaltigkeit in Ihrem Unternehmen erfassen.

* 34 Welche Arten von KI nutzen Sie bereits im Nachhaltigkeitskontext?

Wählen Sie alle zutreffenden Optionen

- ☐ Machine Learning / Predictive Analytics (z. B. Wartungsprognosen)
- ☐ Natural Language Processing (z. B. für Nachhaltigkeitsberichte, ESG-Textanalyse)
- ☐ Bild- und Objekterkennung (z. B. Abfalltrennung, Qualitätskontrolle)
- ☐ Optimierungsalgorithmen (z. B. für Routen, Energieverbrauch)
- ☐ KI-basierte Simulationen & digitale Zwillinge (z. B. Produktionshallen-Simulationen)
- ☐ Generative KI (z. B. Szenario-Entwicklung, Designvorschläge)
- ☐ Multi-Agenten-System (z. B. zur Energiesystemsteuerung)
- ☐ Sonstiges: ______

* 35 Bitte ordnen Sie die folgenden KI-Technologien nach ihrer Relevanz für die Nachhaltigkeit in Ihrem Unternehmen

Ordnen Sie die Elemente in die rechte Liste ein (höchste Bewertung oben). Die Elemente können mit der Maus verschoben werden. Doppelklick verschiebt ein Element in die andere Liste. Bitte wählen Sie maximal 7 Antworten.

Verfügbare Einträge	Ihr Ranking
Machine Learning / Predictive Analytics (z. B. Wartungsprognosen)	
Natural Language Processing (z. B. für Nachhaltigkeitsberichte, ESG-Textanalyse)	
Bild- und Objekterkennung (z. B. Abfalltrennung, Qualitätskontrolle)	
Optimierungsalgorithmen (z. B. für Routen, Energieverbrauch)	
KI-basierte Simulationen und digitale Zwillinge (z. B. Produktionshallen-Simulationen)	
Generative KI (z. B. Szenario-Entwicklung, Designvorschläge)	
Multi-Agenten-Systeme (z. B. zur Energiesystemsteuerung)	

* 36 In welchen Anwendungsbereichen setzen Sie derzeit KI ein, um Nachhaltigkeit zu fördern?

Wählen Sie alle zutreffenden Optionen

- [ ] Energieeffizienzsteigerung
- [ ] Abfallreduktion und Recycling
- [ ] Produktverbesserungen oder Verlängerung von Produktlebenszyklen
- [ ] Personal- und Arbeitsorganisation
- [ ] Monitoring von Nachhaltigkeitskennzahlen
- [ ] Optimierung von Lieferketten und Logistik
- [ ] Kundenkommunikation
- [ ] Nachhaltigkeitsberichterstattung
- [ ] Sonstiges: ______

* 37 Welche der folgenden Herausforderungen erschweren in Ihrem Unternehmen die Nutzung von Daten für KI im Nachhaltigkeitskontext?

Wählen Sie alle zutreffenden Optionen

- [ ] Unzureichende Datenerfassung (z.B. jährliche Erfassung oder fehlende Sensoren)
- [ ] Unzureichende Datenverfügbarkeit (z.B. komplexe IT-Landschaft, dezentrale Speicherung)
- [ ] Unzureichende Datenverteilung (z.B. fehlende Automatisierung)
- [ ] Unzureichende Datenverarbeitung (z.B. fehlende digitale Tools)
- [ ] Unzureichende Datenqualität (z.B. unterschiedliche Granularität, fehlende Standardisierung)
- [ ] Sonstiges: ______

* 38 Welche Risiken nehmen Sie in Ihrem Unternehmen für den Einsatz von KI für Nachhaltigkeitsziele wahr?

Wählen Sie alle zutreffenden Optionen

- [ ] Fehlende interne Kompetenzen
- [ ] Geringe Managementakzeptanz
- [ ] Compliance-Risiken
- [ ] Datenschutz-Bedenken
- [ ] Abnehmende Arbeitsqualität
- [ ] Hohe Energiekosten
- [ ] Regulatorische Unsicherheiten
- [ ] Ethische Fragestellungen
- [ ] Abhängigkeiten von Serviceanbietern
- [ ] Sonstiges: ______

* 39 In welchen zusätzlichen Bereichen möchten Sie KI in Zukunft gezielt für Nachhaltigkeitsziele einsetzen?

Wählen Sie alle zutreffenden Optionen

- [ ] Energieoptimierung (z. B. Gebäude, Produktion, Fuhrpark)
- [ ] Interne Prozessverbesserung (z. B. Automatisierung von Routineaufgaben)
- [ ] Nachhaltige Produktentwicklung (z. B. Materialwahl)
- [ ] Kreislaufwirtschaft (z. B. Recycling, Wiederverwertung, Abfallmanagement)
- [ ] Lieferketten-Transparenz (z. B. faire Arbeitsbedingungen)
- [ ] Automatisiertes Nachhaltigkeitsreporting (z. B. CSRD)
- [ ] Nachhaltige Mobilität & Logistikoptimierung (z. B. Routenplanung)
- [ ] Soziale Nachhaltigkeit (z. B. Diversity, Inklusion)
- [ ] Sonstiges: ____

Unternehmensangaben

* 40 In welchem Bereich findet die Hauptwertschöpfung Ihres Unternehmens statt?

Bitte wählen Sie eine der folgenden Antworten:

- ○ Produktion
- ○ Handel
- ○ Dienstleistung
- ○ Öffentlicher Sektor / Non-Profit
- ○ Sonstiges: ____

* 41 Wie groß ist das Unternehmen, in dem Sie tätig sind (gemessen an der Anzahl der Mitarbeitenden)?

Bitte wählen Sie eine der folgenden Antworten:

- ○ 1-9 Mitarbeitende
- ○ 10-49 Mitarbeitende
- ○ 50-249 Mitarbeitende
- ○ 250-999 Mitarbeitende
- ○ über 1.000 Mitarbeitende

* 42 In welcher Region befindet sich der Großteil Ihrer Kunden?

Wählen Sie alle zutreffenden Optionen

- [ ] DACH-Region (Deutschland, Österreich, Schweiz)
- [ ] Europa (außer DACH)
- [ ] Nordamerika
- [ ] Südamerika
- [ ] Asien-Pazifik
- [ ] Afrika
- [ ] Weltweit

* 43 Auf welchen Themenbereich ist Ihre Rolle im Unternehmen hauptsächlich ausgerichtet?

Bitte wählen Sie eine der folgenden Antworten:

- ○ Digitalisierung
- ○ Nachhaltigkeit
- ○ Schnittstelle zwischen Digitalisierung und Nachhaltigkeit

Appendix B: Operationalization of Constructs and Underlying Literature

Item Code	Item	Reference
DTS_1	Our company pursues an overarching digitalization strategy.	Gollhardt et al., 2020
DTS_2	Our digitalization strategy is embedded in the company's overall strategy	Hortovanyi et al., 2023; Kırmızı & Kocaoglu, 2022
DTS_3	The implementation of the digitalization strategy is steered through measurable goals.	Kırmızı & Kocaoglu, 2022
DTT_1a	Artificial intelligence is used systematically in our company.	Santos & Martinho, 2020
DTT_1b	Internet-of-Things is used systematically in our company.	Nebati et al., 2023
DTT_1c	Cloud services are used systematically in our company	Amaral & Peças, 2021; Ehrensperger et al., 2023
DTT_2	Our ERP system is integrated with other central systems and enables process automation.	Vial, 2019
DTT_3	Our IT infrastructure is flexible and scalable for digitalization projects.	Ehrensperger et al., 2023; Zitoun et al., 2021
DTOP_1	Our core processes are digitalized and supported by digital tools.	Doctor et al., 2023; E. Gökalp & Martinez, 2021
DTOP_2	Our processes enable an agile response to digital challenges.	E. Gökalp & Martinez, 2021
DTOP_3	Our operational processes are continuously optimized.	Kırmızı & Kocaoglu, 2022; Santos & Martinho, 2020
DTOC_1	Our culture fosters digital innovation.	Santos & Martinho, 2020
DTOC_2	Employees are systematically supported in developing digital skills and competencies.	Gollhardt et al., 2020; Rossmann, 2018
DTOC_3	Leaders actively drive the digital transformation.	Rossmann, 2018
STS_1	Our company pursues a clear sustainability strategy.	Pigosso & McAloone, 2021; Sohns et al., 2023
STS_2	The sustainability strategy is embedded in the company's overall strategy.	Sohns et al., 2023; Vásquez et al., 2021
STS_3	The implementation of the sustainability strategy is steered through measurable goals.	Cuevas-Lopez-de-Baro et al., 2025; Sari et al., 2021
STGR_1	We systematically assess sustainability related risks (e.g., supply chain risks arising from human rights violations) across all business units.	Sari et al., 2021; Uhrenholt et al., 2022
STGR_2	Our company complies with ESG related regulatory requirements (e.g., CSRD, EU Taxonomy).	Vásquez et al., 2021
STGR_3	We consider ESG criteria when selecting our suppliers.	Latino, 2025; Okongwu et al., 2013
STOP_1	Our core processes (e.g., product development) incorporate sustainability aspects.	Uhrenholt et al., 2022
STOP_2	Our processes enable an agile response to new sustainability requirements.	Uhrenholt et al., 2022

STOP_3	Our operational processes are continuously developed to enable resource-efficient and sustainable operations.	Cuevas-Lopez-de-Baro et al., 2025; Okongwu et al., 2013
STOC_1	Our culture fosters sustainable thinking and behavior.	Cuevas-Lopez-de-Baro et al., 2025; Sajadieh & Noh, 2024
STOC_2	Employees are systematically supported in developing sustainability related competencies.	Pigosso & McAloone, 2021; Uhrenholt et al., 2022
STOC_3	Leaders actively drives the sustainability transformation.	Sajadieh & Noh, 2024
EC_1	We use digital technologies such as the Internet of Things to automatically capture sustainability data in real time.	Cuevas-Lopez-de-Baro et al., 2025; Latino, 2025
EC_2	We use digital solutions to systematically monitor progress toward sustainability targets.	Breiter et al., 2024
EC_3	We use digital solutions to simulate sustainability scenarios and assess their impacts in advance.	Cuevas-Lopez-de-Baro et al., 2025
EC_4	Our digital technologies support the analysis of sustainability data, e.g., through data preparation, pattern recognition and the derivation of actionable insights.	Graf-Drasch et al., 2023
EC_5	Digital technologies help us reduce resource consumption.	Graf-Drasch et al., 2023
EC_6	Our IT infrastructure enables the systematic integration and provision of sustainability data across different systems.	Latino, 2025
EC_7	Our digital systems support the circular economy, e.g., through reuse, recycling and sharing.	Graf-Drasch et al., 2023
GC_1	We consider sustainability aspects when using digital technologies, e.g., by taking energy consumption into account when deploying AI applications such as ChatGPT.	Breiter et al., 2024
GC_2	We consider sustainability aspects when investing in digital technologies, e.g., the recyclability of hardware or the energy efficiency of new software.	Breiter et al., 2024
GC_3	We consider sustainability aspects in the development of digital products, processes and services, e.g., through environmentally friendly design, low resource intensity during operation and sustainable product lifecycle management.	Graf-Drasch et al., 2023
GC_4	Sustainability aspects influence the prioritization of our digitalization projects, e.g., by favoring sustainability related digital projects over digitalization projects without a sustainability focus.	Graf-Drasch et al., 2023
GC_5	Our digital infrastructure is designed to be sustainable and energy-efficient, e.g., through the use of energy-efficient servers or renewable energy in data centers.	Graf-Drasch et al., 2023
GC_6	In digital transformation initiatives, we consider sustainability aspects, e.g., by offering measures to promote employees' health.	Graf-Drasch et al., 2023

Appendix C: Results of Additional Survey Item

Which of the following digital technologies are currently used in your organization?

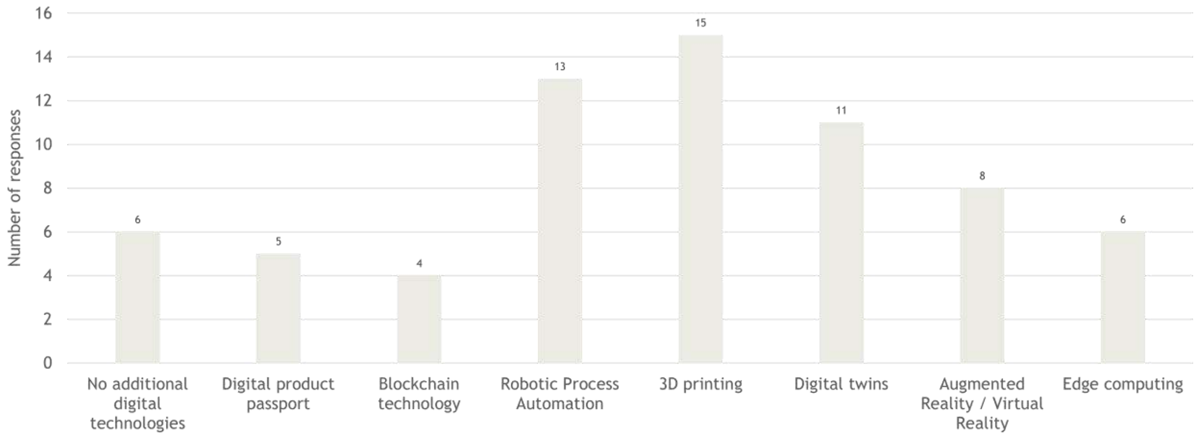

Figure A1 : Graphical Overview of the Descriptive Results of Digital Technologies Currently in Use

Source: Own *illustration*

Declaration Regarding the Use of Large Language Models in Writing Process

In the course of writing this thesis, the author utilized Large Language Models. These technologies were used solely to improve wording and readability. The generation of the underlying scientific content, data, and conclusion was carried out entirely by the author. All outputs produced with the support of these tools were carefully reviewed, verified and edited, as necessary. The author therefore takes full responsibility for the final content and integrity of this work.

Statutory Declaration

I hereby declare that I have completed this work independently and without using any resources other than those specified. All passages that have been taken verbatim or in substance from published works are marked as such.

This work has not been submitted to any other examination authority in the same or a similar form.

Vilnius, 05.02.2026 Johanna Radtke