Digital twin, digital thread, and digital mindset in enabling digital transformation: A socio-technical systems perspective

Abstract

Digital transformation (DT) is revolutionizing industrial businesses, with advanced technologies driving unprecedented change. However, change is uncertain, and industrial managers need clarity on the most effective digital transformation strategies. This study investigates the critical roles of digital twins, digital threads, and digital mindsets as socio-technical enablers of successful DT. We examine the interplay between these enablers and their impact on DT outcomes from the perspective of socio-technical systems theory. We comprehensively analyze these socio-technical enablers and their effects on DT using a variance-based structured equation model (PLS-SEM). Our findings reveal that digital twins and digital threads have direct, significant influences on DT success. Notably, we discover that a digital mindset plays a crucial mediating role in the relationship between digital threads and DT. In contrast, its impact on the digital twin–DT relationship is less pronounced. Based on these insights, we propose an empirically grounded framework to guide scholars, managers, and advisors in navigating the complexities of DT. This framework offers a nuanced understanding of how digital technologies and organizational mindsets interact to drive successful digital transformation. Our research contributes to the growing body of knowledge on the socio-technical systems view of DT. It provides practical implications for industrial managers seeking to optimize their DT strategies.

Keywords: Digital transformation, advanced technologies, digital strategy, industrial business, digitalization, digital twin, digital thread, digital mindset, Industry 4.0.

1. Introduction

Industrial businesses are compelled by advanced technologies to undertake digital transformation (DT), and as new technologies emerge, the urgency of change increases. The manufacturing sector, in particular, is experiencing profound shifts due to Industry 4.0 initiatives, which integrate cyber-physical systems, artificial intelligence, and IoT-enabled smart factories (Pozzi et al., 2023; Ghosh et al., 2022; Hodgkinson et al., 2021). The factories of the future are envisioned as highly interconnected, adaptive, and analytics-driven ecosystems, where AI-powered automation, real-time monitoring, and autonomous decision-making systems enhance productivity, resilience, and sustainability (Soori et al., 2023; Borangiu et al., 2019). However, despite the increasing adoption of DT and the broader push for digital transformation, industrial managers face significant challenges in justifying these capital-intensive initiatives' return on investment (ROI) (Ghosh et al., 2022). The high costs, implementation complexities, and integration difficulties create barriers to scaling digital transformation efforts across industrial operations. Moreover, there remains a critical gap in academic research regarding the strategic pathways that industrial businesses should adopt for successful digital transformation and the key enablers that drive such transitions (Ghosh et al., 2022; Warner & Wäger, 2019). Addressing these knowledge gaps is essential to developing actionable frameworks that guide industrial firms in leveraging digital technologies effectively while mitigating risks, optimizing investment decisions, and ensuring long-term sustainability in an increasingly digitized industrial landscape.

A successful DT does not come from digitizing each business unit or factory (Lakemond et al., 2021); DT would be straightforward in such circumstances. For a successful DT, industrial managers face two types of challenges: (i) selecting and implementing proper digital technologies (technological) and (ii) developing a data-driven decision-making culture (socio-cultural) to introduce new business models, enhance customer centricity, and improve business processes for competitive advantage (Imran et al., 2021; Vial, 2021; Ivančić et al., 2019). Given this context, we draw on Trist and Bamforth's (1951) socio-technical systems (STS) theory, which posits that technology, along with social factors, significantly impacts an organization-wide transformation (Davis et al., 2014). We posit that DT should be analyzed using the STS theoretical lens as it follows the core tenets of STS: DT involves technological and social/organizational changes (Thomas, 2024), requires optimizing both the technical and social systems (Govers & Amelsvoort, 2023) and takes a holistic view of the organization (Govers & Amelsvoort, 2023; Ghosh et al., 2022).

Analyzing DT, we focus on three key socio-technical enablers: digital twin, digital thread, and digital mindset. The digital twin replicates a physical system (machine, process, system, or service) (Grieves & Vickers, 2017). In contrast, a digital thread is the information-relay framework that records the history and traceability of an asset throughout its entire life cycle (Margaria & Schieweck, 2019). The digital mindset is the employees' attitude, behavior, and proactiveness to utilize analytics, algorithms, and AI technologies to create new business opportunities (Neeley & Leonardi, 2022). Socio-technical digital twins integrate diverse data sources using statistical and machine learning models and create virtual representations of assets and their interactions with other systems (Barn, 2022; Rebentisch et al., 2021). Digital thread is an emerging concept in industrial businesses (Cline, 2017; Pang et al., 2021), and from a socio-technical perspective, involves both technological aspects (digital representation of entire assets and data flows across different systems) and social/organizational elements (people and processes those interact with digital threads) (Govers & Amelsvoort, 2023; Pessoa et al., 2022). The digital mindset considers an organization as a complex system of interdependent components (Thomas, 2024; Wuersch et al., 2023) emphasizing organizational structure, processes, culture, and skillsets of the employees around digital strategies (Neeley & Leonardi, 2022; Ghosh et al., 2022).

While researchers are actively investigating various disparate enablers of DT within an organization (Sanchis et al., 2019; Moreira et al., 2018; Schallmo et al., 2018), limited research exists about socio-technical enablers (specifically digital twin, digital thread, and digital mindset) and how they collectively form pathways for DT. Because theory and empirical evidence around DT neglect how technology, digital representation of assets, data flow, and social-organizational context interact, industrial managers are unaware of these socio-technical enablers' cumulative role and function as digitalization mechanisms in their organizations. This is despite traditional industrial businesses often needing more experience with these enablers and facing a steep learning curve to replace long-standing, long-invested, long-integrated, and path-dependent product and service processes. With industrial managers involved in high-stakes, high-value DT projects, we ask our first research question: (1) *How do digital twins and digital threads influence DT in an industrial business?* Further drawing on STS theory, we extrapolate that an organization-wide digital mindset stands integrally as a socio-organizational mechanism channeling industrial digital twins and digital threads as technological enablers of DT. We expect a digital mindset to bridge the relationships between the digital twin's and digital thread's technical capabilities and the digital transformation's strategic initiatives. To effectively implement and leverage industrial digital twins, a digital mindset can foster openness, experimentation, and data-driven decision-making (Fathy et al., 2021), enabling managers to integrate digital twins into core business processes and reimagine DT strategies to drive competitive advantage. By enabling data-driven, proactive decision-making and ensuring interoperability across business processes, a digital mindset helps realize the digital thread's potential for real-time insights and impact and prevent fragmentation.

Thus, we ask our second research question: (2) *To what extent does an organization-wide digital mindset mediate the relationship between digital twins, digital threads, and DT?*

We answer these research questions with data collected through a quantitative study of leading industrial businesses involved in DT initiatives. Our study makes two significant contributions to digital transformation based on STS theory. First, we augment the nascent STS view of DT by incorporating three socio-technical enablers of DT, providing a new conceptual framework of DT. In doing so, our study resolves calls from several scholars (Gebauer et al., 2021; Centobelli et al., 2020) for new insights into specific socio-technical enablers that can accelerate or impede the transformation process. Second, while the DT phenomenon is crucial to technology and innovation management, researchers (Rummel et al., 2022) outline the need for research to embrace the underlying complexity of digital transformation. We directly respond to this need by shedding new light on the complexity and nuance involved in successful DT than is often assumed by the extant literature. We reveal the theory behind integrating the digital mindset as a socio-organizational mechanism channeling technical capabilities embedded in industrial digital twins and digital threads. However, we then show empirically how a digital mindset is an essential mediator in the relationships between digital thread and DT, explaining why a technical systems approach alone to DT may explain the failure of firms to digitally transform successfully, but that a digital mindset does not affect the relationship between digital twin and DT. DT requires more outstanding digital savviness (higher digital mindset) to build enterprise-wide digital threads. Our findings point to an overlooked chronological dimension in uncovering the successes and failures in DT experienced by industrial businesses. Collectively, our two contributions bring granularity to the research body on DT pressed for by researchers and practitioners (Ghosh et al., 2022).

2. Theoretical Background

2.1 Digital Transformation

According to International Data Corporation (IDC) market reports, digital transformation spending will reach $3.4 trillion worldwide in 2026, with a compound annual growth rate (CAGR) of 16.3% (Shirer, 2022). Digital transformation also drives technology innovation and productivity gain in industrial businesses (Fang & Liu, 2024). Though industrial managers are skeptical about digital transformation, a recent IBM report suggests that 60% of organizations have accelerated their digital transformation initiatives since the COVID-19 pandemic (Kost, 2020; IBM Reports, 2022). Advanced technologies such as Internet-of-things (79%), cloud computing (74%), and AI/ML (52%) will drive their industrial performance in the coming years. These technologies upset all industries (Mishra et al., 2023; Kost, 2020), and industrial managers seek DT guidance while simultaneously being under pressure to start digital transformation initiatives in their organizations. However, worryingly, DT projects are rarely well-executed under this pressure (Morgan, 2019). The rewards of success are plentiful, however, as researchers (Warner & Wäger, 2019) suggest that digital transformation improves firms' business performance by providing a better customer experience, streamlining business operations, and helping them innovate their business models by leveraging advanced technologies. Established industrial businesses are not digitally native. Appropriate pathways to implementing digital transformation remain unclear for these firms (Adama et al., 2024; Ghosh et al., 2022; Loonam et al., 2018), especially around the scope of DT initiatives (Correani et al., 2020) and adopting complex digital technologies and strategies can be counterproductive for non-digitally native firms.

Digital technologies push firms to transform their businesses toward service-based business models and away from product-centric models (Shen et al., 2023; Vial, 2021). Digital servitization, which implies the development of new services or augmenting existing services with products by leveraging digital technologies, accelerates the firm's digital transformation (Dalenogare et al., 2023; Khanra et al., 2021; Paschou et al., 2020). For instance, IoT and other advanced technologies are changing value creation, delivery, and capture models and, in turn, digitizing parts of the business to accelerate its digital transformation (Hui, 2014). However, among studies, whether this accelerated transformation is, for better or worse, rewarding or culminating in at least some short-to-medium term pain (beyond the noticeable organizational change) is at best speculated and, worse, undertheorized. For example, researchers (Kohtamäki et al., 2020) caution that digitalizing the manufacturing industry without servitization may hurt firms' revenues. Digital technologies and the digitalization of business activity and processes profoundly impact industrial value chains, business models, and the overall effectiveness of industrial operations (Appio et al., 2021; Porter & Heppelmann, 2014). It is worrying that much of our expectations about the value of digital mechanisms and strategies rely on normative presumptions that using digital technologies inherently means digital transformation. This view needs to be more robust and appropriate.

To augment new and service-based business models, a firm must transform its operations by implementing advanced technologies in its business processes (World Economic Forum, 2016). A digital and physical world convergence as a route to digital transformation blurs the boundaries between a digital initiative and the actual organizational change (Nadkarni & Prügl, 2021; Szalavetz, 2022). For example, computer solution providers like Apple and Google now provide healthcare products and services; Qualcomm, a semiconductor company, has developed a connected healthcare platform; and Tesla, an automobile manufacturer, has entered the energy business. However, DT is more than just about technology; more digitally mature industrial businesses are more likely to possess the requisite skills and organizational structure to take better advantage of digital technologies (Klos et al., 2021; Kane et al., 2015). We then theorize that while implementing digital technologies, including digital twins and digital threads, and developing a digital mindset across the organization to replace outmoded operational processes or technologies, the firm enacts digital initiatives that may facilitate DT. This is our first theoretical assumption. Moreover, a digital mindset and data-driven decision-making culture could impact DT. This is our second theoretical assumption.

2.2 Digital Transformation and Socio-Technical Systems Theory

Technology companies have long been interested in socio-technical design (Mumford, 2006), recognizing that the introduction of new technologies and digital transformation would require some reorganization of work, anxiety as to their staff welcoming them and using them effectively, and how to avoid systems failure (Mumford, 2006). DT involves integrating the latest digital technologies in an interconnected systems environment in which human-technology interactions could play a significant role in the success of such a large-scale initiative (Imran et al., 2021; Mitki et al., 2019). DT can be viewed as a technical and social system that can attain an organization's transformation objectives (Sony & Naik, 2020). The STS view of DT incorporates the principle of integration of technical and social elements, joint optimization, user autonomy and flexibility, and effective collaboration.

Our key socio-technical enablers (digital twin and digital thread) include the application of advanced technologies (technological components) and the employees (socio-cultural components) who manage such a system (Thomas, 2024). The digital mindset (socio-cultural) enabler helps to transform an organization into a data-driven decision-making organization. For example, a digital twin to simulate high-value machine failure can only be adequately implemented if process engineers are appropriately trained.

A successful DT involves optimizing physical systems (using advanced technologies) and social systems (people, skill sets, organization structure, etc.) (Govers & Amelsvoort, 2023). For example, analyzing a manufacturing digital thread using AI-based algorithms can only be successful if manufacturing engineers possess adequate data analysis knowledge (digital mindset). Indeed, an STS view of DT recommends that technological systems be flexible and adaptable to empower employees (socio-cultural) to make and control data-driven decisions; otherwise, adopting such systems will be difficult (Govers & Amelsvoort, 2023). For example, a company could develop a sophisticated digital twin for supply chain orchestration, but supply chain managers may be reluctant to adapt it for higher complexity and limited control.

However, the STS view of DT brings to light several challenges. First, *resistance to change*: a social system will resist a significant shift in its work environment. DT impacts the whole organization, and if the employees are not adequately trained and informed (a digital mindset is not appropriately built), there will be serious resistance to change. Employees will disengage and withdraw from such changes. Second, *skill mismatch*: the social subsystems may need the necessary skills to perform organizational tasks. Retraining and upskilling programs must be implemented for DT to be successful. Third, *complex subsystems*: as increasingly complex technological systems are implemented, they require new interaction with technological and social systems. The STS view, then, sheds light on why DT initiatives may fail to produce the desired outcome.

Though researchers have focused mainly on the technological aspects of DT, some have applied the central tenets of STS theory to DT in different domains. For example, Govers & Amelsvoort (2023) proposed STS-based design thinking for implementing DT projects, whereas Schmid (2019) analyzed the role of socio-technical inertia and its impact on DT, and Hartl & Hess

(2019) studied the socio-technical implications of IT projects for DT and emphasized the role of social systems for the success of such projects. Accordingly, STS theory is an appropriate lens for analyzing DT and socio-technical enablers such as digital twins, digital threads, and digital mindsets for successful transformation.

2.3 Digital Twin

A digital twin (Kritzinger et al., 2018; VanDerHorn & Mahadevan, 2021) replicates a machine, process, system, or service (i.e., the physical system) (Grieves & Vickers, 2017) and enables intelligent products and services for industrial businesses (Tao et al., 2018). It can manage a product or process's full product or service life cycle, collect real-time data, and simulate the asset environment using AI/ML algorithms to facilitate product or service development. Industrial managers can utilize digital twins to make data-driven decisions. It can be used for design and production engineering (Liu et al., 2021), process simulation and modeling (Glatt et al., 2021), maintenance, and asset monitoring (Lu et al., 2020), among other uses. For example, industrial businesses, such as the aircraft industry, utilize advanced technologies (Blockchain, AI/ML, IoT, etc.) to develop digital twins for product development (Mandolla et al., 2019). Similarly, Emirates Team New Zealand leverages Siemens Xaccelerator software to create a digital replica of their racing yacht to develop a faster, better-quality yacht for the America's Cup racing team (Siemens, 2022). Meanwhile, Anheuser-Busch InBev is working with Microsoft to create digital twins for their breweries to improve the process by monitoring product quality in real time (McKinsey & Company, 2024).

Digital twins can enhance the efficiency of socio-technical systems, thereby acting as a key enabler for DT and optimizing the integration of physical and social subsystems by bridging the gap between the physical and digital worlds. They facilitate better decision-making, effective collaboration, and optimization of business assets and processes. Some critical areas of STS enhancement by digital twins include (1) improved decision-making and collaboration and (2) aligning technology and social systems.

1) *Improved decision-making and collaboration*. Digital twins improve organizational decision-making and effective business collaboration. In sociotechnical systems, digital twins facilitate improved decision-making and collaboration using data-driven decisions, real-time performance monitoring, and cross-functional collaboration. For data-driven decisions, digital twins provide a platform for managers, operators, and employees to visualize the performance of the assets and make informed decisions (Attaran & Celik., 2023). Managers leverage digital twins to ideate new and improved product business models. Since industrial managers can simulate virtual versions of a product and test product attributes in a safe virtual environment using a digital twin, it can expedite the new product development (NPD) (Fukawa & Rindfleisch, 2023), thus providing opportunities to enhance the value creation process. For real-time performance monitoring, digital twins facilitate managers' and employees' gauging of asset performance in real-time to aid in making necessary decisions for efficient operations. For example, machine operators can proactively maintain critical assets and improve machine downtimes (Govers & Amelsvoort., 2023). Digital twins are used for the predictive maintenance of critical assets in an organization, and industrial businesses can develop a proactive maintenance management system by analyzing the real-time health data of high-value assets and simulating different boundary conditions, thus improving the overall effectiveness of the assets (Centomo et al., 2020). By utilizing digital twins, employees from different departments (such as design, process, and manufacturing engineers) can collaborate effectively and resolve problems proactively; thus, digital twins foster cross-functional collaboration. Effective collaboration is critical for socio-technical systems where different groups

should work together for higher efficiency (Lorente et al., 2022; Rebentisch et al., 2021). A digital twin platform offers a holistic view of product design and development, and industrial managers can leverage these more advanced digital twins to develop new business models along with their ecosystem partners (Li, 2020). Hence, from the perspective of decision-making and collaboration, digital twins can positively influence DT by transforming the business operations of an industrial company.

2) *Aligning technology and social systems*. STS faces continuous challenges in aligning technologies (AI/ML, IoT, etc.) with social systems (skills, organization structure, etc.). However, digital twins enhance such alignment by leveraging transparent systems and managing organizational changes. For systems, in using digital twins, operators can better visualize complex systems and their real-time performances, thus improving the efficiency of different business processes (Wittenberg et al., 2024; Chang et al., 2021). Concerning managing organizational changes: Digital twins facilitate users' creation of different product- and process-centric sandboxes, where users can simulate various scenarios and plan for changes in critical business workflows and their impacts on employees. In addition, digital twins allow users to simulate different business conditions and tweak business processes for better outcomes. For example, an operator can select different recipes for a machine in a digital twin and assess its performance in advance (Saini et al., 2022; Tao et al., 2022). Digital twin enhances an industrial business's operations and helps optimize industrial assets using digital simulations accelerating DT. For example, GE Power utilizes digital twins to simulate different operation scenarios before using the assets in production. It allows GE Power engineers to perform what-if scenario analysis upfront and tweak the assets to maximize throughput (Melesse et al., 2020). Managers can, then, take necessary actions before deploying such systems by identifying potential impacts on employees.

Digital twins foster innovations by promoting the organization's inspiration, ingenuity, and tenacity (Purdy et al., 2020). According to the vice president (VP) and chief technology officer (CTO) of GE Digital, digital twins influence cultural changes within an organization, and industrial managers utilize digital twins for product and process improvements (D. T. Consortium, 2022).

Based on this discussion, we propose the following:

Hypothesis 1: Digital twin positively influences DT in an industrial business.

2.4 Digital Thread

Industrial managers are developing a digital thread platform for the holistic analysis of business processes from concept to commercialization (Margaria & Schieweck, 2019). Digital threads help accelerate product development and deployment in the era of IoT and Industry 4.0 (Cline, 2017). The digital thread is an information-relay network that allows complete product traceability from design to manufacturing (Margaria & Schieweck, 2019), thus helping managers optimize their business and facilitating digital transformation. Most of our current industrial systems are localized, and it is not easy to integrate different business systems such that they can share real-time data for proactive decision-making. Some authors (Cline et al., 2017; Jagusch et al., 2021) suggest that digital twins and threads are the foundation blocks for digital transformation. For example, with advancements in cloud technology, industrial IoT, and AI/ML technologies, industrial managers can develop digital threads for their products by integrating operational technology data (such as sensor data, machine log, and machine health data) and information technology data (such as enterprise resource planning, supply chain management, service management, etc.), enhancing digital transformation (Borlase, 2017; Srinivasan, 2020).

Like digital twins, digital threads can enhance the efficiency of socio-technical systems and accelerate DT. In an STS, the technological subsystems (such as technology, processes, tools, etc.)

and social subsystems (people, workflows, teams, etc.) should interact and share information for better performance, and an enterprise-wide digital thread shares product and process information with employees at different stages of production enabling faster data-driven decision makings. Digital threads can improve the performance of STS and facilitate DT through (1) aggregated data from inception to commercialization, (2) improved collaboration and communication, and (3) enhanced human-machine interactions.

1) *Aggregate data flow from inception to commercialization*. Digital threads provide continuous data streams from design to development, manufacturing to sales, and after-sales service. They allow technical and socio-cultural subsystems to interact and exchange information by aggregating operational and information technology data and ensuring end-to-end traceability of products and processes (Helu et al., 2017; Margaria et al., 2022). To do so, digital threads aggregate operational data during production (manufacturing execution systems, product life cycle management, etc.) with back-end information technology data (such as supply chain management, enterprise resource planning, etc.), and thus provide enhanced visibility and traceability, which we expect will accelerate DT initiatives (Ghosh et al., 2022).

Digital threads also provide end-to-end visibility and traceability of a product from conception to commercialization. Complex technological systems can be aligned with social systems, such as hybrid workflows (manual and automatic), regulatory compliances, and organizational objectives as part of more complex digital threads. Such digital threads enhance a firm's overall operational visibility and control by aggregating data from design, manufacturing, sales, distribution, and field service (Nanry et al., 2015). For example, Siemens has delivered digital thread software to the United States Department of Defense to monitor and manage manufacturing operations in different defense programs (Sampson, 2020). Thus, we expect digital thread to positively influence DT by optimizing the operations of industrial businesses through its ability to aggregate large data from across the product lifecycle.

2) *Improved collaboration and communication*. Disjointed collaboration and communication with involved stakeholders affect the performance of a social-technical system. Digital threads enhance such collaboration and should facilitate DT through effective and efficient collaboration among ecosystem-based businesses. Digital threads provide an integrated platform where product, process, and manufacturing engineers can interact with sales and service engineers as they can communicate with a single source-of-truth data platform. Digital threads integrate the business ecosystem and impact the firm's culture so employees and partners can share information openly and work as extended teams (Hennessey, 2021). Moreover, it encourages model-based engineering (MBE), where workers shift from the conventional drawing-centric approach to a systematic model-based approach where all workers from engineering, manufacturing, sales, and support work on the same data, thus improving information sharing (Davis & Sharma, 2023; Neiding & Scott, 2021). Digital threads then raise the collective understanding within the organization about the role, use, and function of digitalization in ways that should help industrial businesses develop model-based enterprises and new business models (Davis & Sharma, 2023). For example, Rolls-Royce developed a usage-based business model for a jet engine by integrating flight health data with supply chain and maintenance management data (digital thread) to provide value-based services to its customers (Royce, 2017). Circular, a UK-based traceability-as-a-service platform provider, created a digital thread of conflict minerals such as Cobalt mining and its distribution to automotive manufacturers by leveraging Oracle's Blockchain Platform (Kshetri, 2021). Thus, digital threads enable a platform ecosystem, positively influencing DT as they facilitate the development of new business models for the leading actor(s) and their complements.

3) *Enhanced human-machine interactions*. Digital threads improve the interaction between machines and humans (operators), fostering flexible workflows and boosting the socio-technical system's performance through user empowerment and human-machine coordination. Concerning user empowerment, digital threads empower employees as they analyze real-time data and can understand the nuances of complex systems and their impact on process performance. Regarding human-machine coordination, digital threads aggregate information from technological systems and human interactions, creating a socio-technical system where machines and humans can coexist and help each other for data-driven decision-making. For example, GE leverages digital threads alongside digital twins of critical equipment so that operators can monitor the equipment's performance and take necessary actions for any equipment anomalies (Kumar et al., 2020).

Based on these arguments, we surmise that:

Hypothesis 2: Digital thread positively influences DT in an industrial business.

2.5 Digital Mindset

The mindset in cognitive psychology refers to people's thinking and belief systems, whereas "a digital mindset is a set of attitudes and behaviors that enable people and organizations to see how data, algorithms, and AI opens up new possibilities and to chart a path for success in a business landscape increasingly dominated by data-intensive and intelligent technologies" (Neeley & Leonardi, 2022: 51). Digital mindset refers to the mindsets of industrial employees (Tabrizi et al., 2019), which influences DT (Hildebrandt & Beimborn, 2022). Despite limited research on digital mindsets, researchers have suggested that a lack of prevalent digital mindsets can hinder DT projects, and a digitally savvy workforce is necessary for successful DT (Ghosh et al., 2022; Jones et al., 2021). The digital mindset is not only the aptitude of the employees to use digital technologies in their organizations, but it consists of a set of attributes and behaviors by which the industrial managers can foresee opportunities continuously such that they can improve their own, their team's, and organization's performance (Lewis, 2020). Frankenberger et al. (2020) observe that companies are struggling to maintain their legacy businesses and simultaneously trying to launch and grow their digital businesses, dubbing this 'The Digital Transformer's Dilemma'. However, successful companies should have the right talent and mindset. This right talent and mindset are called the 'digital mindset'. To accelerate DT, applications of digital twins and threads coupled with a prevalent digital mindset are necessary. As such, we posit that the digital mindset is an intermediary bridge between the digital twin, digital thread, and digital transformation.

A digital mindset enables the integration of digital technologies into day-to-day business processes and workflows so that the organization does not view technologies as a disruptive force but rather as an enabler of DT. When digital technologies are seamlessly integrated with human workflows, such transformation improves firm performance, and a digital mindset enables digital transformation through such integration. The mediation role of digital mindset in digital transformation is seen in numerous examples of real-world business practice. For example, a company with a strong digital mindset, such as a Chinese automobile manufacturer, BYD, leverages Siemens's digital solution and exploits digital twins and digital threads to foster product development and process improvement (Siemens, 2020). An automobile startup, Uniti, a Swedish electric vehicle startup, leverages its digital mindset and integrates digital twins into its digital manufacturing processes (digital threads) to introduce a new vehicle to the market in less than two years (Hartman, 2021). As companies are developing cognitive digital twins with AI with cognitive capabilities (twins can learn at run-time), the employees' digital mindset and digital expertise are critical for such twin developments and digitization projects (D.T. Consortium, 2022). Data-driven decision-making and integrating real-time data for decision-making are essential for digital twin development, and engineers with digital mindsets will be more interested in developing digital twin models for their business processes (McKinsey & Company, 2024). Digital twins are not static; engineers need to readjust the twin models continuously by learning from the ongoing business processes. Thus, engineers with digital mindsets will be more inclined to continuous learning and adaptations. As digital twins span multiple business groups, engineers should collaborate across organizations, and a digital mindset could foster those collaborations (Schalkwyk, 2024). A digital mindset is essential for digital transformation. Engineers with digital mindsets will be receptive to the changes and interested in implementing new technologies and processes that could foster digital transformation and create new business models by leveraging digital twins (Neeley & Leonardi (2022). Managers with digital mindsets can identify how digital technologies unlock new business values by leveraging technologies and accelerating digital transformation (Schalkwyk, 2024).

Companies are creating more data than ever. Utilizing the data for digital transformation requires a comprehensive enterprise-wide digital thread framework and a proper data culture born from a digital mindset (Kniker et al., 2021). Similarly, for digital twins and their ability to generate digital transformation in organizations, how well exploited digital twins rely upon the prevalence of a digital mindset and the data culture a digital mindset brings. For instance, the example of Emirates Team New Zealand demonstrates how their embedding of a digital mindset led to extreme improvements by rapidly improving their racing yacht through developments from digital twins, such that in 2024, the team became the first in modern America's Cup history to win three Cups in a row (America's Cup, 2024). Indeed, their success demonstrates how digital thread became embedded in development processes (cf. America's Cup, 2024) through the solid digital mindset held by the team. Like the digital twin, engineers with digital mindsets will be more interested in developing digital threads for data-driven decision-making. A digital mindset helps individuals take a holistic view of the products and processes, which are critical requirements for digital thread development (Lehner et al., 2024). Similarly, cross-functional collaborations are required for digital thread development, and engineers with digital mindsets are more prone to such cooperation (Schalkwyk, 2024).

Based on the above, we posit that the digital mindset is an intermediate facilitator of digital transformation that positively mediates the effects of digital twins and digital threads on DT. Thus, we propose:

Hypothesis 3: Digital Mindset positively mediates the relationship between Digital Twin and DT for an industrial business.

Hypothesis 4: Digital Mindset positively mediates the relationship between Digital Thread and DT for an industrial business.

The conceptual framework and hypothesized relationships are presented figuratively) in Figure 1.

<<Insert Figure 1 here>>

3. Research Methodology

3.1 Survey instrument

Online Survey:

We selected online surveys as one of the best methods for collecting the necessary information from the respondents (Wright, 2005). Before sending the primary survey to the respondents, we pre-tested by interviewing four managers from an industrial manufacturing company for clarity and addressed any wording and measurement issues (Churchill & Iacobucci, 2002). The first questionnaire was revised, and a pilot study was conducted with 15 respondents from the industrial manufacturing, high-technology, and healthcare industries. Based on their feedback, the questionnaire was revised again, and more information about each question was added for clarity and understanding. The final questionnaire is given in Appendix I.

Data collection:

We selected the firm as a unit of analysis for this study and approached executives and managers of industrial businesses. Executives decide on high-value, multi-year digital transformation projects, and the managers implement those initiatives. Data were collected via surveys, a widely preferred method in business research due to its efficiency in gathering large-scale quantitative data (Griffis et al., 2003). All industrial businesses with significant investment in DT were the target population for our study. Since there is no specific SIC classification of DT, in phase 1 (March 2019 to February 2020), we consulted industrial executives and managers from leading high technology and manufacturing companies (elite informants) and, based on their suggestions, we included all the members' companies (159) of the Industry IoT consortium (https://www.iiconsortium.org/cgibin/iicmembersearch). We also selected the top 100 companies from IoT One, 2019 (https://www.iotone.com/iotone500), and the 125 industrial IoT startup companies from CB Insights, 2019 (https://www.cbinsights.com/research/top-startups-iiot/). As DT initiatives are strategic initiatives requiring substantial monetary commitments from top executives, we determined that companies with more than $1B in revenue and publicly listed companies (such that information is available for those companies) would be the target for the study. We selected 70 companies in turn. Since DT initiatives are strategic and can (and typically do) span across the entire spectrum of an organization, 3 to 4 managers were contacted in each company. Thus, we collected the data from multiple recipients to ensure a fuller and more robust perspective of their DT initiatives. We sent 384 questionnaires and received complete responses from 110 executives and managers. Thus, the sample rate in Phase 1 was 28.6%. In phase 2

(November 2022 to May 2023), we contacted 156 executives and managers from LinkedIn.com groups and respondents who did not respond in phase 1. We received complete replies from 54 executives and managers. Thus, the response rate in phase 2 was 34.61%. The response rates for Phase 1 and Phase 2 surveys are appropriate (Nulty, 2008; Dillman, 2017) and together, we received 164 responses. Industries represented in the final sample were as follows: industrial manufacturing (29%), high technology and manufacturing (22%), software and services (13%), healthcare and life sciences (11%), semiconductors (11%), telecommunications (9%), and oil and gas (5%) (Figure 2).

<< Insert Figure 2 >>

3.2 Construct Measures

For this study, a 7-point Likert scale was applied to survey items (see Appendix 1) where a rating of 1 indicates 'strongly disagree,' and 7 indicates 'strongly agree.' The measurement of DT includes ten items and is adopted from the research of prominent digital transformation researchers (Nwankpa & Datta, 2017; Kontić & Vidicki, 2018). Digital Mindset has five items, and the measurement is adapted from academic literature (Neeley & Leonardi, 2022; Kaganer et al., 2014). Digital Twin has five items, and the measurement is derived from digital twin researchers (West, T.D., and Blackburn, M., 2017; Leiva, 2016). Finally, Digital Thread has five items, and the measurement is adapted from Leiva (2016). Since size (number of employees) and the firm's annual revenue could impact DT, these two measurements were used as control variables in the analysis. The measures and sources are given in Appendix 2.

3.3 Analysis Framework

We selected a variance-based structural equation model (Partial Least Square, PLS-SEM) and not a covariance-based structural equation model (CB-SEM) for our study. CB-SEM is primarily used for confirmation, establishing, and testing a theory; however, PLS-SEM is a prediction-oriented approach primarily used for explorative study (Hair et al., 2017). Since the roles of socio-technical enablers, such as digital twin, digital thread, and digital mindset, are still evolving, this study is explorative; hence, PLS-SEM is justified. Per PLS-SEM guidelines, the sample size should be 10 times the number of arrows pointing to the dependent variable (Hair et al., 2017). In our research, the sample size should be 50 as five arrows point to the dependent variable. However, in our study, we took a conservative approach. We followed the inverse square root method (Kock & Hadaya, 2018) with a minimum path coefficient (pmin) <= 0.2, a significance level < 5%, and a statistical power of 80%, which gave us a sample size of 153, however, we selected 164 as our sample size for final analysis.

4. Data Analysis and Results

4.1 Descriptive Statistics & Nonresponse Bias

We performed descriptive statistics for the sample data to check the mean, standard deviation, and normality of the sample data (Table 1). The mean varied from 4.793 to 6.067, whereas the standard deviation ranged from 1.06 to .02. The skewness fell between +2 to -2, and Kurtosis fell between -7 to +7, indicating a normal data distribution (Byrne, 2013).

<< Insert Table 1 here>>

Nonresponsive bias arises when several key informants have yet to respond to the survey instrument when they may have had unique views about our subject of interest. The most common approach to test for nonresponse bias is a paired t-test examining for significant differences between a random grouping of early and late respondents. Late respondents are akin to no responders in that they have been late in responding to the survey and need multiple follow-up communications to do so. We selected the first twenty-five and last twenty-five respondents and performed the paired t-tests. No significant differences are found between early and late respondents along the variables of interest in this study (Table 2). Accordingly, we conclude that nonresponse bias is unlikely to have corrupted our data.

<< Insert Table 2 here>>

4.2 Validity and Reliability

We used the PLS-SEM model to analyze our data and leveraged SmartPLS 4 software as it utilizes bootstrapping (10,000 subsamples), overcomes data normality issues, and is widely used for such models (Hair et al., 2019). We used Cronbach's Alpha and Composite Reliability to test the reliability and validity of the study (Table 3). The Cronbach's Alpha values for the constructs varied between 0.858 and 0.962, and the composite reliability values varied between 0.868 and 0.966, which are well above the commonly used threshold of 0.70 or above (Goldsmith & Hofacker, 1991). The average variance extracted (AVE) values ranged from 0.663 to 0.746, higher than 0.50, indicating the study's convergent validity (Hair et al., 2019). The loading of all measurement items is more than 0.7, and the variance inflation factors (VIFs) are less than 5, indicating no collinearity issues with the measurements.

<< Insert Table 3 here>>

For discriminant validity, we performed the Fornell and Larcker criteria (Fornell & Larcker, 1981) (Table 4). The bold value in each construct column is the square root of the respective AVEs, and the values under the bold value are the constructs' correlations. All bold values are more significant than their correlations, and hence, the discriminant validity of the constructs is established.

<<Insert Table 4 here>>

We collected data from multiple recipients from the same company (3 to 4 respondents) to avoid common method bias (CMB) (Flynn et al., 2018). We also notified the respondents that the questions carry no weightage, the responses would be used for academic research, and their names would remain confidential. We also segregated the questions to avoid answer biases for dependent and independent variables (Podsakoff et al., 2003). During data analysis, collinearity statistics of the inner model and the VIF values of all relationships are less than 3.3 (Table 3), indicating no CMB (Kock, 2015).

4.3 Hypotheses Testing

We tested the structural model in SmartPLS4 using a 10,000 resampling bootstrapping technique, as shown in Figure 1. In this model, we have two independent variables, Digital Twin (DTwin) and Digital Thread (Dthread), and one dependent variable (Dtrans). We also have a mediator variable, Digital Mindset (Dmindset), and two control variables, FIRMSIZE and FIRMREV.

As shown in Table 5, Digital Twin Positively influences DT (βeta = 0.351, t-value = 3.862, and p-value = 0.000); **hence H1 is supported**. Digital Thread influences DT (βeta = 0.145, t-value = 1.579, and p-value = 0.057**); hence, H2 is supported**, and Digital Maturity positively influences DT (βeta = 0.518, t-value = 5.731, and p-value = 0.000).

Digital Mindset does not mediate the relationship between Digital Twin and DT (βeta = -0.011, t-value = 0.199, and p-value = 0.421); **hence H3 is not supported**. Digital Mindset positively mediates the relationship between Digital Thread and DT (βeta = 0.222, t-value = 3.818, and p-value = 0.000); **hence H4 is supported**. The control variable FIRMSIZE does not influence DT (βeta = -0.034, t-value = 0.467, and p-value = 0.320), and the control variable FIRREV does not influence DT (βeta = -0.007, t-value = 0.092, and p-value = 0.463).

<<Insert Table 5 here>>

4.4 Robustness Testing

Nonlinear effects

In the PLS-SEM path model, we assume the constructs' relationships are linear; however, this may not be the case, and we should test for linearity (Sarstedt, 2008; Sarstedt et al.,2020). To test the relationships, we adopted the quadratic effect (Hair et al., 2019), considered a polynomial model, and added a quadratic term like the interaction term (Rigdon et al., 2010). Our study demonstrates that the relationships are linear, as the p-values are insignificant (Table 6).

<<Insert Table 6 here>>

Assessment of endogeneity

We used the Gaussian copula approach to assess the constructs' endogeneity (Park & Gupta, 2012); the results are shown in Table 7. All Gaussian copulas (DTwin, DThread, and DMindset) p-values are > 0.05, indicating nonsignificance. We also checked the combinations of the constructs, and all of them are nonsignificant. Thus, the robustness of the structural model is established (Hult et al., 2018).

<<Insert Table 7 here>>

Assessment of unobserved heterogeneity

Unobserved heterogeneity is a challenge in PLS-SEM when subgroups of data show different model estimates (Sarsted, 2008). Finite mixture PLS (FIMIX-PLS) identifies such estimates (Hahn et al., 2002; Sarsted et al., 2020). We started with one segment solution using the default setting in FIMIX-PLS (stop criterion 1.0E-10, maximum iteration 5000, and no repetitions 10). To determine the number of segments, we found a sample size of 74 using G*Power (an effect size of 0.15 and a power level of 95%). Thus, the study required 2 to 3 segments for analysis (Number of samples/sample size, i.e., 164/74 = 2.2). We ran FIMIX-PLS for 2 and 3 segments with the same configuration (Table 8). As per the analysis, if AIC_3 and CAIC indicate the same segment number, the results should point to that many segments (Sarstedt et al., 2011). However, in our analysis, AIC_3 indicated three-segment solutions, and CAIC indicated two-segment solutions. AIC_4 and BIC indicated three-segment solutions. MDL_5 pointed to the one-segment solution. Thus, all different criteria pointed to varying numbers of segments. Therefore, unobserved heterogeneity was not critical for our analysis.

<<Insert Table 8 here>>

5. Discussion and Contributions

5.1 Discussion

Drawing on socio-technical systems theory to develop a conceptual framework of socio-technical enablers of DT, we examined the role of digital twins and digital threads in DT and analyzed the role of digital mindset as an intermediate factor potentially influencing their relationships with DT. Based on our results, we find evidence that the digital mindset is one of the most critical enablers for DT. Researchers (Neeley & Leonardy, 2022; Sharma, 2015; Kane et al., 2015) argue that a digital mindset is a complex contributor to DT. For example, Moderna has utilized digital knowledge effectively in developing Covid19 vaccine (Neeley & Leonardi, 2022). However, focusing attention on digital knowledge in isolation overlooks the significance of the organization as a complex system of interdependent components—an essential aspect of organizations as socio-technical systems (Thomas, 2024; Wuersch et al., 2023).

Our result shows a direct positive influence of digital twins on DT. This result is consistent with the views of digital twin scholars (Kritzinger et al., 2018; VanDerHorn & Mahadevan, 2021). For example, Digital Twins, IoT, AI, and cloud computing have accelerated product design and development processes, including idea generation, market research, product design, prototypes, product development, and testing (Lo et al., 2021). In the physical world, digital technologies such as IoT, big data, analytics, and predictive machine learning models have analyzed product usage data for anomaly detection, failure analysis, root cause analysis, etc. Digital Twin is changing the business innovation landscape through real-time continuous evaluation of the products and reconfiguring them for quality, helping digital prototype development faster at a cheaper rate and extending the limits of our innovation (Purdy et al., 2020). It improves customer experience (Singh et al., 2022) and empowers managers for data-driven decision-making (Wang et al., 2021). Digital twin applications in the industry are rapidly growing in supply chain management, transportation management, asset optimization, product traceability, and design customization (Attaran & Celik, 2023). GE has developed digital twins for different businesses. They have created a digital network twin for power grid management, are experimenting with a digital twin in healthcare for personalized medicine, are developing new medical devices, and are leveraging a digital twin for GE's Lafayette aircraft engine facility for better performance. Similarly, Siemens' digital industry software has developed comprehensive and executable digital twins for new product development (Greenfield, 2022).

Our study draws into stark light the deficiency in theory and practice caused by neglecting how technology, digital representation of assets, data flow, and social-organizational context interact for DT. Extrapolating from STS theory, we envisaged that an organization-wide digital mindset stands integrally as a socio-organizational mechanism channeling industrial digital twins and digital threads as technological enablers of DT. While this is indeed the case for digital threads, the mediation effect of the digital mindset on the digital twin and digital transformation was not supported. Contrary to popular belief among businesses and as extrapolated from STS theory, the βeta value of our hypothesis is negative, but not statistically significant, indicating that a higher digital mindset does not intervene in the relationship between the digital twin and DT. Though digitally savvy industrial firms such as GE, Siemens, BYD, etc., have adopted digital twins, most incumbent firms have standard business practices. They may suffer from path dependency that prevents effective exploration or use of digital twins in their organizations. These industrial businesses may have high digital mindsets, but adopting digital twins is slow as they face acute challenges including initial investment, clear business objectives, and fragmented business systems (Wagner et al., 2019). The implementation of digital twins is domain-specific, and as digital maturity and mindsets across different domains are not consistent, developing digital twins for those domains is difficult (Sharma et al., 2022). That is, our results suggest a disconnect between the digital mindset as a social organizational aspect and digital twins as an ethical organizational aspect highlighting the limits of socio-technical theory in explaining successful DT and the context around assuming the technical benefits of digital twins without accounting for the organization's social context. We suggest this difference provides an explanation for the differences in the effectiveness of DT efforts undertaken by established industrial businesses. Incumbent firms generally implement and customize on-premise business systems for their specific use cases. Though the digital mindset may be higher, most of these systems from these organizations are not adequately integrated; thus, data sharing is challenging (Davis, 2022) and developing an enterprise-wide digital twin becomes complex and potentially incompatible—as appears to bear out in our results. Some companies may have a high digital mindset; they cannot implement digital twins for data security challenges. Successful digital twin deployments are not feasible unless a standardized data-sharing infrastructure is implemented (Alcaraz & Lopez, 2022). Implementing digital twins in incumbent firms is not straightforward as enterprise data resides in siloed legacy systems, and making those systems cloud-ready may take considerable time. Thus, changing the mindsets of the legacy developers and developing an enterprise-wide digital twin for DT may happen in the future (Attaran & Celik, 2023).

We examined the role of digital thread in DT by exploring the direct influence and mediated effect of the digital mindset. The result shows a direct positive impact of digital threads on DT. Some researchers (Needing & Scott, 2021) suggest that the digital thread helps industrial businesses develop model-based enterprises (MBE) to create new products and businesses. The digital threads break the silos of information across different value chain systems in an industry and make the data available for analysis and decision-making, thus enhancing industrial DT (Hatoum et al., 2023). A digital thread is a single source of truth that can establish consistency, collaboration, and synchronization of data across different business silos in upstream and downstream business systems, align businesses for better performance, and accelerates DT (Taber et al., 2020). For example, Volvo CE created a digital thread for product architecture so that different design and development teams across Volvo can manage hardware and software complexities and introduce new products (Miller, 2021). The digital threads can connect business processes, systems products, and enterprise asset management systems across the entire value chain. They can enhance DT, including higher operating efficiency, cost reduction, and risk mitigation (Walters, 2023).

The mediation effect of the digital mindset on the digital thread and DT transformation is supported, indicating that the digital mindset positively influences the relationship between the digital thread and DT. As a firm's digital mindset increases, it can develop enterprise-wide digital threads, and it has a positive impact on DT. As digital thread development across the organization is complicated and requires strong system integration capabilities, large, digitally savvy companies can invest in integrating different business processes to create digital threads, which in turn will accelerate DT. As mentioned in the previous section, digitally savvy companies (high digital mindset), such as GE, Siemens, etc., have developed digital threads to accelerate DT. In a company like Volvo, with a higher digital mindset, the digital threads accelerate enterprise-wide DT by transforming an organization into an agile organization by collaborating across products, processes, and people and scaling digital integration within the enterprise (White, 2020). Like digital twins, implementing digital threads across an enterprise is challenging due to data silos, difficulty integrating legacy systems, and lack of proper integration with ecosystem partners (Sherard, 2024). The digital threads also create serious security risks, as bad actors can only gain access to the integrated digital threads with a proper cloud security infrastructure (Kevan, 2022). Thus, more digitally savvy organizations with a higher digital mindset can develop appropriate security infrastructure to implement enterprise-wide digital threads, accelerating DT.

5.2 Contributions to Theory

This research makes several contributions to the socio-technical system's (STS) view of DT and the roles of socio-technical enablers. Specifically, our study responds to calls from several scholars (Gebauer et al., 2021; Centobelli et al., 2020) for new insights into specific socio-technical enablers that can accelerate or impede the transformation process. Importantly, while we reveal the socio-technical systems theory behind integrating digital mindset as a socio-organizational mechanism channeling technical capabilities embedded in industrial digital twins and digital threads, our empirical results demonstrate the flaws in this theory. In particular, a digital mindset is an essential mediator in the relationships between digital thread and DT, explaining why a technical systems approach alone to DT may explain the failure of firms to digitally transform successfully. But a digital mindset has no effect on the relationship between digital twins and DT.

Collectively, these insights suggest that refining the socio-technical view of the organization requires accounting for how context and technology interact in social and technical terms to appreciate the value of effort and investments made toward DT and whether the intended DT occurs or not.

First, the study reveals that digital twins are critical socio-technical enablers of DT (Kritzinger et al., 2018; VanDerHorn & Mahadevan, 2021). Specifically, we advance an STS theory perspective on digital transformation, revealing its reliance on the interplay between technological artifacts and human/social processes. Digital twins provide a real-time, bi-directional digital interface where digital and physical systems continuously interact, shaping industrial businesses' technology and social systems. For example, in smart manufacturing, which accelerates digital transformation, design engineers can determine the nuances of different equipment before installing them on the factory floors, ensuring that the social factors (worker's safety, ergonomics, efficiency) are included in the decision-making. Reflexibility (self-monitoring and feedback) is another core aspect of STS theory, and the digital twins extend that by providing real-time monitoring of high-value assets for operational efficiency and providing predictive analysis by modeling potential technological and social changes. STS theory has traditionally emphasized the coexistence of physical and digital organizational structures, and digital twins extend that by creating a digital-first environment and enabling continuous digital-physical coverage.

Digital thread research has been evolving for the last decade, and researchers suggest that digital thread positively influences digital transformation (Akay et al., 2023; Pang et al., 2021). STS theory emphasizes that technology does not function in isolation but is co-shaped by human, social, and organizational dynamics, and the digital thread extends that by connecting machines, data, and humans at different phases of the product life cycle and provides real-time collaborations with stakeholders, improving operational efficiency and reducing miscommunication. Like the digital twin, the digital thread supports the notion of STS's reflexibility through real-time data flow. It provides a framework for real-time analysis to detect anomalies and suggests corrections, thus enhancing digital transformation. STS theory often involves reconfiguring organizational structures, and digital threat accelerates that by bridging the gaps between organizational silos and cross-functional collaboration. Manufacturing companies across the globe have started utilizing digital threads to connect the data from design to manufacturing and other processes for more intelligent products and more innovative ecosystems (Margaria & Schieweck, 2019). Our study supports that. This finding emphasizes the need for companies to enhance their digital mindset through strategic initiatives, training programs, and talent acquisition to leverage digital threads fully.

A digital mindset is critical in facilitating and shaping digital transformation within STS theory, which examines the interaction between technology, human actors, and organizational structures (Imran et al., 2021). Contrary to popular belief (Davey, 2024), the research reveals that a digital mindset does not moderate the relationship between digital twins and digital transformation. This insight challenges assumptions about the necessity of a mature digital culture for successful digital twin implementation. The study suggests that even less digitally mature firms can benefit from digital twins, though they may need help with siloed systems, data integration, and real-time data availability.

A digital mindset bridges the digital thread's technical capabilities and the digital transformation's strategic initiatives. Without a digital mindset, organizations may fail to integrate the digital thread into their transformation efforts, limiting its impact. The digital thread generates vast interconnected data from various business processes. Without digital mindsets, industrial managers may not pay attention to the data or be unable to analyze the data for successful DT. The digitally savvy managers emphasize interoperability such that enterprise-wide digital threads can be generated and not fragmented across business silos. Though digital threads can provide real-time insights into business processes, a digitally savvy workforce embraces those insights for proactive decision-making (Bianchini et al., 2024). Without a digital mindset, the digital thread will remain a passive data stream and not an active enabler of DT.

5.3 Practical Implications

Our research has identified and analyzed the influence of digital twins, digital threads, and digital mindsets on industrial businesses' DT. Companies should develop strategic training and development initiatives to train their existing workforce on analytics, AI, and other data management tools and technologies. They should augment their workforces with data scientists and AI subject matter experts to enhance digital knowledge across the organization.

Digital twins can profoundly impact DT, and industrial managers should prioritize digital twin development. Industrial managers should adopt digital twins and model twins for business optimization. Design engineers should develop digital twins of their products and experiment with their virtual products in a risk-free environment, leading to faster time to market and better product quality. Digital twins can be developed for testing and validation, and engineers can test boundary conditions with such twins. Product utilization data from the fields can be fed to the digital twins for design changes and reliable product development. Industrial businesses should develop a digital twin roadmap starting with new product development, product quality enhancement, and process improvements. Digital twins for customer service/support are another area of importance. As observed in our study, higher digital maturity (higher digital mindset) can negatively impact digital twin development and DT. The incumbent firms have higher industry competencies and may be reluctant to deploy new technologies, such as digital twins, in their factories; however, the managers should experiment with new technologies that can significantly impact their DT journeys. As industrial businesses deploy more AI-based solutions, managers should accelerate the development of digital twins.

Our study suggests that the digital thread influences DT. The digital thread is a popular concept, and developing an enterprise-wide digital thread is complex and costly; managers should develop digital threads for their business processes, which can help them create new products and services, improve product quality, optimize asset utilization, and improve overall organization efficiency. Our study indicates that a digital mindset significantly impacts the usage of digital threads and DT. As managers progress in their digital transformation journeys and develop increasingly digitally connected business ecosystems, they should take advantage of the digital threads for product/service innovation, service optimization, enhanced customer experience, and business efficiency.

6. Conclusion

This study provides a comprehensive analysis of the socio-technical enablers of digital transformation (DT), focusing on the roles of digital twins and digital threads and the mediating effect of the digital mindset. Our results demonstrate the direct benefit of digital twins and digital threads for successful DT; moreover, as the digital mindset increases in an organization, the relationship between digital thread and DT is strengthened. The relationship between these enablers and DT is complex and nuanced, challenging simplistic assumptions about digital initiatives. The study has several limitations, as these will condition its implications and contributions. Since the study is cross-sectional, the cause-and-effect relationship cannot be justified by the result with certainty. In future research, a longitudinal study is preferred

(Rindfleisch et al., 2008). In this research, we empirically studied the enablers of DT without focusing on any industry vertical. However, the strategies can vary based on the industry characteristics, which the study has yet to account for but would be a worthy direction for future researchers to focus on.

Our research substantially contributes to STS views on DT by providing theoretical reasoning and empirical evidence that challenges the normative assumption equating any digital initiative with digital transformation. Specifically, it demonstrates the potential pitfalls of speculating about the benefits of advanced technologies without considering the broader context of DT. By highlighting the complex interplay between digital technologies, organizational mindset, and successful DT, we pave the way for more sophisticated approaches to digital transformation in research and practice. As the digital landscape continues to evolve, further research in this area will be crucial for organizations seeking to navigate the challenges and opportunities of the digital age effectively.

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Figure 1: Conceptual Model

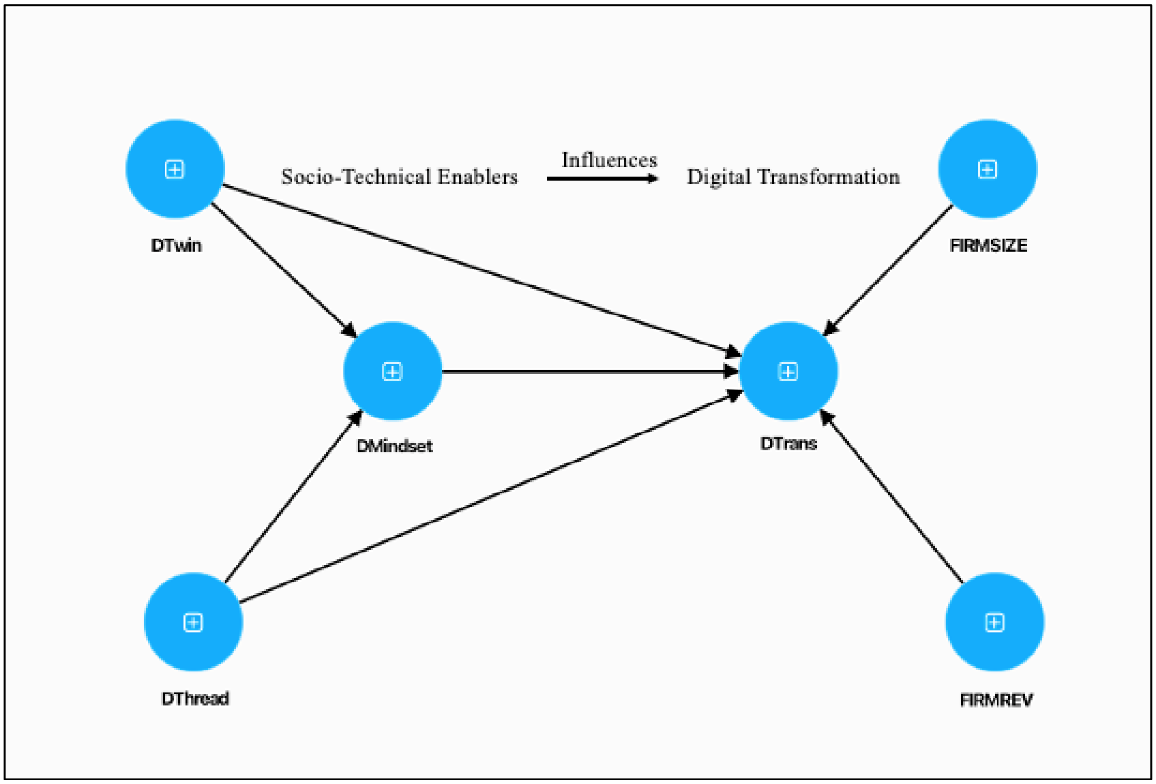

Figure 2: Distribution of survey respondents

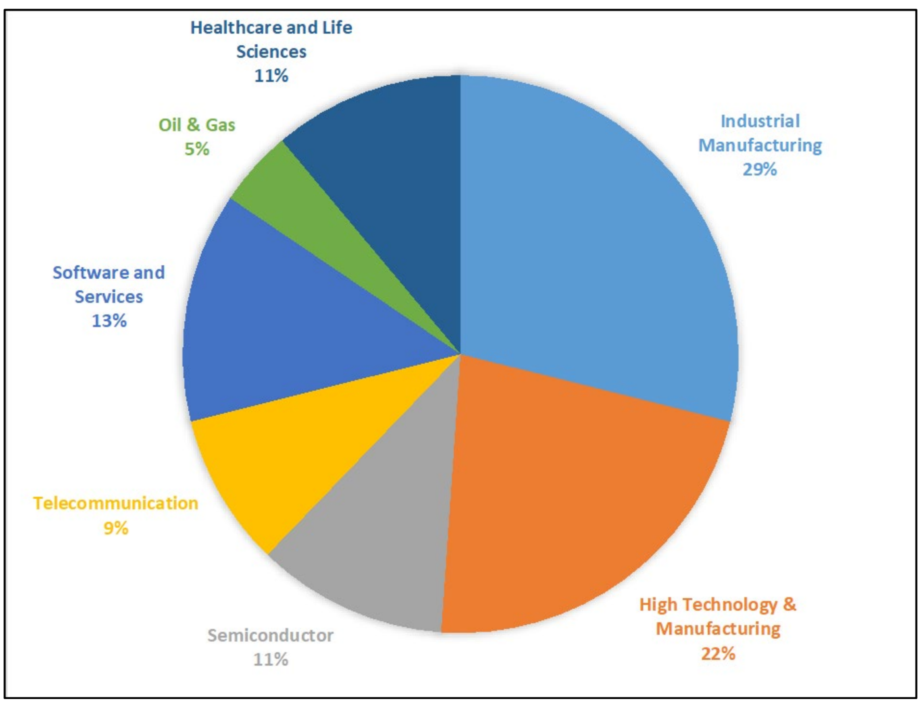

Table 1: Descriptive Statistics

Measures	Minimum	Maximum	Mean	Std. Deviation	Skewness	Kurtosis
Dtwin1	2	7	5.951	1.098	-1.466	2.72
Dtwin2	1	7	5.64	1.383	-1.327	1.519
Dtwin3	1	7	5.634	1.348	-1.464	1.887
Dtwin4	1	7	5.689	1.267	-1.467	2.224
Dtwin5	1	7	5.470	1.323	-1.059	0.888
DThread1	2	7	6.067	1.06	-1.437	2.277
DThread2	2	7	6.000	1.126	-1.241	1.322
DThread3	1	7	5.744	1.233	-1.096	1.254
DThread4	2	7	5.933	1.138	-1.221	1.481
DThread5	2	7	5.902	1.072	-1.093	0.992
DMaturity1	1	7	5.409	1.383	-0.988	0.857
DMaturity2	1	7	5.402	1.223	-0.992	1.29
DMaturity3	1	7	5.793	1.207	-1.462	2.825
DMaturity4	1	7	5.579	1.325	-1.188	1.581
DMaturity5	2	7	5.713	1.069	-0.855	0.91
DT1	1	7	5.543	1.372	-1.291	1.887
DT2	1	7	5.610	1.412	-1.157	1.161
DT3	1	7	5.524	1.399	-1.116	0.986
DT4	1	7	5.433	1.466	-1.157	0.997
DT5	1	7	5.366	1.51	-0.952	0.362
DT6	1	7	5.457	1.429	-1.034	0.872
DT7	1	7	5.329	1.535	-0.915	0.448
DT8	1	7	5.311	1.488	-1.073	0.922
DT9	1	7	5.409	1.456	-0.99	0.579
DT10	1	7	5.415	1.456	-1.013	0.589
FIRMSIZE	1	7	4.982	2.029	-0.598	-1.131
FIRMREV	1	7	4.793	1.914	-0.29	-1.365

Table 2: Paired T-tests

Variable		N	Mean	Std. Dev	t-statistics	Sig (2-tailed)
Digital Twin	Early	25	5.84	1.125	-.252	.803
	Late	25	5.90	.651		
Digital Thread	Early	25	5.90	.891	.507	.617
	Late	25	5.78	.856		
Digital Mindset	Early	25	5.31	1.140	-.872	3.92
	Late	25	5.55	.654		
DT	Early	25	5.26	1.338	-1.606	.121
	Late	25	5.67	.605		

Table 3: Construct Reliability and Validity

Construct and items	Loading	VIF
Digital Transformation (α = 0.962, CR = 0.966, AVE = 0.746)		

We have developed new business models by leveraging digital technologies	0.838	3.800
We have incorporated digital services into our business	0.846	4.384
We have enhanced our customer experiences by implementing digital tools and solutions	0.877	3.915
We have integrated most of our business processes for information sharing	0.885	3.934
We make data-driven business decisions across our organization	0.868	4.006
We have implemented digital training and development for our employees	0.852	3.846
We have developed a digital culture in our organization	0.865	4.121
We have integrated our systems with ecosystem partners for real-time information sharing	0.897	4.535
Digital technologies have improved our new product development projects	0.894	4.604
We are leveraging digital technologies for better customer service	0.810	2.682
Digital Twin (α = 0.875, CR = 0.927, AVE = 0.666)		
Using Digital Twins, we bridge the physical and digital worlds	0.583	1.377
Using Digital Twins, we simulate the actual production environment	0.809	2.081
Using Digital Twins, we detect product shortcomings in advance	0.873	2.575
Using Digital Twins, we design new products with complex requirements	0.903	2.916
Using Digital Twins, we test product quality in a virtual environment	0.870	2.326
Digital Thread (α = 0.881, CR = 0.906, AVE = 0.674)		
Digital Thread helps our engineers to gain new insights about our products	0.775	2.134
By developing Digital Threads, we improve the reliability of our products	0.848	2.523
Digital Threads improve our transportation and logistics operations	0.827	1.783
By leveraging Digital Threads, we integrate our supply chain networks with our customers and partners	0.828	2.410
Utilizing Digital Thread, we maintain manufacturing history (from design, manufacturing, sales, service, etc.) for traceability	0.824	2.373
Digital Mindset (**α = 0.858, CR = 0.862, AVE = 0.637)**		
The managers in our firm have a clear vision for digital transformation	0.802	2.114
The managers in our firm empower employees to implement digital strategies	0.780	1.984
The managers in our firm encourage employees to make decisions for DT	0.812	1.851
The managers in our firm encourage employees to make decisions based on data	0.818	2.219
The managers in our firm encourage employees to experiment with DT	0.778	1.972

α : Cronbach's Alpha, CR: Composite Reliability, AVE = Average Variance Extracted

Table 4: Discriminant Validity (Fornell & Larcker criterion)

Constructs	DMaturity	DThread	ODT	DTwin	FIRMAGE	FIRMREV
DMindset	**0.798**					
DThread	0.415	**0.821**				
DTrans	0.578	0.370	**0.864**			
DTwin	0.256	0.647	0.437	**0.816**		
FIRSIZE	0.013	0.027	0.027	0.168	**1**	
FIRMREV	-0.002	0.190	0.057	0.279	0.616	**1**

Table 5: Hypothesis Testing

Path	βeta	SE	t-statistics	p-value
DMindset -> DTrans	0.518	0.090	5.731	0.000***
DTwin -> DTrans **(H1)**	0.351	0.091	3.862	0.000***
DThread -> DTrans **(H2)**	0.145	0.092	1.579	0.057*
FIRMSIZE -> DTrans	-0.034	0.074	0.467	0.320
FIRMREV -> DTrans	-0.007	0.077	0.092	0.463
DTwin -> DMindset -> DTrans **(H3)**	-0.011	0.055	0.199	0.421
DThread -> DMindset -> DTrans **(H4)**	0.222	0.058	3.818	0.000***

Critical t-values: ***p ≤ 0.01, t= 2.32; **p ≤ 0.05, t= 1.645; *p ≤ 0.1, t= 1.282

H1 – Supported, H2 – Supported, H3 – Not Supported, H4 - Supported

Table 6: Assessment of nonlinear effects

Nonlinear relationship	Coefficient	p value
QE (DMindset) -> DTrans	0.008	0.858
QE (DTwin) -> DMindset	0.115	0.088
QE (DTwin) -> DTrans	0.01	0.848
QE (DThread) -> DMindset	0.041	0.481

Note: QE denotes quadratic effect

Table 7: Assessment of endogeneity test using the Gaussian copula approach

Test	Construct	Coefficient	p value
Gaussian copula model 1 (endogeneous variable: DTwin)	DTwin->DMindset	0.305	0.077
	DTwin->DTrans	0.157	0.091
Gaussian copula model 2 (endogeneous variable: DThread)	DThread->DMindset	0.228	0.141
	DThread->DTrans	0.117	0.144
Gaussian copula model 3 (endogeneous variable: DMindset)	DMindset->DTrans	0.044	0.81
Gaussian copula model 4 (endogeneous variable: DTwin, DThread)	DTwin->DMindset	0.252	0.209
	DTwin->DTrans	0.13	0.23
	DThread->DMindset	0.102	0.559
	DThread->DTrans	0.052	0.562
Gaussian copula model 5 (endogeneous variable: DTwin, DMindset)	DTwin->DMindset	0.305	0.077
	DTwin->DTrans	0.144	0.206
	DMindset->DTrans	0.044	0.81
Gaussian copula model 6 (endogeneous variable: DThread, DMindset)	DThread->DMindset	0.228	0.141
	DThread->DTrans	0.108	0.251
	DMindset->DTrans	0.044	0.81
Gaussian copula model 7 (endogeneous variable: DTwin,DThread, DMindset)	DTwin->DMindset	0.252	0.209
	Dtwin->DTrans	0.119	0.323
	DThread->DMindset	0.102	0.559
	DThread->DTrans	0.048	0.601
	Dmindset->DTrans	0.044	0.81

Table 8: Fit indices for one-to-three-segment solutions

	Number of segments		
Criteria	1	2	3
AIC (Akaike's information criterion)	823.671	774.414	741.601
AIC_3 (modified AIC with Factor 3)	832.671	793.414	**770.601**
AIC_4 (modified AIC with Factor 4)	841.671	812.414	**799.601**
BIC (Bayesian information criterion)	851.57	833.312	**831.497**
CAIC (consistent AIC)	860.57	**852.312**	860.497
HQ (Hannan-Quinn criterion)	834.997	798.324	**778.096**
MDL_5 (minimum description length with factor 5)	**1035.165**	1220.902	1423.082
LnL (LogLikelihood)	**-402.836**	-368.207	-341.801
EN (normed entropy statistic)	0	0.476	0.619
NFI (non-fuzzy index)	0	**0.55**	0.611
NEC (normalized entropy criterion)	0	85.994	**62.458**