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Assessment Tool for Measuring the Sustainability Effects of Digital Technologies in Production Systems

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Abstract

Digital transformation is often declared as a major driver of sustainable manufacturing, yet the influence of digital technologies on sustainability at the production level is frequently assumed but not analysed in a systematic manner. This research endeavours to fill this gap by developing and validating a causality-based sustainability assessment framework for manufacturing production systems, including a measurement tool. By establishing four distinct digital technology functional clusters, Monitoring & Visibility, Analytics & Prediction, Automation & Cyber-Physical Systems, and Human-Centric Digital Technologies, this research clearly associates each functional cluster with their corresponding environmental, economic, and social sustainability key performance indicators (KPIs) through defined enabling mechanisms. The scope of the cluster-KPI measurement relationship is confined to the extent to which causal logic can be reasonably established, thus providing analytical clarity and precluding the attribution of speculative impacts. The operationalised framework is then used to develop a measurement tool that employs before-and-after measurement logic, relative percentage changes, and threshold-based effect classifications. By not combining heterogeneous indicators into an aggregated composite score, the measurement tool produces complete transparency by providing cluster-specific and KPI-specific effect profiles, permitting structured interpretation within manufacturing production systems. The research methodology follows a design-oriented process consisting of systematic literature review, developing the sustainability assessment framework, establishing the operationalised collection of measurement variables, and empirical validation of the research findings through validation by expert interviews. The results of the validation process are reflective of the framework's conceptual soundness, practical applicability, and feasibility while demonstrating the need for consistent classification and contextual verification when utilising the framework. This study contributes to the digital sustainability assessment literature theoretically by proposing a structured, causality-based approach to sustainability assessment and practically by providing a transparent decision support tool for practitioners to evaluate the sustainability impact of digital technologies in manufacturing production systems.

Key-words: Digital Technology, Sustainable Manufacturing, Sustainability Assessment, Industry 4.0, Production Systems, Causality-Based Evaluation

Abstract in italiano

La trasformazione digitale è spesso dichiarata come uno dei principali motori della produzione sostenibile, tuttavia l'influenza delle tecnologie digitali sulla sostenibilità a livello produttivo è spesso data per scontata, ma non analizzata in modo sistematico. Questa ricerca si propone di colmare questa lacuna sviluppando e convalidando un quadro di valutazione della sostenibilità basato sulla causalità per i sistemi di produzione manifatturiera, che include uno strumento di misurazione. Definendo quattro distinti cluster funzionali di tecnologie digitali, Monitoraggio e Visibilità, Analisi e Previsione, Automazione e Sistemi Cyber-Fisici e Tecnologie Digitali incentrate sull'uomo, questa ricerca associa chiaramente ciascun cluster funzionale ai corrispondenti indicatori chiave di prestazione (KPI) di sostenibilità ambientale, economica e sociale attraverso meccanismi abilitanti definiti. L'ambito della relazione di misurazione cluster-KPI è limitato alla misura in cui è possibile stabilire ragionevolmente una logica causale, fornendo così chiarezza analitica ed escludendo l'attribuzione di impatti speculativi. Il quadro operazionalizzato viene quindi utilizzato per sviluppare uno strumento di misurazione che utilizza la logica di misurazione prima e dopo, le variazioni percentuali relative e le classificazioni degli effetti basate su soglie. Evitando di combinare indicatori eterogenei in un punteggio composito aggregato, lo strumento di misurazione garantisce una trasparenza completa, fornendo profili di effetto specifici per cluster e KPI, consentendo un'interpretazione strutturata all'interno dei sistemi di produzione manifatturiera. La metodologia di ricerca segue un processo orientato alla progettazione che consiste in una revisione sistematica della letteratura, nello sviluppo del framework di valutazione della sostenibilità, nella definizione della raccolta operativa delle variabili di misurazione e nella convalida empirica dei risultati della ricerca attraverso interviste con esperti. I risultati del processo di convalida riflettono la solidità concettuale, l'applicabilità pratica e la fattibilità del framework, dimostrando al contempo la necessità di una classificazione coerente e di una verifica contestuale durante l'utilizzo del framework. Questo studio contribuisce alla letteratura sulla valutazione della sostenibilità digitale, sia dal punto di vista teorico, proponendo un approccio strutturato e basato sulla causalità alla valutazione della sostenibilità, sia dal punto di vista pratico, fornendo uno strumento di supporto decisionale trasparente per i professionisti che desiderano valutare l'impatto delle tecnologie digitali sulla sostenibilità nei sistemi di produzione manifatturiera.

Parole chiave: Tecnologia Digitale, Manifattura Sostenibile, Valutazione della Sostenibilità, Industria 4.0, Sistemi Produttivi, Valutazione Basata sulla Causalità

Contents

Introduction

Digital transformation is becoming a defining strategy for companies within the manufacturing sector globally. The accelerated adoption of advanced sensors, analytics platforms, automation systems, and human-machine interfaces are transforming how production environments operate and are enabling digital technologies to be integrated into shop floor processes faster than ever before. Furthermore, many manufacturers face increasing pressures to improve their environmental, economic, and social performance; rising energy costs, scarcity of resources, increasing legislation, and societal expectations have moved sustainability from being an issue only to being at the very core of daily operations. In these circumstances, digitalisation is routinely cited as a major enabler of sustainability in the manufacturing sector. For example, monitoring systems are expected to improve resource efficiency, predictive analytics are expected to reduce waste and downtime, automation is expected to stabilise processes and improve safety, and digital work instruction systems are expected to build a workforce's skill base. These expectations have contributed to a widespread arrangement of digital technologies that are assumed by many to be inherently suited for maintaining sustainability objectives. On the contrary, while such claims are prevalent, there is often an inadequate structuring, measurement inconsistency, and implicit rather than explicit demonstration of the sustainability outcomes from the implementation of digital technologies at the production level. Manufacturers are investing heavily into digital projects, but very limited systematised assessments have occurred that demonstrate if, or to what extent, digital technologies provide measurable sustainability outcomes. Furthermore, when digital projects are evaluated, they are most often evaluated against indicators of productivity or cost; while sustainability impacts are described qualitatively or embedded in broader performance assessments without a clear attribution logic. From an academic research perspective, the gap is severe. Although synergy between digital transformation and sustainability has been highlighted extensively in literature, few studies have provided any structured mechanisms for measuring sustainability effects at the level of manufacturing production systems. In most cases, existing methodologies remain conceptual, comprise aggregated heterogeneous indicators into composite indices, or fail to appropriately distinguish between technological capability and achieved sustainability performance. Consequently, there are very few guidelines for organisations who would like to evaluate digital sustainability effects in a causally defensible and production-related manner.

This thesis fills the gap in research by developing a structured framework and assessment tool for assessing the sustainability impact of digital technologies in manufacturing production systems. The primary aim of this research is to establish a cause-and-effect approach that creates explicit links between digital technology functions and sustainability performance indicators of the production level by defining mechanisms. The research provides a tool for assessing the effects of digitalisation rather than simply determining if digitalisation continually enhances sustainability performance. The study formulates the framework for digital technologies into four functional clusters: Monitoring and Visibility; Analytics and Predictive Analytics; Automation and Cyber-Physical Systems; and Human-Centric Digital Technologies. These functional groups demonstrate the different functions of digital technologies in manufacturing systems, ranging from data generation and intelligence development to physical actions and support for humans. Next, the framework will clearly demonstrate the connections between these functional clusters of technology and the environmental, economic, and social dimensions of sustainability such as sustainability indicators that can be affected directly at the production level. Finally, the connections between the clusters and the sustainability KPIs will be specifically defined using their causal mechanisms, limiting the impact assessment to operationally justifiable relationships. The framework will be operationalised into an assessment tool using a before and after measurement-driven approach to quantify the sustainability effects measured as the relative difference in the selected sustainability KPIs using set thresholds and contextual verification procedures. Notably, the assessment tool will not create a single composite measure of sustainability. Instead, the results from the assessment tool will maintain transparency by displaying the effect profiles with respect to each cluster and KPI. This way, the framework will effectively identify where and how sustainability benefits do occur and where they do not occur, enabling reflective governance rather than superficial benchmarking. The development of the framework and assessment tool will follow a methodical research process. The literature review will follow a methodical analysis of the functions of the digital technologies and the dimensions of sustainability performance in the context of manufacturing. Using the understanding of the structure of the digital technologies and the sustainability performance dimensions, the framework and assessment tool will be created and developed in an iterative approach. Throughout the development of the framework and assessment tool, they will continue to be evaluated using expert interviews with practitioners who hold advanced experience in manufacturing operations, digital legacy transformations and sustainability governance. The goal of the evaluation will be to validate that the proposed framework and assessment tool are relevant, complete, clear, feasible and practically useful. The thesis is designed to answer several overarching research questions, including: How can the functional sustainability roles of digital technologies in manufacturing production systems be systematically structured? What causal relations exist between digital technologies and the measures of sustainability performance, and what are the mechanisms by which technology affects sustainability performance at the production level? How will these relationships be operationalised in a transparent and repeatable assessment tool? Finally, to what extent is the proposed framework validated through expert assessment to be practically applicable and conceptually robust? The scope of this thesis will be methodologically defined to maintain clarity in the analysis and evaluation.

Limited to sustainable production-level impacts of manufacturing systems only is the focus of this research. The impact of upstream supply chain on manufacture, corporate ESG reporting frameworks and product life cycles is beyond the scope of this research. While the framework will analyse realised rather than projected sustainability outcomes, it's not designed to be a benchmark instrument or digital capability assessment model. Therefore, by limiting the scope of this research to measurable and causally verifiable relationships of production systems, the research gives priority to interpretability and operational relevance. There are both theoretical and practical contributions of this research. Theoretically, this study assists the development of a causation-based approach to assessing digital sustainability in manufacturing. First, this research provides a functional clustering of digital technologies that are directly linked to production level sustainability indicators. Second, this research operationalises these causational functional clusters into a structured evaluation mechanism. Third, this framework is a non-aggregative framework and provides a basis for providing transparent attribution pursuant to each of the functional clusters, thereby improving conceptual clarity of digital sustainability research. Practically, this assessment tool provides manufacturing organisations with an organised methodology to evaluate the extent to which digital initiatives produce quantifiable sustainable impacts. The assessment tool supports evidence-based reflective practice, cross-functional dialogue and disciplined attribution of enhanced performance. This assessment framework provides the manufacturing industry with a means to quantify the sustainable value of digital transformation, thereby providing for increased transparency and accountability in digital governance. The balance of the thesis is structured in the following manner. Chapter 1 presents the theoretical foundations of the digital transformation of the sustainable manufacturing research. Chapter 2 provides the systematic literature review that informs the conceptual foundation of this framework. Chapter 3 details the research methodologies used in this investigation. Chapter 4 introduces the framework developed in this study to include the digital technology clusters and sustainability KPI structure. Chapter 5 provides details on the operational assessment tool and measurement logic. Chapter 6 presents the empirical validations of the assessment tool and resulting discussion and refinements. Lastly, Chapter 7 focuses on the primary findings, theoretical contributions, managerial implications, limitations, and recommendations for future research. By integrating structured conceptual development with empirical validations, this research contributes to the strengthening of the analytical foundations for evaluating the sustainability impacts of digital technologies in manufacturing production systems. Furthermore, this research establishes that the sustainable impacts of digital technologies can be evaluated in a structured manner when the functional roles, causal mechanisms and quantifiable indicators of assessment are explicitly defined and appropriately employed.

1 Theoretical Background: Digitalisation and Sustainability in Manufacturing

1.1. Sustainability in Production Systems

Because of the heavy reliance on energy, materials, workforce, and capital resources associated with manufacturing and production systems, they play a key role in sustainability. Production processes have large environmental impacts through energy consumption, greenhouse gas emissions, and material waste, while also affecting economic performance and social conditions from both producers to suppliers through their supply chains [1]. As a result, sustainability considerations have become a necessary component of designing, managing, and operating production systems.

When researching the manufacturing sector, sustainability is often viewed from a TBL perspective which integrates the environmental, economic, and social aspects of performance [2]. The TBL framework illustrates that successful sustainable manufacturing must include all three aspects rather than solely focusing on one area. To achieve long-term success in manufacturing, sustainability must be considered at an operational level when evaluating how process design, technology use, and daily decision making on the shop floor affect sustainability outcomes [3].

1.1.1. Environmental Sustainability in Production Systems

Production systems can achieve environmental sustainability by minimizing their harmful impacts on our planet. Therefore, energy consumption, seamless manufacturing, greenhouse gases, and waste are all problematic effects of production practices [3]. Manufacturing Equipment consumes tremendous amounts of energy during operation and produces multiple by-products from different types of raw materials. It is therefore essential to understand how much energy and other resources (including greenhouse gases) are being used during the production process to help improve energy efficiency through the design of the manufacturing systems for production purposes to better determine the quantity of raw materials used and their efficiencies in manufacturing practices.

The notion of achieving production sustainability is no longer limited to simply complying with regulations; it also means reducing resource consumption and/or reducing environmental burden by improving production stability (through improved management), improving production efficiency (through using more efficient equipment), or optimizing the production process (through better planning) in order to reduce the volume of production that occurs during production while maintaining the same level of production quality [1].

1.1.2. Economic Sustainability in Production Systems

Long-term competitiveness, efficiency, and financial viability characterize the ability of a manufacturing operation to produce goods in a sustainable manner. The primary goal of economic sustainability is to provide the same level of productivity, quality, lead time, flexibility and equipment utilization over time as is provided through traditional means of production. The performance of a company is measured using these metrics [3].

Production systems with high variability, frequent downtime or quality loss will incur higher operational expenses and will be less competitive than those production systems with stable and consistent production operations. Therefore, manufacturers must rely upon the use of effective allocation of resources, the continual improvement of the production process and the use of sound operational decision making to achieve long-term financial viability [4].

1.1.3. Social Sustainability in Production Systems

Manufacturing systems that promote social sustainability focus on creating a healthy work environment that is socially, ergonomically, and physically sustainable. Due to physical, cognitive, and ergonomic risks associated with exposure to repetitive tasks, physically demanding tasks, and highly automated workplaces [5], productivity and production environment will benefit from promoting a culture of health and safety through proactive workplace design, balanced workloads, job enrichment/training opportunities, and effective human/machine interaction. Improving social sustainability will not only enhance the well-being of the worker but also improve operational efficiencies by reducing workplace injury/absenteeism/workforce instability [6].

1.1.4. Interdependencies Between Sustainability Dimensions

Environmental, economic and social sustainability is usually perceived as three different dimensions of sustainability; however, production systems are generally very much interrelated and dependent on each other, e.g. increasing production efficiency often results in reduced environmental impacts and reduced production costs as well as improved working conditions. Conversely if some aspect of one sustainability dimension is ignored this will likely have adverse effects on the other sustainability dimensions and the overall effectiveness of the production system [2].

The existence of interdependencies between sustainability dimensions indicates that adopting an integrated sustainability perspective is necessary when analysing sustainability in production systems. A knowledge of the interplay between sustainability dimensions as well as the associated trade-offs will provide the conceptual basis for the sustainability assessment methodologies discussed in later chapters.

1.2. Digital Technologies in Manufacturing and Production Systems

The use of digital technologies has fundamentally transformed how manufacturing and production systems are monitored, designed and controlled. Digitalisation, the integration of digital technologies into the physical assets of production to enable data-driven decision-making, improved process visibility and enhanced coordination between manufacturing systems, can be defined as integrating various interdependent technologies into a single concept of interaction between physical processes, information systems and human operators [7].

Digital technologies enable visibility into operations and enhanced control of processes and facilitate coordination among various manufacturing functions. These digital technologies continuously collect and analyse data which has changed how production-related information is generated and used on the shop floor and have changed how the manufacturing system performs and behaves overall.

1.2.1. Digitalisation of Production Systems

Digitalising refers to using digital technologies systematically to represent, monitor and manage an organisation's manufacturing processes. Traditional manufacturing systems generally have limited feedback and visibility (i.e., production process data may be collected at infrequent time intervals or by manual input), while digitalised manufacturing systems constantly collect and acquire data from multiple machines, processes, and products and provide a near real-time view of the current status and performance of manufacturing processes [8]. The digital integration of physical manufacturing processes with information systems enables production planning, execution and control to be better coordinated with one another through increased frequency. Therefore, digitalising production systems allows them to respond more effectively to interruptions, changes in demand and unpredictability in production.

1.2.2. Core Digital Technology Categories in Manufacturing

Digital technologies used in manufacturing can be grouped into classes based on their functions supporting the production system. The first group, consisting of technologies used for collecting, transmitting and storing data (i.e., sensors and industrial communication systems), provides the capability to collect and transmit data related to the production process and machine and serve as a baseline to provide the basic information to monitor the system [7].

The second group consists of technologies used to process and analyze data and convert data into usable information. Data-processing technologies assist in the operations and management analysis by providing data for production process improvement, including generating performance metrics, identifying anomalies and optimizing manufacturing processes using data-driven analysis and insight [9].

The third group is cyber-physical technologies [10] that integrate the digital and physical production systems; examples include cyber-physical systems and digital twins, which can be used to virtually model and simulate production systems and perform predictive analysis to help make more informed production system decisions.

1.2.3. Automation and Human–Machine Interaction

A major factor in enabling the evolution of production systems will be the application of automation technologies. Each will contribute to the execution of repeatable and efficient processes. Digital automation systems differ from traditional fixed automation by integrating sensing, control and software components, thereby enabling adaptive and flexible control of the execution of manufacturing processes. Digital automation systems will provide the ability to adapt dynamically to changes in operating conditions and production requirements [8].

Digitalisation is having an equally significant impact on human-machine interaction on the shopfloor. Operators are increasingly using digital-based interfaces, dashboards and decision-support systems, which are changing how work is completed and how decisions are made. The effectiveness of human-machine interactions is essential for the effective use of digital technologies by operators and for the production of safe and efficient products [11].

1.2.4. Integration of Digital Technologies in Production Systems

The use of digital technologies contributes to the integration of production systems across functional and organisational boundaries, in addition to supporting the development of individual applications. Vertical integration links the performance of shop floor-related activities with planning and enterprise-level systems, and horizontal integration facilitates coordination between production lines and operational units. Digital technologies enable the integration of production systems by providing standardised data exchange and shared data visibility for all systems used by the production facilities [12].

As digital technologies continue to impact the way in which production systems are executed, there is an increasing need for the production system to be seen as a fully connected and adaptive system rather than a series of independent processes. The understanding of this connectivity and adaptability among digitalised production systems provides a basis for evaluating the broader impact of digital technologies on the performance of the manufacturing and production systems, including the impact on sustainability, which is the focus of this thesis.

1.3. Digital Technologies in Manufacturing and Production Systems

The potential role of digital technologies as enablers of sustainability-related improvements in manufacturing and production systems is being increasingly recognised. Although the contribution of digital technologies towards achieving sustainability will primarily be indirect in the sense that digital technologies do not lead to sustainability outcomes in and of themselves, they do affect the way in which production processes are monitored, controlled and improved. By enabling the availability of information and the decision-making process associated with production operations, digital technologies impact operational activities that ultimately impact the environmental, economic and social performance of activities within the production environments. The performance and sustainability of the production output from the production environment is highly dependent upon the availability, accuracy and timeliness of information related to the performance characteristics of the production process, consumption of resources and the behaviour of the production system. Digital technologies will provide the necessary basis for the acquisition of data on a continuous basis, for monitoring production in near real time and for the provision of advanced data analysis. With the ability to acquire, monitor and analyse information regarding the production processes in the production environment as a result of applying digital technologies, more reliable and timely decisions can be made regarding the sustainability of the performance of production systems across multiple dimensions.

1.3.1. Enabling Mechanisms in Digitalised Production Systems

The sustainability impacts of digital technologies in the manufacturing sector can be understood using a set of enabling mechanisms linking how technology is used with operational results. A primary enabling mechanism is that of increased transparency provided by digital tools; through enhanced detailed and timely visibility into machine conditions, process parameters, and production flows, digital technologies enable operators to identify deviations from standard operations and production and act to correct them [8]. Another enabling mechanism for sustainability is process optimisation; by utilising real-time performance data analyses, combined with modelling and simulation technologies, organisations can evaluate alternative operating conditions and configurations of processes enabling systematic production process improvements that have resulted in less resource consumption and waste generation, while increasing process stability [9]. Digital technologies also provide operators and managers with analytical tools and visual aids (i.e. interfaces) to assist them in evaluating alternative actions and in selecting the best course of action (i.e. decision support) through changing the way in which operational behaviour occurs rather than through a direct relationship.

1.3.2. Environmental Sustainability Enablement

By providing organisations with the tools to facilitate the efficient use of energy and materials and by reducing the environmental impact associated with their manufacturing activities, digital technologies facilitate/manufacturing environmental sustainability through their ability to monitor how a process is being performed and to detect inefficiencies and abnormal situations. Digital modelling/simulation technologies allow for an organisation to evaluate alternative process configurations and operational strategies in the virtual world before they are implemented on the physical production line. By implementing alternative operations through modelling/simulation technologies before the actual implementation, organisations experience a reduced need to conduct experiment-based operational methods (i.e. trial and error), which results in the incorporation of environmentally efficient production planning and execution processes [9]. Digital technologies provide organisations with tools to manage and improve the environmental impact of their operations through data-driven and preventative green management processes, thus facilitating/diversifying/creating ways to sustain an environmentally sustainable state.

1.3.3. Economic Sustainability Enablement

Economically, digital technologies enable organisations to create and sustain economic sustainability through the greater operational efficiency, reliability, and consistency of their production systems. Through the increased visibility provided by digital tools into how processes are being completed, organisations have an improved ability to identify and mitigate downtime, bottlenecks, and quality defects; supporting sustained production performance. Organisations use digital tools to facilitate/assist/hasten the operational decision-making process, which is essential in an environment of change and uncertainty, such as in the manufacturing sector. By decreasing uncertainty and enhancing the ability to execute production processes consistently, organisations are creating and supporting long-term economic sustainability through improved productivity and optimum resource management.

1.3.4. Social Sustainability Enablement

The influence of digital technology on production systems and their social sustainability is reflected in changing working conditions, task execution, and human-machine interaction. Digital interface systems, monitoring technology and decision support systems all change how operators interface with machines and processes with regard to physical workload and situational awareness. Digital technologies facilitate training and skill development through simulation environments, digital work instructions and performance feedback. When designed and implemented appropriately, the aforementioned capabilities can create a safer, more ergonomically and more engaging work environment. However, the social sustainability implications of digital technology will be largely dependent on how it is integrated into the work system and organizational practices [11]. Digitalisation may also reshape occupational hazards and safety-related issues, therefore warranting careful attention when designing and implementing systems [13].

1.3.5. Integrated Sustainability Perspective

Though digital technologies can singularly lead to environmental, economic, or social sustainability, the greatest potential of digital technologies is derived from their collective ability to enable integrated improvements across all three dimensions of sustainability. For example, optimised processes, as enabled by digital technologies, may lead to reduced resource consumption, increased operating efficiency and reduced physical strain on workers. On the other hand, poorly designed digital interventions may create trade-offs of increased cognitive workload and/or skill mismatches. By recognising digital technologies as enablers of sustainability and not direct influences; there arises a need to understand the various mechanisms through which they affect production systems. This perspective provides the conceptual basis for the identification and assessment of sustainability impacts of digital technologies; which will be re-conceptualised in the systematic literature review and assessment framework presented in the following chapters.

1.4. Sustainability Assessment and Measurement Approaches

Considering increasing regulatory pressure, stakeholder expectations, and the acknowledgment of the importance of long-term competitiveness, assessing the sustainability performance of manufacturing organizations has become a fundamental requirement. Without structured measures of sustainability, it is not possible to effectively monitor, compare, or incorporate sustainability initiatives into managerial decision-making. Measurement serves to convert the strategy of sustainability into actual sustainable practices and to support the continuous improvement process [14].

Manufacturing systems are an area where sustainability assessment is especially important because of the direct impact of production activities on environmental performance, economic efficiency, and social working conditions. Measurement enables manufacturing organizations to assess trade-offs, assess the effectiveness of improvement initiatives, and justify investments made for new technologies and processes. Thus, sustainability assessment has progressed into a necessary aspect of managing industrial performance rather than an activity that is predominantly utilized for reporting purposes only [15].

As a result of the above circumstances, there is an increase in attention paid to the assessment of the sustainability impacts of digital technologies within manufacturing. Current research exhibits various assessment models and evaluation methods through which the relationship of digital technologies and sustainability can be assessed based on sustainability impact rather than results associated with sustainability. These models and evaluation methods differ greatly in terms of their research purpose, technological scope, sustainability dimension, and methodology.

Examples of these differences are: some studies are conceptual or framework-based and attempt to structure the relationship between Industry 4.0 technologies and sustainability dimensions without providing operational measuring instruments [16]; other studies have employed empirical & quantitative models as tools for assessing digitalization with respect to sustainability performance using survey methods along with structural equation modelling techniques [17]; a third group of studies examine decision-support and prioritization tools, such as multicriteria decision analysis (MCDA), which are primarily meant for assisting in selecting technology rather than post-implementation evaluation of impact [18]; and a fourth group of studies utilize a Life Cycle Assessment (LCA), which is aimed at incorporating digital technologies into structured environmental impact assessment, with these studies primarily focused upon environmental sustainability [19].

To facilitate a systematic comparative analysis of the studies, and consequently identify their limitations, Table 1.1 presents an overview of selected assessment models that directly discuss the sustainability impact of digital technologies in manufacturing. Assessment models are compared according to research purpose, technological focus, sustainability coverage based on the triple bottom line, and research methodology employed.

Table 1.1: Comparative Overview of Assessment Models on Sustainability Impact of Digital Technologies in Manufacturing.

Authors / Year	Research Purpose	Technology Focus	Sustainability Focus (TBL)	Research Approach	Identified Gap / Limitation
Kamble et al. (2018)	Propose a conceptual framework linking Industry 4.0 technologies to	IoT, AI, Big Data, Robotics, Cloud	Environmental, Economic, Social	Conceptual model based on literature review.	Provides high-level conceptual relationships but does not operationalize how firms can systematically assess and quantify sustainability effects at production level.

	sustainability outcomes.				
Bai et al. (2020	Assess sustainability contribution of key Industry 4.0 technologies.	IoT, AI, Robotics, CPS, Cloud, AM	Environmental, Economic, Social	Survey data analysed via SEM.	Emphasizes comparative evaluation and prioritization of technologies, with limited guidance on how organizations can measure realized sustainability performance following implementation.
Tjahjono et al. (2020)	Examine the relationship between Industry 4.0 adoption and sustainability-related performance outcomes.	IoT, Automation, Analytics	Environmental, Economic	Survey data analysed via SEM.	Focuses on statistical relationships at aggregate level; does not provide detailed insights into operational mechanisms or multi-dimensional assessment within production systems.
Zimmermann et al. (2019)	Analyse how Industry 4.0 technologies support sustainable production system transformation.	Industry 4.0 technologies	Environmental, Economic, Social	Conceptual and qualitative analysis based on industrial cases and literature synthesis.	Addresses transformation processes conceptually yet lacks a structured evaluation logic to assess sustainability impacts across different technology domains in a comparable manner.
Agnusdei & Del Prete (2022)	Evaluate sustainability implications of additive manufacturing technologies.	Additive Manufacturing	Environmental, Economic, Social	Systematic literature review with bibliometric and content analysis.	Concentrates on a single technology domain; does not extend assessment logic to broader digital technology portfolios in manufacturing environments.
Leirmo et al. (2024)	Investigate the impact of digitalization and Industry 4.0 adoption on	Industry 4.0 technologies	Environmental, Economic, Social	Quantitative empirical analysis based on firm-level survey data.	Treats digitalization as an aggregated construct, limiting the ability to distinguish sustainability contributions of specific

	sustainability performance.				technologies or functional clusters.
Buhaya & Metwally (2024)	Examine how digital technologies influence sustainability performance considering organizational practices.	IoT, Big Data, Blockchain, Cloud	Environmental, Economic, Social	Survey-based empirical model analyzed using PLS-SEM.	Investigates mediation effects at firm level but does not establish a production-system-oriented structure for linking technology integration levels with sustainability outcomes.
Torbacki (2025)	Prioritize digital technologies according to their sustainability potential in manufacturing.	IoT, AI, Robotics, Cloud, Additive Manufacturing	Environmental, Economic, Social	Multi-Criteria Decision Analysis using expert judgment.	Focuses on ranking and prioritization based on expert evaluation; does not address post-implementation performance measurement within operational production contexts.
Popowicz et al. (2025)	Integrate digital technologies into sustainability assessment using Life Cycle Assessment logic.	IoT, Blockchain, Big Data, AI	Environmental	Systematic literature review and conceptual integration framework aligned with ISO LCA standards.	Primarily addresses environmental evaluation through LCA; limited consideration of integrated TBL assessment and practical applicability for routine managerial evaluation in production systems.

1.5. Discussion and Emerging Gap

The comparative analysis shown in Table 1.1 illustrates recurring limitations in current assessment methods. A primary limitation of current studies is the emphasis on conceptual or prioritization models, which can be useful in structuring relationships or ranking technologies but do not provide a practical means of measuring sustainability effects that a manufacturing organisation can repeatedly apply for assessing the effects of sustainability following the implementation of technology [18]. A second limitation is that the empirical examination of firm-level relationships generally lacks an explicit linkage between sustainability outcomes and the technological or operational mechanisms used in production systems [17]. Thirdly, Life Cycle Assessment approaches generally focus on understanding how to assess the environmental impact of a technology, requiring substantial amounts of data and modelling effort and thus limiting their utility as lightweight managerial assessment tools [19].

Overall, these limitations indicate that while there is widespread acknowledgement of the need to develop a framework for measuring sustainability, current approaches have not produced a comprehensive manufacturing-focused assessment tool for systematically linking the adoption of digital technologies, enabling characteristics, and outcomes of sustainability across all three components of the triple bottom line. Therefore, the motivation for undertaking the systematic literature review discussed in Chapter 3, and the framework and assessment tool developed in this thesis, stems from the desire to address this gap in the current body of literature.

2 Systematic Literature Review

2.1. Objectives and Methodology of the Systematic Literature Review

To create a precise and thorough base for the creation of a Framework for Sustainability Assessment and a Tool for Sustainability Assessment for the role of Digital Technology in Manufacturing Systems, this dissertation utilizes a Systematic Literature Review (SLR). Digitalisation, manufacturing and sustainability research is fragmented conceptually and methodologically across several disciplines and therefore requires a structured literature review to assimilate current knowledge, find dominant research patterns and identify gaps warranting the proposed contribution to the literature.

The goal of the SLR is to consolidate and analyse peer-reviewed academic literature to investigate how digital technology impacts on manufacturing process performance as well as develop indicators of those impacts from environmental, economic, and social perspectives. Rather than providing a descriptive summary of each article, the SLR aims to collect and organise all common analytical elements necessary to develop a Framework for Sustainability Assessment and a Tool for Sustainability Assessment. The SLR will identify (i) the digital technologies used within manufacturing; (ii) the sustainability indicators used to measure their effect; (iii) the causal mechanisms between technology and sustainability; (iv) and the limitations of existing methodologies for assessing sustainability.

To ensure transparency and reproducibility, the researcher applied the same procedure used by other researchers conducting SLRs within Management and Engineering Research. The SLR was conducted using the following four stages: (i) identification of relevant literature; (ii) screening; (iii) eligibility testing; and (iv) synthesis in accordance with internationally recognised guidelines for SLRs [20], [21]. This process minimised researcher bias and allowed subsequent chapters to easily track the relationship between the literature SLR researched and the resulting analyses provided in the subsequent chapters.

The literature search was limited to recognised academic databases that represent the best available source of information on manufacturing systems, digital technologies and sustainability research: Scopus; Web of Science; Science Direct; IEEE Xplore. The databases contain quality peer-reviewed conference proceedings, journal articles and the literature within these databases is frequently used in SLRs of Industry 4.0 and Sustainable Manufacturing [22]. The search was limited to publications written in English, which were peer-reviewed. This ensured that the research conducted by these researchers was academically sound and able to be compared to other researchers' findings.

The development of a search strategy was undertaken to ensure that the broad and multidisciplinary nature of the topic could be fully captured. In doing so, three main groups of keywords were used to create search strings for each respective keyword group. These groups of keywords consisted of digital technologies, manufacturing systems and sustainability performance. Furthermore, many synonymous and closely related variations were also included in the keyword groups to assist with the multiple definitions within each of the three-axis of keywords.

Specifically, the following search string structure was applied:

- **Digital technology terms**: "digital technolog*" OR "Industry 4.0" OR "smart manufacturing" OR "cyber-physical system*"
- **Manufacturing context terms**: "manufacturing" OR "production system*" OR "factory"
- **Sustainability terms**: "sustainab*" OR "environmental" OR "economic" OR "social"

These keyword groups were combined using Boolean operators to form representative search strings, such as:

("digital technolog*" OR "Industry 4.0" OR "smart manufacturing" OR "cyber-physical system*")
AND ("manufacturing" OR "production system*" OR "factory")
AND ("sustainab*" OR "environmental" OR "economic" OR "social")

In addition, targeted searches were performed to capture technology-specific studies and sustainability assessment research, using combinations such as:

("Internet of Things" OR "IoT" OR "artificial intelligence" OR "digital twin")
AND "manufacturing"
AND "sustainability assessment"

To allow for the distinctive indexing systems & query syntax in each database, the search terms were altered throughout the different databases but kept identical in the way of concept. Duplicate references were predominately eliminated after they were initially found. Next, references' titles and abstracts were assessed for relevance to the study scope. To include in the further analytic phase, the references had to provide study addresses on manufacturing and/or production systems as well as studies using digital technology or initiatives for digitalisation. They must also study outcomes of interest to sustainability. The studies chosen at this point were screened against the full-text source for sufficient analytical depth on the technologies they examined, the indicators they used for sustainability outcomes, the relationships of/through causality and/or the measures of assessment. For the last studies chosen to be included in the final analysis, an extraction of relevant data was completed systematically from all studies. Emphasis was given during extraction to documentation of characteristics of digital technologies, manufacturing environments and types of sustainability addressed by the indicator used to measure.

During the synthesis process, a thematic and analytical approach rather than strictly descriptive was used. The research was compared iteratively developed recurring patterns within each study, grouped technologic types, sustainability indicators and causality structures together into similar categories to develop a taxonomy of digital technologies, a composite measure of sustainability indicators and a map of causality between technologic and sustainability indicators. Limitations of existing approaches to assess sustainability emerged during the synthesis process; mainly there are no integrated production-level tools available to manufacturing firms for the systematic evaluation of sustainability impact due to the use of digital technologies [3]. The analytical basis of systematic review supported the remaining chapters of this discussion; the technology groupings, sustainability indicator groupings, and causality groupings identified in Chapter 3. Supported the development of the proposed framework and tool for sustainability measurement, while the limitation of the existing research will provide justification for both the empirical validation and methodological choices presented later in the document.

2.2. Digital Technologies for Sustainable Production

Digital technology is at the heart of current transformation within manufacturing and production processes in the era of Industry 4.0. In addition to the well-publicised benefits of digital technologies to productivity, flexibility and cost savings, digital technology is increasingly being studied for its role in supporting environmental, economic and social sustainability initiatives. In the literature, digital technologies are primarily characterised as interconnected elements of socio-technical production systems that change the way information is generated, processed and utilised to make operational and strategic decisions [23]. The literature on sustainability-oriented manufacturing continues to report that digital technologies provide manufacturers with improved visibility, control and coordination across production systems. Manufacturing systems are generally complex, resource demanding environments, and traditional production systems do not often have real-time visibility of machine condition, process performance, and materials flow in production. Digital technologies overcome this limitation through continuous data collection, advanced analysis, and rapid execution, therefore allowing for more proactive and preventative approaches to managing sustainability [24]. The literature also identifies significant inconsistencies in the way digital technologies are defined and analysed, limiting the development of effective methods for evaluating sustainability. To help address these challenges, several authors suggest that analysis of digital technologies should be based on the functional role performed by the technology, rather than simply the technical characteristics of the technology itself [25]. To that end, this study adopts a functional clustering approach to synthesise digital technologies that have been identified through the systematic literature review. The clustering of digital technologies was developed inductively during the synthesis stage of the review and reflects how digital technologies provide value across the various stages of observation, decision-making and execution, as well as governance, throughout the manufacturing process.

Through analysis, four distinctive digital technology clusters (C1-C4) were derived which represent different support functional layers to digitalised manufacturing systems. The digital technologies grouped in each cluster share a common primary use; however, each cluster analytically represents distinct sets of digital technologies based on the primary function of the technologies within each cluster. Also, evidence exists that the digitalisation of manufacturing systems and the realisation of sustainability enhancements are achieved through integrated application of digital technologies across clusters.

The first cluster (C1), Smart Sensing and Connectivity Infrastructure, provides the fundamental enabling capability for digitalised manufacturing systems. The primary purpose of C1 is to create real-time visibility into all machines, processes and flow of materials. C1 technologies are comprised of industrial sensors, Industrial Internet of Things (IIoT) platforms, radio frequency identification (RFID), machine vision systems and cyber-physical systems. The key characteristic that defines the C1 technologies is that they collect and transmit data from the physical production environment without performing any advanced interpretations or optimisations of that captured data. In terms of contributing to the sustainability of manufacturing systems, the contribution of C1 technologies is indirect but crucial in establishing the data foundation to identify inefficiencies, discrepancies and waste by creating continuous visibility into energy usage, material consumption, equipment status and environmental conditions [24]. This visibility layer is necessary for the realisation of digital sustainability at higher tiers. The second cluster (C2), Data Intelligence and Virtual Modelling, is focused on converting the data into insights which facilitate data-driven decision-making and optimisation. The technologies that comprise C2 include data analytics, artificial intelligence, machine learning, simulation tools and digital twin technologies. The technologies that are in C2 and are built upon the data generated from C1 technologies, are characterised in that they can analyse, forecast and assess the behaviour of the system. Unlike C1, C2 technologies do not directly interact with the physical production process but rather provide optimisation and simulation capabilities. In the community of manufacturing studies with a sustainability focus, C2 technologies are linked to decreased energy use, reduced waste and scrap generation, improved resource efficiencies and enhanced production planning through predictive and prescriptive analytics [26]. Virtual experimentation and sustainability trade-off assessments can be carried out using digital twins before implementing in a physical sense thus providing a better basis for informed, proactive sustainability decision making [27].

The Automated and Adaptive Execution Systems (C3) is the third cluster that represents the layer of production operations that is involved in the physical execution of production tasks through direct digital intervention. Included in this cluster are industrial robots, collaborative robots (cobots), autonomous systems, and additive manufacturing technologies. C3 technologies' unique characteristic is their ability to apply digital data physically to production-related processes, thereby converting digital decisions into material products. In contrast to industrial robots and autonomous systems, which focus on efficiency, precision, and repeatability, cobots are explicitly designed to support human operators and assist them in executing production activities. From a sustainability perspective, C3 technologies have the potential to increase material efficiency, decrease rework, enhance flexibility, and improve occupational safety through automating dangerous or ergonomically taxing tasks. However, there is a significant amount of literature indicating that the sustainability impact of C3 technologies is contingent upon the specific production context and often involves compromise, particularly in terms of energy usage and worker impacts.

The Digital Systems to Enable Human-Centric Production System and Governance (C4) is the fourth cluster and is concerned with enabling safe, skilled, and responsible use of digitally manufactured systems. Included in this cluster are augmented and virtual reality (AR/VR), human–machine interfaces (HMIs), wearable technology, blockchain, and cybersecurity solutions. In contrast to the C1–C3 clusters, which are predominantly concerned with performance of the technical system, C4 technologies are distinguished by their emphasis on human interaction, organizational governance, and trust. AR/VR and advanced HMIs facilitate training/skill development and ergonomic execution of tasks, while wearables monitor and promote the safety and well-being of workers. Blockchain and cybersecurity solutions provide secure operation of systems through maintaining data integrity and traceability, and as such are essential to fostering reliable and transparent manufacturing practices. Overall, the four clusters together provide a coherent operational logic for analysing digital technologies within the context of sustainable manufacturing. C1 establishes visibility, C2 establishes optimization, C3 provides execution, and C4 provides support for people and governance. The layered approach to understanding the relationship between sustainability and technology provides clear evidence that impacts of sustainability arise not from stand-alone technologies, but through the coordinated use of multiple technologies to support operational functions. Therefore, the cluster-based approach has provided a strong analytical foundation for establishing links between digital technologies and sustainability indicators and causal relationships within the remainder of the systematic literature review.

2.3. Sustainability Indicators in Digitalised Manufacturing Systems

To evaluate the sustainability of manufacturing systems, appropriate characteristics need to be established that are both conceptual will fulfil sustainable development and will be able to operate in real time, complying with production operations. Waste and Energy are the most common concerns of sustainability. Manufacturing systems typically a strong interdependence between capital-intensive assets, process complexity and operator and technology interactions, have a high resource consumption, and have extensive interdependencies between process flows. Therefore, the indicators will need to have operational and measurable capabilities within the manufacturing environment to capture production level activity, be sensitive to operational changes, and be capable of identifying how digital technology has impacted the performance of manufacturing systems. Most of the proposed sustainability indicator sets in current literature have been tested within the context of manufacturing operations. The Majority are found to be either too generalised or not specific to a manufacturing environment say through using generic level measures (such as corporate financial reporting or generic ESG metrics) or high level (on a corporate level) sustainability indexes which generally are not linked to production operations or digital technologies. Therefore, some recent studies have been identifying a need for diminutive subsets of Sustainability Key Performance Indicators (KPI's) grouped by production commitment, to measure digitalized manufacturing system sustainability impacts on a systematic, actionable basis [28]. This paper attempts to provide an evaluation of the digital manufacturing operational-indicator groups (identified in Section 3.2 C1-C4) by synthesising Sustainability indicators that are production specific and digital manufacturing specific in their intent. The resulting indicators represent how digital technology can impact resource efficiencies, process effectiveness, capacity utilisation, and employee health and safety levels.

2.3.1. Environmental Sustainability Indicators

The sustainable manufacturing of goods environmentally refers to how manufacturers effectively utilize energy, materials and natural resources, whilst also minimizing waste and emissions. Manufacturing contributes an extensive share of industrially caused environmental impact, therefore environmental indicators that can assess how digital technology contributes to sustainability are relevant.

Energy consumption represents one of the primary environmental indicators because it directly indicates machine operating efficiency, process stability and production planning decisions. Digital technologies found in the Smart Sensing and Connectivity Infrastructure technology cluster (C1) allow for granular monitoring of energy use, while technologies associated with Data Intelligence and Virtual Modelling (C2) enable optimally designed and predictive controlled execution strategies for operations. These two factors show that energy consumption levels are relatively susceptible to digitalization, as they are indicative of environmental improvements attributed to being digitally enabled [29]. Water consumption is somewhere prominent in process-intensive manufacturing sectors where water is utilized for cooling, cleaning and or processing materials. Inefficient use of water is often due to insufficient operational visibility of the process. Digital monitoring and analytics technologies (C1 and C2) enhance measurement precision and provide process-level control, therefore making water consumption levels an excellent indicator of resource stewardship amongst manufacturers [30]. Waste generation demonstrates the amount of material inefficiencies that occur because of poor-quality products, remanufactured products and or an unstable process. Waste creates both environmental impact and thus is also expensive impact upon manufacturers. Digital technologies influence waste generation, indirectly, through improved quality measuring techniques, predictive maintenance and adaptive execution systems (C2 and C3), which therefore yield the ability of the manufacturer to limit scrap and material loss. As such, waste generation indicators are therefore indicative of the benefits sustainable manufacturing demonstrates from digital technology enhancing process reliability [28]. One of the best-known environmental indicators that demonstrate the total climate change impact of the manufacturing industry is Greenhouse Gas (GHG) emissions from manufacturing activities. GHG emissions from manufacturing activities are primarily due to energy use and manufacturing process emissions. As digital technologies allow for increasingly refined production-level data tracking, manufacturers can normalise GHG emissions against output produced as well as link it to operational performance. Thus, GHG emissions represent an important indicator for determining whether digital optimisation activities help support climate change sustainability objectives [31].

2.3.2. Economic Sustainability Indicators

Economic sustainability in manufacturing is fundamentally rooted in operational performance and production efficiency rather than financial accounting outcomes. Sustainable manufacturing systems need to remain competitive whilst using resources efficiently and ensuring process stability. Therefore, the economic sustainability indicators for manufacturing systems should represent how effectively the manufacturing system converts input to output for creating value. Quality performance reflects process stability and effectiveness, and is typically measured using defect or scrap rates. Poor quality as a result of production instability can also result in the need for rework, or lead to increased material usage, higher energy consumption, and additional labour for the manufacturing facility. Digital technologies afforded by C2 are used for real-time monitoring of product quality and providing predictive analytics for quality performance. Automated and Adaptive Execution (C3) systems are also used for improving precision and repeatability of product quality. Together, therefore, quality performance can illustrate how digital technologies support both economic and environmental sustainability [31]. Lead time is used to measure responsiveness within the system, as well as flow efficiency through the system. Long or highly variable lead times can indicate low system visibility and poor decision-making practices. Digital technologies created in C1 and C2 provide better visibility within production schedules which increases planning accuracy and enables faster response to disruptions, and enhance coordination between production stages. As such, lead time can be a key indicator of the manufacturing system's agility through digital systems, in addition to supporting economic sustainability [32]. Productivity is typically expressed as output within a given unit of time, and therefore reflects the efficiency with which resources are used within the production process. Digital technologies contribute to improving productivity through the reduction of idle time, improving the coordination of both operators and machines, and enhanced support for data-driven decision-making. Therefore, productivity is a direct measure of the economic benefits derived from digitalizing the manufacturing process [29]. Equipment utilisation can be defined as how effectively production assets are being utilised relative to their available capacity. There are many factors that result in low equipment utilisation; however, some of the most common causes include unplanned down time, ineffective use of scheduling, and lack of or poor execution of the maintenance strategy. Digital technologies created in C1 and C2 will provide the ability to monitor equipment performance in real time, and predictive maintenance; however, digital technologies developed in C3 can support the ability to execute adaptively. As a result, equipment utilisation is particularly relevant when assessing the economic impact of the use of digital technology in asset-intensive manufacturing environments [28].

2.3.3. Social Sustainability Indicators

Social sustainability in manufacturing is strongly linked to the human aspect of manufacturing including work conditions, human–machine interaction (HMI), and workforce development. Digitalisation has fundamentally changed the way work is performed and will continue to change the way work is performed; hence social sustainability indicators are becoming increasingly important for evaluating sustainable manufacturing. Occupational safety is the most accepted social sustainability measure in the manufacturing industry and normally results from the acute physical risks involved in manufacturing. Digital technologies developed in C1 enable real-time safety monitoring; digital technologies C3 have automation capabilities for hazardous tasks; and C4 technologies such as human-centred interfaces and wearable technology can all help support worker safety. As such, occupational safety metrics would provide a good indication of the impact of digital technologies on social sustainability [33]. Occupational health and ergonomics (long term worker safety) extend beyond just the acute aspect of the employee's physical work environment and involve measuring the overall physical and psychosocial well-being of an individual worker. Poor ergonomics, overly complex workload, and exposure to excessive levels of noise and/or vibration will lead to significant physical and mental health issues over time. Digital technologies developed in C4 provide the ability to assess ergonomics, workload, and provide improved support for completing tasks; thus, these social sustainability indicators are critical for determining the long-term social sustainability impact of digital technologies on manufacturing systems [30]. The training of staff within an organisational context is indicative of the organisation's willingness to develop their workforce's capability and adaptability. Digitalised manufacturing systems require continuous upgrading of skill sets to ensure technologies are used effectively and responsibly. One common measure of training among employees is in hours per employee, which is also a common metric to evaluate employee training and would therefore be relevant in the context of digital transformation since inadequate training will negatively affect both the performance of manufacturing systems and the well-being of workers [31].

2.3.4. Final Sustainability KPI List

The synthesis process resulted in a final set of 11 sustainability KPIs, comprising four environmental, four economic, and three social indicators. This set is deliberately reduced to maintain operational feasibility while preserving analytical completeness. All selected KPIs are directly relevant to manufacturing processes, measurable at the production level, and highly sensitive to digital technologies across clusters C1–C4.
To consolidate and clarify the rationale for KPI selection, Table 2.1 summarises the final sustainability KPIs, highlighting their relevance for manufacturing systems and their sensitivity to digital technologies. This table provides a visual synthesis of the indicator framework and supports the causal analysis developed in the subsequent section.

Table 2.1: Sustainability KPIs for Digitalised Manufacturing Systems

Sustainability Dimension	KPI	What It Measures	Production Relevance
Environmental	**Energy**	Energy consumption of production processes	Energy use is directly influenced by machine operation, process efficiency, and production scheduling. DTs can significantly affect real-time energy visibility and optimisation, making it a sensitive and measurable production-level indicator.

	Water	Water consumption in manufacturing operations	Water use is process-dependent and particularly relevant in cooling, cleaning, and surface treatment operations. Digital monitoring and optimisation technologies can directly influence water efficiency at machine and line level.
	Waste	Production waste and scrap generation	Waste reflects process variability, quality deviations, and operational inefficiencies. It is highly sensitive to predictive analytics, automation precision, and human error reduction, making it directly linked to digital production technologies.
	GHG Emissions	Production-related carbon emissions	GHG emissions represent the environmental footprint of production activities. Digital optimisation and modelling tools can support emission reduction strategies through improved operational efficiency.
Social	**Occupational Safety**	Frequency of accidents and acute safety incidents	Manufacturing environments involve physical risks associated with machinery and manual operations. Digital monitoring, automation, and human-centric systems directly affect exposure to hazardous tasks and safety performance.
	Occupational Health & Ergonomics	Long-term physical and cognitive well-being of workers	Production tasks may involve repetitive motions, physical strain, and cognitive workload. Collaborative robots, wearables, and ergonomic monitoring systems can directly influence worker health and workload conditions.
	Staff Training	Workforce capability development and digital skills	Digital transformation in manufacturing requires new technical and analytical competencies. The effectiveness of digital technologies depends on workforce capability, making training a production-relevant and technology-sensitive social KPI.
Economic	**Quality**	Conformance of production outputs	Quality performance reflects process stability and execution precision. Digital monitoring, predictive analytics, and automation directly influence defect reduction and process consistency at the shop-floor level.
	Lead Time	Production and delivery responsiveness	Lead time is influenced by process coordination, bottlenecks, and variability. Digital planning, monitoring, and adaptive execution systems directly affect flow efficiency in manufacturing operations.

Productivity	Output efficiency of the production system	Productivity captures the efficiency of resource utilisation in production. Automation, optimisation, and real-time monitoring technologies directly contribute to throughput improvements.
Equipment Utilization	Effective usage of production assets	Equipment utilisation reflects downtime, idle time, and capacity usage. Predictive maintenance, real-time monitoring, and execution optimisation directly influence machine availability and utilisation rates.

2.4. Causal Mechanisms Linking the Digital Technologies and Sustainability

Although there is evidence that shows how digital technologies can lead to sustainable manufacturing, the few studies that currently exist do not provide a causal explanation as to why digital technologies can create sustainability outcomes or how they affect the sustainability performance of manufacturing entities. The lack of clear causality creates difficulties for researchers and practitioners alike when integrating the theoretical aspects; applying theoretical findings in practice; and when exploring multiple technology and sustainability dimensions at the same time. Therefore, this section will utilise an analytical method focused on causality to systematically explore the way each of the identified clusters of technology (Section 3.2) provides for the operational mechanisms contributing to environmental, social and economic sustainability within manufacturing systems (Section 3.3).

In this study, the term causality is defined as a functional relationship between a cluster of digital technologies enabling specific operational mechanisms that lead to observable changes in sustainability-related performance indicators. The analysis of the identified clusters of technology and their relationship to sustainability performance indicators (KPIs as identified in Sections 3.3 and 3.4) is conducted by mapping each of the technology clusters to the applicable KPI(s) across the triple bottom line perspective. For each cluster-KPI pair, a dominant causal mechanism is identified and substantiated by literature evidence, with direct, indirect and non-existent causal relationships identified where applicable. To promote clarity in the analysis and avoid double counting of effects, the causality analysis is organised by technology cluster and sustainability perspective. The primary focus of the causal analysis is to capture the functional role of technology clusters within the molecular manufacturing systems rather than the isolated assessment of individual technologies. This methodology supports the holistic and multi-dimensional aspect of the digital transformation process. Causality tables are provided in Appendix A, and the causal logic of the analysis is synthesised in narrative form in this section. The structured methodology will provide a coherent theoretical foundation from which measurement design and formulation of the sustainability assessment framework will be built.

2.4.1. Causality Between Smart Sensing & Connectivity Infrastructure (C1) and Environmental Sustainability KPIs

Digitalized manufacturing systems rely on smart sensing and connectivity infrastructure (C1), which represents the foundational layer in digitalized manufacturing systems by providing a continuous acquisition of real-time data of machines, processes, and flow of material. C1 technologies such as industrial sensors, IIoT platforms, and cyber-physical systems do not directly optimize or execute production activities; however, their contribution to environmental sustainability derives from the causal mechanism of real-time visibility, which improves awareness, accuracy of measurement, and allows for informed operational decision-making within the manufacturing system.

In terms of energy consumption, through real-time sensing and connectivity, there is continuous measurement of energy used by individual machines and processes. This visibility provides manufacturers with the ability to identify their most energy-intensive operations, operational energy consumption when machinery is idle, and any abnormal patterns in the consumption of energy that can be masked by aggregated energy data. As Contini and Peruzzini [34] describe systems that measure energy consumption using sensors have demonstrated to manufacturers where to identify plagues in their process area, which allows them to implement corrective actions such as to reduce idle running, thereby allowing for manufacturers to reduce overall energy consumption. With respect to water consumption, smart sensing and connectivity technologies enable manufacturers to continuously monitor their water consumption at the machine, process, or facility level. This visibility provides manufacturers with the ability to identify their most water-intensive operations, abnormal patterns in their water consumption, and any water loss (e.g., leaks). Ghobakhloo [35] discusses how digital connectivity and real-time monitoring systems create transparency related to the amount of water being consumed and assist manufacturers in managing their water consumption more efficiently through the timely identification of inefficiencies and facilitating the implementation of corrective actions for resource conservation.

In terms of waste generation, C1 technologies contribute to environmental sustainability through the provision of visibility into production processes and material flows. Continuous measurement of process parameters, defect rates, and scrap quantity enable manufacturers to identify when and where material loss occurs during production processes. As reported by Contini and Peruzzini [34], increasing the transparency of processes results in the identification of the sources of waste, at both the machine and process levels, thus facilitating the implementation of targeted quality and process improvement initiatives that will reduce waste and scrap in production. Recent literature does not demonstrate a strong causal relationship between smart sensing and connectivity infrastructure, and GHG emission reductions. As GHG emissions from manufacturing are typically calculated from the combined consumption of energy and materials, as well as the use of emission factors, and are not typically directly measured, smart sensing and connectivity technologies increase accuracy and granularity of the activity data that is relevant to carbon accounting. Huang and Badurdeen [36] emphasize that without complementary optimization or execution mechanisms, smart sensing and connectivity technologies will not, by themselves, lead to the reduction of GHG emissions; therefore, C1 technologies are best viewed as providing the basis for accurately measuring GHGs, instead of directly reducing GHG emissions.

Throughout the causality analysis, smart sensing and connectivity infrastructure (C1) will contribute to environmental sustainability; however, the contributions to environmental sustainability, enabled by C1 technologies through real-time visibility of energy use, water consumption, and waste generation through the real-time visibility provided to manufacturers, create the preconditions required for manufacturers to improve their environmental performance. For example, manufacturers will require the integration of higher-level digital technology clusters focused on optimization and execution to achieve measurable reductions in their environmental impact.

2.4.2. Causality Between Smart Data Intelligence and Virtual Modelling (C2) and Environmental Sustainability KPIs

Data Intelligence and Virtual Modelling technologies (C2), form the analytical and decision support layer of digitally enabled manufacturing systems. The technologies that make up this cluster include data analytics, artificial intelligence (AI), machine learning (ML), simulation tools and digital twins. Whereas the Smart Sensing and Connectivity Infrastructure (C1) primarily provides visibility, the technology in C2 provides a contribution to environmental sustainability through the predictive, simulation and optimisation based causal mechanisms that shape how production decisions are made and how systems behave. The literature identifies two primary causal mechanisms of how energy consumption is managed: predictive energy management and simulation-based energy optimisation. Predictive analysis models leverage both historical and real-time production data to predict future energy demands and consumption behaviours, thereby allowing organisations to undertake proactive management of their energy consumption, such as by performing load shifts, avoiding peak demand and developing energy-aware production planning. Cagno et al. [37] demonstrate that predictive energy management systems have been successfully used by manufacturers in a variety of industrial environments to provide utility companies with advanced notice of energy-intense production periods so that manufacturers can appropriately adjust their schedule, ultimately leading to a demonstrable reduction in overall energy consumption. In contrast to predictive-based energy management approaches, simulation-based and digital twin models allow for the virtual testing of alternative production configurations or operating strategies. Billey and Wuest [38] and Khodadadi and Lazarova-Molnar [39] illustrate that simulation-based evaluations facilitate the selection of the most energy-efficient alternatives prior to physical implementation, thereby minimising the energy waste associated with trial-and-error testing in a manufacturing facility.

Similarly, with respect to water consumption, the technologies within the C2 cluster contribute to water savings via water optimisation through data-driven techniques and water management through predictive techniques. Analytical models and digital twins of industrial water systems provide continuous monitoring, forecasting and simulation of water use behaviours. Emeka and Chikwendu [40] illustrate how digital twin-based water management systems can help identify inefficient water use early in a process, allowing users to proactively adjust their water usage to improve water efficiency and reduce the amount of reduced water they consume. Recent studies assessing the integration of digital twins into water management systems reaffirm the importance of predictive modelling's role in supporting sustainable use of water in an industrial environment [41]. Lastly, in respect to waste generation, the technology cluster of C2 impacts overall environmental performance by influencing the quality of a production process through predictive quality and process optimisation techniques. Data-driven analytical techniques and machine-learning models evaluate production data to identify production process parameters contributing to product defects, scrap and rework. Contini and Peruzzini [34] illustrate the use of predictive quality analytics to detect potential deviations early enough in a process so that defect creation is still possible. Wuest et al. [40] demonstrate that virtual testing can lead to minimising waste due to material losses from defect creation through stabilising processes and improving decision quality; thus, the technologies represented within the C2 cluster are directly related to a reduction in waste through stabilising production processes and delivering high-quality outcomes.

C2 technologies enable carbon footprint modelling, assessment, optimisation of GHG (greenhouse gas) emissions, and carbon-aware planning and scheduling. These models use digital twin, simulation, and analytical methods to quantify manufacturing carbon footprints and identify carbon-intensive processes by integrating energy and material consumption with emission factors. Digital twin-driven carbon emissions management studies show that these models facilitate the virtual evaluation of scenarios for lower-carbon production before implementation, which enables informed decision-making regarding emissions reduction [42]. Optimisation models that incorporate carbon emissions as an objective together with more traditional performance measures can lead to the selection of process plans, machine assignments, and schedules with lower carbon impacts. Recent contributions to the Journal of Cleaner Production and Sustainability demonstrate how carbon-aware scheduling can achieve noticeable reductions in production-related GHG emissions without sacrificing operational performance [43]. Furthermore, analytical optimisation research in applied mathematics and systems engineering supports applied research demonstrating that carbon objectives are feasible entities within production planning models [44]. In summary, the causal analysis supports that Data Intelligence and Virtual Modelling technologies have a strong and direct effect on environmental sustainability KPIs. C2 Technologies support the prediction, simulation and optimisation of how resources are used in manufacturing systems beyond that which would be achieved through transparency; rather, they actively influence both resource utilisation and environmental performance in manufacturing systems. However, their effectiveness is dependent on the input data quality and the incorporation of analytical findings into operational decision-making, emphasising the complementary nature of both technology clusters focused on sensing and execution- based capability development.

2.4.3. Causality Between Automated and Adaptive Execution Systems (C3) and Environmental Sustainability KPIs

C3 technologies are the execution layer of digital manufacturing systems. C3 creates a direct correlation between digital decisions and resulting physical production activities. C3 includes industrial robots, collaborative robots, autonomous systems, and additive manufacturing technologies. Unlike C1 and C2 that primarily impact sustainability through visibility and decision-making, C3 impacts environmental sustainability because of the efficiency, precision, and repeatability of execution. Therefore, C3 technologies impact environmental KPIs through direct physical, as opposed to informational or analytical, means of affecting the environment.

C3 technologies have the potential to impact environmental performance by promoting energy-efficient robotic execution and utilization. Industrial robotic systems can optimise energy consumption through efficient execution; this is achieved through the optimisation of motion planning, task sequencing, and execution strategies to reduce unnecessary movements and idle time. Studies conducted within the ScienceDirect database, have shown that efficient execution by robots is associated with a significant reduction in overall energy consumed in manufacturing, especially within high-volume and repetitive processes [45]. As a result, the use of energy-efficient robotics during the design and programming phases contributes directly to the reduction of energy consumption at a per-operation level.

Conversely, the literature reviewed for this meta-analysis does not support a strong evidence base with respect to water consumption due to the influence of automated execution systems. Water usage in manufacturing is primarily determined on a per-process basis by cooling, cleaning and chemical processing, all of which are independent of execution by robotics/automation. As a result, the relationship between C3 technologies and water consumption is, at best, indirect and contextual, and there are no specific measures of the sustainability effects related to water that have been supported within the C3 cluster.

With respect to waste generation, C3 technologies exhibit a direct and well-supported causal relationship based on the repeatability and precision of robotic execution. Innovative robotic and automated execution systems have the potential to eliminate the variability inherent to manual or semi-automated execution by executing the same tasks consistently, thereby improving the stability of production processes. In a meta-analysis of published work conducted by Springer, empirical studies demonstrate that increased execution precision has a positive impact on the reduction of defects, scrap, and wasted materials in manufacturing processes [46]. As a result, the use of robotics/automation will directly contribute to the reduction of waste by eliminating defects at the point of execution, rather than waiting until after production is completed.

C3 technologies impact the environmental performance of GHG emissions through indirect emission reductions related to energy efficiency. Lifecycle assessment studies, at the present time, demonstrate that a decrease in energy use per unit produced would result in an equivalent reduction in GHG emissions associated with a particular production system – provided that the energy mix remains constant. LCA studies related to the ScienceDirect database indicate that energy-efficient robotic systems will generate lower lifecycle CO_2 emissions in manufacturing operations; however, this relationship will be highly influenced by each system's design, utilisation, and production context [47]. Thus, the causal relationship between C3 technologies and Greenhouse Gas emissions is indirect and mediated through improvements in energy efficiency rather than through direct reductions in emissions.

Overall, the causality analysis indicates that Automated and Adaptive Execution Systems contribute to environmental sustainability primarily through execution-level efficiency and precision. While strong causal relationships are identified for energy consumption and waste generation, the effects on water consumption are not supported by direct evidence, and GHG emission reductions occur indirectly through improved energy efficiency. These findings highlight that the environmental sustainability impact of C3 technologies is highly dependent on system design choices and must be assessed in conjunction with complementary sensing and optimisation technologies.

2.4.4. Causality Between Human-Centric Digital Systems (C4) and Environmental Sustainability KPIs

Digital systems that are based on human beings (C4) are aimed at enabling responsible and safe interaction with digitalised manufacturing. Technologies included in this cluster are human–machine interfaces, digital work instructions, augmented reality (AR), virtual reality (VR), governance platforms and decision support systems. All the C1–C3 clusters offer visibility (through their ability to capture/monitor environmental performance), optimisation (by enhancing the visibility of operations and materials) and physical execution of production processes. Unlike C1–C3, the environmental impacts of the C4 cluster arise from two interrelated areas human-centric decision support and governance. Therefore, C4's impact on the environment is primarily indirect and mediated via managerial or behavioural factors. C4 technologies influence energy consumption-related environmental performance via human-centric decision support that promotes/informs energy-aware operations. Decision support systems provide operators and managers with contextual information, feedback, and performance indicators related to consumption of energy, assisting in making timely, well-informed operational energy decisions. Research in Decision Support Systems highlights that when an operator or manager has energy-related information integrated into decision interfaces, they are more likely to adopt energy-efficient behaviours when making operational decisions, such as investigating new operational schedules or avoiding unnecessary machine use. This leads to improved energy efficiency [48]. C4 technologies achieve this by enhancing human judgement using digital information rather than through automated optimisation.

In terms of water consumption, C4 technologies provide governance-enabled transparency/decision infrastructure to enhance coordination, monitoring, and accountability in the management of industrial water. Through the integration of data across organisational units and levels of decision making, governance-oriented digital platforms increase transparency and provide managerial oversight of water use, enabling more effective allocation to help reduce consumption through institutional/organisational rather than technical processes [49]. In this way, C4 technologies promote water-related sustainability through reducing consumption by improving the processes of governance rather than through direct process intervention. C4 technologies exert their influence on reducing waste generation indirectly through two interrelated mechanisms. The first mechanism supports waste reduction through human-centric circular decision tools and their support of designers/engineers' decision-making processes by promoting and guiding their design selections with a circulatory mentality; this promotes waste minimisation throughout the entire product lifecycle. Research published in Emerald demonstrates that design-focused systems associated with Industry 4.0 increase designers' ability to produce waste-reducing designs by providing timely feedback on material usage, recyclability, and waste implications throughout the entire design and production process [50]. The second mechanism addresses execution-based waste generation by providing error-reducing technologies (i.e., digital work instructions and error-reducing technologies) that improve task clarity and standardisation while facilitating compliance with task requirements. Research reported in IEEE publications has demonstrated that these error-reducing technologies (digital work instructions and operator guidance systems) reduce execution errors/variances and non-compliance, resulting in lower amounts of scrap and material loss during manufacturing [51]. Collectively, these technologies reduce waste via human decision-making and task execution instead of via automated control and optimisation.

There is no significant empirical evidence within the literature on the relationship between C4 Technologies and Gross Greenhouse Gas (GGH) Emissions Reduction through a direct causation-based relationship. It is suggested that C4 Technologies (i.e. Human-Centric and Governance-Enabling Digital Systems) may assist indirectly in the reduction of GHG emissions by creating improved awareness, reporting and governance however there are no cluster-specific chains of causation identified within the data which link C4 Technologies to a measurable reduction in production-based GHG emission. Therefore, at this time, no valid environmental outcome for C4 Technologies could be established for GGH emissions reduction, due to the indirect relationship established through a chain of causations.

The results of the causality study establish that C4 Technologies, as Human-Centric and Governance-Enabling Digital Systems, contribute to environmental sustainability indirectly, and behaviourally through the enhancement of the Awareness, Quality of Decision, and Governance structures of people. C4 Technologies contribute primarily to environmental performance through the enhancement of the Awareness, and Quality of Decision, and Governance Structures of people, not through the direct control or optimization of the Production Processes. While the C4 Technologies function in this capacity, their effectiveness relies heavily upon the Organizational Context, User Engagement and Integration with complementary sensing, optimization, and execution technologies.

2.4.5. Causality Between Smart Sensing and Connectivity Infrastructure (C1) and Social Sustainability KPIs

C1 Smart Sensing and Connectivity Infrastructure improves social sustainability in manufacturing through continuous monitoring and real-time information about working conditions. While industrial sensors, IIoT platforms, cyber-physical systems, and wearable technologies do not directly affect how tasks execute or how organisations are structured; they support social sustainability by providing a mechanism for real-time hazard detection, monitoring, and preventative safety, health and workforce development interventions.

In terms of occupational safety, C1 technologies provide real-time hazard detection and monitoring of safety-related issues by continuously tracking machine status, environmental conditions, and worker proximity to machines. Empirical research published in Safety has shown that sensor-based safety monitoring systems provide an early warning mechanism that allows for timely corrective actions, which has resulted in a reduction of accidents within the manufacturing sector [52]. In addition, research published by World Scientific has shown that CPS-based safety architectures have improved situational awareness by providing a means of integrating multiple sources of sensory information to achieve system-level safety monitoring rather than safety monitoring with limited, independent safety controls [53]. Together, these two sets of findings provide evidence of a strong causal relationship between C1 technologies and improvements in occupational safety.

C1 technologies also contribute to occupational health and ergonomics through continuous monitoring of the physical and environmental exposure of workers. Wearable and sensor-based systems enable continuous assessment of an operator's posture, physical load, vibration, noise, and environmental conditions. Research published in Applied Ergonomics has shown that continuous monitoring of exposures allows for early identification of ergonomic risks and long-term health stressors that are frequently missed by periodic assessments, providing opportunities for preventive occupational health intervention prior to the onset of chronic disorders [54]. More recent studies have also shown in Sensors that real-time physiological and environmental monitoring provides the basis for dynamic assessments of operator workload and fatigue, allowing managers to enhance their ergonomics management practices for their digitally enabled production systems [55].

C1 technologies also improve the social sustainability of staff training by providing data-driven insights for identifying training needs. Real-time production and machine data generated by connected systems reveal abnormal operating behaviours, recurrent errors, and ineffective usage of machinery that may be indicative of an operator or maintenance technician's lack of skill. Research on digital manufacturing systems found in EBSCO and Google Scholar have reported that C1-based data-driven insights provide the basis for developing targeted, needs-based training programmes to enhance workforce capabilities, as the training content is linked to operational deficiencies, rather than merely providing generic training opportunities [56]. This mechanism allows managers to demonstrate the effectiveness of their staff training initiatives because they are directly tied to actual operational data.

Overall, the findings of the causal analysis clearly demonstrate that C1 Smart Sensing and Connectivity Infrastructure contributes to social sustainability by generating enabling, preventative, and information-based contributions to occupational safety, occupational health and ergonomics, and staff training. By providing real-time transparency about safety, health, and skill performance, C1 technologies provide the infrastructure required to enhance performance in those areas. The long-term impact of these contributions to social sustainability will depend on how organisations utilise this information to drive organisational actions, training policies, and support digital interventions.

2.4.6. Causality Between Data Intelligence and Virtual Modelling (C2) and Social Sustainability KPIs

Social sustainability in manufacturing is aided by Data Intelligence and Virtual Modelling Technologies (C2) through their role in performing predictive and anticipatory analyses of human-related threats, as well as human-related capabilities. The technologies that comprise Chapter 2 (C2) include: data analytics, machine learning, artificial intelligence, and simulation-based modelling tools. While real time monitoring is primarily supported by technologies within Chapter 1 (C1), the contribution of C2 technologies to social sustainability occurs through predictions made using predictive modelling and evaluation through scenario-based evaluation; therefore, enabling organizations to proactively address social issues before they occur.

C2 technologies enable predictive safety and accident prevention through occupational safety by providing the opportunity for predicting the likelihood of safety incidents by analysing accident historical records, records of near misses, and other contextual production information. Predictive models provide an analysis of the potential that a safety incident may occur based on the different operational variables within a manufacturing; empirical studies illustrate that using predictive theories/high-risk situations are identified prior to the occurrence of the incidents, enabling proactive safety interventions such as inspections, adjustment of processes and preventive maintenance prior to incidents occurring [57]. Consequently, the safety management process will move from reactive analysis of incidents toward proactive risk mitigation. C2 technologies advance occupational health and ergonomics through predictive health risk analysis and ergonomic modelling. C2 technologies utilize machine learning and simulation to analyse the ergonomic risk associated with workload, fatigue, posture, and/or repetition based on alternative task configurations and/or different production scenarios. Research in this field supports that the use of predictive analysis for assessing ergonomics assists in determining risk for injury to musculoskeletal structure and cognitive workload prior to completing the task. In addition, the use of scenario-based modelling allows for the comparison of different workstation configurations and task allocation, therefore enabling informed decisions to be made which minimize potential long-term occupational health issues.

C2 technologies address social sustainability through predictive identification of employee skill gaps and employee capability; thus, enhancing social sustainability through employee training. Predictive analytic models support this process through integrating the requirements of the job, performance data and current as well as future projections for technology usage to assist in the identification of gaps in competencies [58]. Studies relating to workforce analytics demonstrate that use of predictive analytics models allow for the development of data-driven training and reskilling plans, and therefore, prepares the organization for the challenge associated with digital transformation, rather than reacting to performance deficiencies following implementation. Strategic workforce development via digital transformation enhances long-term employability of employee in the manufacturing industry [59].

Overall, our analysis of the relationship between Data Intelligence and Virtual Modelling Technologies and social sustainability has concluded that C2 technologies are essential in shifting organizations toward a proactive, forward-thinking method of managing safety, occupational health, and providing for the future talent development of employees within the digitalized manufacturing industry. Furthermore, C2 technologies support the organizations' goals of protecting employees, health risk management and preparing their workforce for continued evolution in technology through a predictive planning process [60]. To adequately enhance the effectiveness of these mechanisms, the utilization and implementation of high-quality data, validate models and organizational decision-making processes which incorporate analytical findings is essential to the success of C2 technologies.

2.4.7. Causality Between Automated and Adaptive Execution Systems (C3) and Social Sustainability KPIs

Automated and Adaptive Execution Systems (C3) influence social sustainability in manufacturing by directly intervening in the execution of production tasks. This cluster includes industrial robots, collaborative robots, and other autonomous execution systems that physically perform or support manufacturing operations. Unlike sensing or analytical technologies, the social sustainability contribution of C3 technologies arises through changes in task allocation, human–machine interaction, and skill requirements, which directly affect worker safety, health, and competence development.

With respect to occupational safety, C3 technologies contribute through risk reduction enabled by controlled automation and human–robot interaction (HRI) safety design. By reallocating hazardous or high-risk tasks from human operators to robotic systems, automation reduces direct human exposure to dangerous environments. In addition, modern robotic and collaborative systems incorporate HRI safety mechanisms such as collision avoidance, force limitation, and safe speed and separation monitoring. Empirical research demonstrates that these design features significantly reduce accident risks by ensuring safe coexistence of humans and robots in shared workspaces [61]. Complementary studies further show that controlled automation enables systematic safety improvements by standardising task execution and reducing unpredictable human–machine interactions in hazardous operations [62].

For occupational health and ergonomics, C3 technologies influence social sustainability through physical workload reduction and ergonomic risk mitigation. Collaborative robots and automated systems support workers by taking over repetitive, force-intensive, or ergonomically unfavourable tasks. Studies on human–

robot collaboration show that redistributing such tasks from humans to robots reduces musculoskeletal strain, physical fatigue, and long-term ergonomic risk, contributing to improved occupational health outcomes [63]. Additional research confirms that automation-supported task allocation leads to measurable reductions in physical workload and supports sustainable work design when appropriately integrated into production systems [64].

In the case of staff training, C3 technologies generate social sustainability impacts through upskilling and competence development driven by automation adoption. The introduction of robotic and automated systems changes job profiles and increases demand for skills related to robot operation, programming, supervision, and maintenance. Empirical studies on manufacturing automation show that successful implementation of robotic systems requires structured training and reskilling initiatives to ensure workforce competence and system safety [65]. Through this mechanism, C3 technologies contribute to long-term workforce sustainability by promoting continuous learning and skill development aligned with evolving technological requirements.

Overall, the causality analysis indicates that Automated and Adaptive Execution Systems influence social sustainability primarily through task reallocation, physical workload reduction, and skill transformation. While these technologies can significantly improve occupational safety and health when properly designed and implemented, their social sustainability benefits depend on effective human–robot interaction design and sustained investment in workforce training. These findings underscore the importance of integrating C3 technologies with human-centric and governance-oriented systems to maximise their positive social impact.

2.4.8. Causality Between Human-Centric and Governance-Enabling Digital Systems (C4) and Social Sustainability KPIs

The effects of Human-Centric and Governance-Enabling Digital Systems (C4) on social sustainability within manufacturing are a result of the way workers interact with digitalised production systems and the way work-related information is communicated, understood and acted upon. This C4 cluster encompasses various technologies including augmented/virtual reality (AR/VR) systems; sophisticated human-machine interfaces; wearable technology; and digital training platforms. The contribution of C4 technologies to social sustainability differs from execution-oriented technologies, as it occurs through improved situational awareness, cognitive support, and experiential learning that will ultimately enhance worker behaviour and regard for safety, health, and competency development.

Concerning occupational safety, C4 technologies support safety through immersive remedial safety information and enhanced situational awareness. Immersive, wearable C4 technologies provide workers with situation-specific safety information, visual notifications and interactive guidance that can assist them in performing appropriately in potentially dangerous and rapidly changing contexts. Empirical collectives/test results show that provision of visual and interactive safety instruction via immersive safety systems reduces human error and enhances hazard recognition through alignment of safety instruction with the immediate environment of the worker [66]. Additional research studies have demonstrated that immersive technologies have enhanced situational awareness in multifaceted manufacturing environments and have positively impacted both the safety decision-making of the worker and the level of successful compliance with safety procedures [67]. Thus, this enhancement of safety through C4 technologies is a function of their ability to shape the perceptions and behaviours of workers rather than through applying physical control to a worker's tasks.

In addition to their impact on occupational safety, C4 technologies support occupational health (including ergonomics) through both cognitive and ergonomic workload support through the application of human-centric interfaces. Human-centric digital systems enhance ergonomic evaluations by providing real-time performance feedback that relates to the worker's posture, the quality of their interaction with their environment, and their completion of tasks, as well as reducing cognitive workload through clear task-related information and improved interface design. Investigations conducted in this arena have concluded that enhanced interaction design provides an avenue of managing stress and fatigue by improving humans' interactions with machines and reducing information overload and enabling more naturally intuitive interactions [68]. Additional studies, validate that human-centric interfaces provide the means for performing proactive assessments of ergonomics and improving the organisation of work through taking into consideration cognitive and physical workload factors in the design of the system [69].

The effect of C4 technologies on training employees is through immersive digital training and experiential learning. The use of AR/VR technologies to create training systems provide workers the opportunity to conduct "practice" sessions of complex or high-risk tasks, as well as to provide an avenue to experience learner error in a "real-world" situation (vs. actual work site). Studies demonstrate that experiential learning supports improved retention of knowledge, enhances speed of onboarding, and improves the enhancement of workforce capabilities by providing workers the opportunity to repeatedly practice and receive instantaneous feedback, all within a realist virtual environment [70]. In addition, additional research studies validate that the capabilities of C4 technologies to support continuous learning through the utilization of custom content based on the worker's needs, performance and progression develop the long-term capabilities of the workforce [66].

To summarize, C4 technologies primarily impact social sustainability through the support and development of human perception, cognition and learning. The primary influence of C4 technologies on occupational safety, health and training are the result of the use of either cognitive or behavioural influences on behaviour and cognition, rather than from the physical or automated execution of assigned tasks. Accordingly, whether C4 technologies are successful in achieving their intended applications are directly predicated upon the extent to which end-users adopt them, the quality of their interfaces, and the extent to which C4 technologies are integrated into traditional organisational practices. When appropriately employed, C4 technologies will play a critical role in supporting the provision of safe, healthful and capable workers through the provision of safe, healthful, and capable workers in digitized environments.

2.4.9. Causality Between Smart Sensing and Connectivity Infrastructure (C1) and Economic Sustainability KPIs

The Smart Sensing and Connectivity Infrastructure (C1) promotes the economic sustainability of manufacturing through real-time visibility across the production process and system states. Tools, such as industrial sensors and IIoT platforms, manufacturing execution systems, and cyber-physical systems, do not improve or optimise production performance directly; however, by providing greater visibility and awareness, C1 tools support the rapid detection of deviations, more rapid responses to disruptions, and more accurate and informed short-term operational decisions. C1 technologies enable real-time quality visibility and early deviation detection using sensor-based monitoring systems which continuously monitor both process parameters and quality-related parameters. Therefore, deviations from the target condition can be detected at an early stage. Empirical evidence shows that the timely identification of process instability, through concrete action, can reduce defect rates and scrap prior to the propagation of quality losses throughout the production system [71]. It can be concluded that the causation is relationships based on preventive actions resulting from visibility rather than post-process inspection or optimisation.

C1 technologies contribute to improvements in lead time by providing real-time production status transparency. Continuous visibility of machine states, work-in-progress volumes, and material flows provides managers with the ability to identify bottlenecks, disruptions, and delays faster within the production system. Research on evaluating sustainable manufacturing performance indicates that real-time visibility enables the more rapid resolution of disturbances and improves the coordination of activities across production stages, which ultimately leads to reductions in both production and delivery lead times [72]. Therefore, lead-time improvements result from the improved response capability of production operational staff, rather than from the structural redesign of processes.

With respect to productivity, C1 technologies affect economic performance through the reduction of downtime because of real-time monitoring. Continuous monitoring of machine conditions and operational states increases the awareness of stoppages, performance losses, and anomalous behaviours. Research into digitalised production systems has shown that real-time monitoring enables operational staff to make more rapid maintenance interventions and operational adjustments thereby minimising unplanned downtime and maximising throughput [73]. Thus, productivity improvements occur because of the improved reaction speeds, and minimised losses, rather than a result of increased nominal capacity. C1 technologies contribute to equipment utilisation through both utilisation transparency and operational awareness. Continuous monitoring of the actual usage of machines, idle time, and availability increases the transparency of how equipment resources are utilised in production. Empirical evidence shows that improved visibility of utilisation enables better short-term operational decisions, such as reassigning tasks and /or adjusting schedules, leading to a higher effective utilisation of equipment without changing the physical capacity [71]. As with other economic KPIs, the causation mechanism is indirect and driven by information.

In summary, a review of the past research will reveal that C1 constitutes both an enabling and a foundational cause of the economic sustainability of Smart Sensing and Connectivity Infrastructure, through the provision of real-time transparency across quality, flow, productivity, and equipment use, creating the conditions for economic performance improvement. Nevertheless, to achieve sustained and structural improvements to the economy, C1 technologies will need to be integrated with higher-order analytical and execution-driven technologies, thus highlighting the complementary nature of the succeeding digital technology clusters.

2.4.10. Causality Between Data Intelligence and Virtual Modelling (C2) and Economic Sustainability KPIs

The implementation of C2 Digital Intelligence and Virtual Modelling technologies supports the economic sustainability of the manufacturing industry by utilising predictive analytics, virtual experiments and optimising the production system. Technologies that comprise the C2 encompass analytics, machine learning, simulation and digital twins. While the primary economic benefit of C1, have Smart Sensors and Connectivity Infrastructure, technologies is transparency, the economic implications of both Data Intelligence and Virtual Modelling technologies arise primarily through predictive processes and optimisation, which allows for wise decisions to be made before physical systems are changed. Use of C2 technologies contribute to quality through predictive quality modelling and optimising virtual processes; for instance, data analytics and machine learning can be employed to conduct predictive quality modelling through current and historical data and predict the number of acceptable quality units in different production process configurations. The manufacturing industry has also, proven the positive impact of predictive quality process modelling for managing quality proactively through optimising process variables virtually, before netting a defect, which is associated with decreased scrap and an increase in product quality [74]. Thus, there is a causal relationship between the use of predictive quality modelling versus reactive inspection as it relates to quality management processes; specifically, this relationship indicates that by using predictive quality modelling, a shift is made to actively/ systematically prevent defects within the quality management process.

The application of C2 technologies also enhances the time to market through optimising the planning and production flows of products by utilising virtual simulation technologies to support the analysis of the production and resource processes by developing and validating a digital model of a production system. By analysing and applying virtual simulation models in developing the layout of a production system, a production system can assess various layouts, scheduling options, and resource allocation based on each potential demand and capacity scenario. Evidence from studies indicates that analysing and planning to produce using virtual simulation provides key insight into eliminating any potential bottlenecks and developing more efficient flow strategies for production; therefore, manufacturers can choose a production configuration that minimises the amount of time the product sits in a waiting state, thus reducing lead time without relying on physical trials and errors [75]. Ultimately, C2 contributes to reduced lead time primarily through improving system-level (i.e. process) planning rather than incremental improvements in operations.

C2 technologies contribute to enhancing productivity by supporting the modelling of performance and optimising throughput. Performance modelling and the analysis of alternatives (e.g. batch size, routing methods, employee allocation) associated with throughput can be accomplished using virtual simulation technologies and analytical modelling. The manufacturing industry has also, shown that performance modelling through data-driven decision-making is positively related to an increase in throughput; specifically, this is accomplished through the identification of production configurations that provide maximum production and minimum loss/variance [76]. As such, C2 technologies can provide manufacturers with a mechanism to increase productivity while not incurring any additional physical capacity.

C2 technologies also enhance capacity and resource utilisation through model-based analysis of capacity and resource utilisation. For example, by using analytical and simulation-based methodologies to analyse how machines and resources are used (i.e. production model), it will support identifying under-utilisation, over-utilisation and imbalance resource utilisation across production alternatives. Studies of manufacturing systems through modelling have shown that these types of analyses are beneficial in identifying the best operational/production requirements to increase equipment utilisation and improve resource allocation to meet capacity demands [77]. In conclusion, therefore, C2 technologies improve equipment utilisation primarily from an improved planning perspective rather than through increased asset investment.

Overall, C2 causative analysis demonstrates that Data Intelligence and Virtual Modelling technologies have a demonstrated direct causative impact on the Key Performance Indices of Economic Sustainability (KPIs). By providing predictive insights, model validation and optimisation, C2 technologies enable manufacturers to enhance quality, decrease lead time, enhance throughput and enhance equipment utilisation in a proactive systematic manner. Further, the structure and duration of the C2 impact is the result of the fact that the C2 impact on manufacturer's economic performance is independently defined structurally versus those associated with technologies supporting visibility. Finally, C2 technologies are also complementary to execution-level automation technologies.

2.4.11. Causality Between Automated and Adaptive Execution Systems (C3) and Economic Sustainability KPIs

Because Automated and Adaptive Execution Systems (C3) affect how production is physically executed, they enhance economic sustainability for manufacturing. The C3 cluster consists of industrial robots, collaborative robots, and various automated execution technologies that substitute for or assist human labour at the execution level. In contrast to sensing and analytical technologies, the economic influence of C3 technologies is derived from their execution level efficiency, consistency, and stability, which influence the quality, lead time, productivity and equipment utilisation of production. C3 technologies enhance quality through consistency of execution and automated quality control. Collaborative and robotic systems minimise the variability from manual execution of tasks by providing repeatable and precise operations. Robotic automation studies show a link between execution consistency and reduced defect and scrap rates due to the reduction of human variability in processing conditions and task performance [78]. Furthermore, automated and assisted quality control systems built into robotic workstations allow for early detection and correction of quality deviations, thus improving quality performance through execution driven controls, rather than through post-process inspections. C3 technologies enhance lead time by enabling cycle time compression through automation. By eliminating manual delays and creating stable production flow, automation reduces the amount of time to process and handle; Research has shown that the use of robotic execution to replace manual handling and repetitive tasks has reduced waiting times, interruptions, and variability because of automation, and led to shorter, more predictable production lead times [79]. For example, flow stabilisation and faster execution are the causal mechanisms, as opposed to optimized planning and scheduling.

In addition to improving throughput, C3 technologies also impact economic sustainability through increasing productivity based upon human-robot collaborations through task automation. Automated execution systems enable human workers to concentrate on higher-value tasks by reallocating labour intensive, physically demanding or time-consuming tasks to robots while increasing system throughput. Research related to human-robot collaborations has demonstrated task reallocation increases output efficiency and productivity by shortening cycle times and balancing workloads between humans and robots [80]. Finally, C3 technologies enhance economic sustainability of equipment utilisation by reducing downtime and increasing the stability of automated operation. Automated systems provide a more consistent operation of machines and significantly reduce sources of variation due to the manual execution of tasks. There is evidence, for example, that the combination of automation with structured maintenance and monitoring systems reduces equipment downtime and increases machine availability; therefore, enhancing effective equipment utilisation [81]. In these cases, improvements in utilisation are attributable to the increased stability of operation rather than the increase in the installed capacity.

To summarize, C3 technologies have a direct, execution-related impact on economic sustainability performance measures (KPIs) through improving consistency, reducing cycle times, increasing throughput, and stabilising equipment operation. High-quality, lead-time, productivity, and equipment utilisation improvements can be sustained using C3 technologies; however, the extent to which they are effective economically will depend upon sound system design, task designation and the integration of complementary sensing and analytical technology.

2.4.12. Causality Between Human-Centric and Governance-Enabling Digital Systems (C4) and Economic Sustainability KPIs

C4 technologies improve economic sustainability in manufacturing by improving human operator's engagement with production systems and the way operational information is conveyed and acted upon. C4 encompasses digital work instructions, augmented and virtual reality systems, advanced human–machine interface, and operator support tools. The economic contribution of C4 is based not on the type of automation involved but rather on the indirect benefits that stem from reductions in errors, learning assistance, and increased human-machine collaboration, which in turn yield positive impact on operational performance. As it relates to the quality of manufactured goods, the positive influence of C4 is attributed to the enhanced level of accuracy achieved through reducing errors and consistently following procedures with the use of digital guides. Digital work instructions and visual guides reduce ambiguity and reliance on tacit knowledge by providing context-sensitive, standardised task instructions to the operators. Numerous empirical studies have demonstrated that the use of augmented-reality-based work instructions has resulted in significant reductions in assembly and/or process errors while improving compliance with standard operating procedures and, as a result, improving outcomes for quality and reducing defects. The primary causal mechanism of the economic impact of C4 is through improving the execution of human tasks vs. automating control of those tasks.

Regarding lead time, C4 has a positive impact on manufacturing economic performance through a combination of reduced amount of rework completed and shorter amount of time taken to complete tasks. By presenting task-related information at the point of use, digital guides facilitate an operator's understanding of how to complete a task and how to execute the task quickly thereby reducing the potential for the operator to create errors that necessitate rework. Research on the effectiveness of operator support systems demonstrates that the reduction of both execution errors and rework contributes to shortening lead times of operational activities through smoother processes with diminished disruptions and fewer correction loops. Improvements in lead time, therefore, are indirectly attributable to better execution by the operator and not due to changes in either production planning or production capacity.

With respect to productivity, C4 contributes to productivity improvements by enabling greater efficiency and quicker learning for the operator. Human-centric user interfaces effectively reduce the cognitive load required of the operator by presenting information to the operator in such a way that it is intuitive and task-specific, as well as supporting operator's development of skills through embedded guidance and feedback. In studies on human-centric manufacturing systems, the data indicate that human support tools increase both the efficiency and the productivity of the operators through faster learning and the consistency and effectiveness with which they complete their assigned tasks. The basis for productivity gains from C4 technologies is derived from improved human performance and not from having greater degrees of automation. C4 technologies improve economic sustainability for equipment utilisation through improved levels of coordination between humans and machines. By using advanced user interfaces for performing setup, providing digital guidance for equipment setup and developing an operator-centred schedule, the likelihood of an operator making an error in completing equipment setups, miscommunicating with other individuals and generating unnecessary downtime is reduced. Research associated with the Operator 4.0 concepts demonstrates that by increasing human-machine coordination, the number of operational disruptions will decrease while the operational stability of the equipment will improve; therefore, ultimately, this will result in greater effective equipment utilisation and will not require investment in physical assets.

In summary, the behavioural and organisational mechanisms that both contribute to and facilitate the economic sustainability of Human-Centric and Governance-Enabling Digital Systems have been established through the analysis of causality. C4 technologies create value from error reduction, learning support, and improved coordination that ultimately contribute to quality improvement, reduction in lead time, increased productivity, and improved equipment utilisation indirectly and in a complementary manner. Therefore, the economic benefit of using C4 technologies is directly related to the levels of user adoption, quality of the user interface and human alignment with the organisation's practices.

The causal analysis for manufacturing sustainability, based on digital technology clusters, shows that the different types of clusters–KPI relationships can be distinguished according to their level of strength or types of causality (e.g., direct cause, indirect cause, and no cause). However, while establishing a strong theoretical foundation, the current analysis does not identify how to reliably and consistently operationalise and measure manufacturing sustainability as a basis for developing and assessing sustainability measurement frameworks at the level of manufacturing systems. In the next chapter, we build on the causal structures present at the cluster–KPI level to develop a systematic research methodology to design a framework for measuring sustainability in manufacturing systems.

2.5. Interactions Between Digital Technology Clusters

The causality approach discussed in section 3.4 assessed how individual clusters of digital technologies contribute to environmental, social, and economic sustainability through different and unique mechanisms specific to each cluster. Each cluster is treated as an independent unit within the assessment framework to allow for proper attribution of sustainability impacts. However, the literature indicates that digital technology in a manufacturing system does not operate in isolation on its own. In many cases, one cluster of digital technologies can provide additional capabilities to other clusters that enable the other cluster to operate more effectively, reliably, or in an operationally relevant manner.

This section presents a limited and controlled viewpoint to examine interactions between various clusters of digital technologies. Instead of focusing on modelling hierarchical dependency or cumulative maturity, the analysis focuses on identifying how a selected cluster of digital technologies can enhance the output of another cluster without changing the way sustainability impacts are measured. The interactions described above are not included in the assessment logic or used in determining the sustainability indicators. Their role is to clarify the concept related to and provide a context in which digital sustainability impacts occur within an integrated manufacturing environment.

2.5.1. Interaction Between Smart Sensing and Connectivity Infrastructure (C1) and Data Intelligence and Virtual Modelling (C2)

Smart Sensing and Connectivity Infrastructure (C1) strengthens the outputs of Data Intelligence and Virtual Modelling technologies (C2) by improving data availability, quality, and temporal resolution. Advanced analytics, machine learning models, simulations, and digital twins generate more accurate and actionable outputs when they are supported by continuous, real-time data streams collected directly from production systems.

The smart manufacturing literature consistently highlights that the value of data-driven analytics is closely linked to the quality and granularity of input data. Without sufficient sensing and connectivity, analytical models are typically constrained to static datasets or simplified assumptions, limiting their predictive accuracy and optimization potential. The National Institute of Standards and Technology emphasises that sensing and connectivity capabilities significantly enhance the effectiveness of analytics by enabling real-time monitoring, prediction, and optimization of manufacturing processes [82]. Similarly, studies on digital twins demonstrate that virtual models deliver higher operational value when they are continuously synchronised with physical systems through sensor-based data acquisition [83].

From an interaction perspective, C1 does not directly generate the optimization or prediction outcomes attributed to C2. Instead, it amplifies the quality and reliability of C2 outputs, allowing analytical insights to more accurately reflect real production conditions. As a result, sustainability improvements associated with C2, such as energy efficiency gains or waste reduction through predictive optimization, are more pronounced when supported by advanced sensing and connectivity infrastructures.

2.5.2. Interaction Between Data Intelligence and Virtual Modelling (C2) and Automated and Adaptive Execution Systems (C3)

Data Intelligence and Virtual Modelling technologies (C2) also strengthen the outputs of Automated and Adaptive Execution Systems (C3) by providing decision logic, optimization recommendations, and predictive insights that inform execution-level actions. While execution systems can operate using predefined rules and fixed control strategies, their ability to adapt to changing conditions and achieve higher levels of performance is enhanced when analytical output guide execution decisions.

Research on smart manufacturing systems shows that analytics-driven decision support plays a central role in enabling adaptive execution. For example, predictive maintenance applications rely on analytical models to forecast equipment failures and recommend maintenance actions, thereby improving execution stability and reducing unplanned downtime [84]. Similarly, simulation and optimization models are used to evaluate alternative operating strategies and generate setpoints that guide automated execution, reducing trial-and-error and performance variability at the shop-floor level [4].

In this interaction, C2 does not perform execution activities itself, nor does it alter the physical capabilities of automated systems. Rather, it empowers C3 by transforming operational data into actionable guidance, enabling execution systems to operate in a more adaptive, efficient, and sustainability-oriented manner. Consequently, sustainability effects measured at the execution level, such as productivity improvements or scrap reduction, remain attributable to C3, while being contextually strengthened by analytical support from C2.

By clearly distinguishing causal relationships (Section 3.4) from interactions that strengthen outputs (this section), the framework maintains analytical transparency while acknowledging the systemic nature of digitalised manufacturing systems. This distinction provides a coherent transition to Chapter 4, where the research methodology and measurement design are developed based on cluster-level sustainability impact assessment.

2.6. Sustainability Measurement Approaches and Research Gaps

Attention to sustainability in manufacturing has risen substantially in the literature recently due to digital transformation and Industry 4.0 opportunities. The body of current research has taken on many forms for evaluating sustainability, such as indicators, assessment tools, and evaluation frameworks that account for environmental, social, and economic performance. Yet, this growing body of research has numerous limitations regarding the capability to accurately assess digital technology's sustainability impact on production systems.

Most of the literature on sustainability in manufacturing takes an indicator-based measurement approach that evaluates sustainability performance via a set of environmental, social, and economic Key Performance Indicators (KPIs). The use of well-established metrics, like energy consumption, emissions, productivity, occupational safety, or quality performance, is common practice within these approaches. While indicator-based methods provide comparability and transparency, they tend to aggregate sustainability performance without correlating it back to the underlying technological and operational drivers. This renders the capacity of the assessment to explain why specific digital technologies resulted in observed improvements in sustainability performance limited.

Several studies have examined the composite index/scoring construct as a method for evaluating manufacturing sustainability. Composite indices aggregate multiple indicators into one single index score of sustainability via weighting types or multi-criteria decision-making processes. Composite indices provide for benchmarking and decision support; however, composite indices routinely include arbitrary weightings and do not provide explanation for how a specific digital technology impacts each individual indicator. More recently academics have introduced the concept of a digital maturity model or readiness assessment to determine how well an organisation has adopted Industry 4.0 technologies and how their use aligns with sustainability goals. Such maturity models provide valuable information on the digitalisation of manufacturing; however, they mainly measure technology adoption rather than the impact of the technology on sustainability. Sustainability is often represented in the maturity model indirectly or at a high level by the absence of measurable operational performance indicators that have clearly identifiable causal mechanisms.

A comparatively limited but increasing corpus of literature provides causal-orientation/model-based approaches for evaluating sustainability impact using simulation and analytics methods, along with digital twin and other means of analysis. This body of work presents a greater understanding of how digital technology affects resource usage, emissions, or productivity within manufacturing with respect to specific circumstances. Nevertheless, the primary application of the model-driven method has been based primarily on one technology, at a single process level and with a focus on one scope of sustainability. The complexity of the model development process, combined with difficulties in the collection of data required, acts as significant barriers to the ability to use the model-driven method as a workable means of measuring sustainability within manufacturing businesses.

Synthesis of the results of sections 3.2-3.4 shows that several significant gaps in research can be noted. First, there is a lack of integrated assessment frameworks, which systematically associate clusters of digital technologies to sustainability KPIs across all three dimensions of the triple bottom line. Studies which have been done mostly have a focus on either digital technologies or sustainability outcomes, with relatively few looking at their interrelationship via clearly established causal pathways. Second, current measurement methodologies usually do not differentiate between the different functions of digital technologies, which may result in either double counting of effect or misattribution of impact on sustainability. Third, many proposed models lack transparency as to their operation and therefore pose challenges for practitioners with how sustainability scores are produced, and as such how to repeat assessments in real manufacturing environments.

Moreover, few studies link the causal findings to measurable tools that can be immediately applied by manufacturers. Where these tools exist, they often use qualitative assessment methodologies and/or expert judgement, thus constraining the independence and replicability of the results. As a result, there is a requirement for a structured measurement approach, which combines causal reasoning with clearly outlined cluster-specific measurement variables, in addition to quantitative or semi-quantitative indicators that are rooted in operational data. In response to these research gaps, this thesis proposes the development of a causally driven sustainability assessment framework and measurement tool for use in manufacturing systems. Informed by the clusters of digital technology, sustainability KPIs, and causal mechanisms presented in the systematic literature review, the proposed approach will provide a foundation for the research methodology discussed in the following chapter, which details the development process for the framework as well as the design of the sustainability assessment tool.

3 Research Methodology

3.1. Research Design and Approach

The research methodology for this study is an applied design-oriented research approach aimed at developing and validating a structured framework and practical assessment tool to evaluate how digital technologies support the sustainability performance of manufacturing production systems. In this study, the focus will not be on testing established hypotheses, but rather on the conceptual development, operationalisation, and empirical validation of the assessment tool and framework for use in manufacturing firms. Because the research objective is exploratory with a focus on solutions, a mixed methods methodological approach was used. The mixed-methods approach combines systematic literature reviews (SLR) with the development of the assessment tool and framework, followed by an empirical validation process. The objective of using a mixed-methods approach allows for the integration of extant scientific evidence with real-world evidence to ensure the development of both a theoretical foundation for the assessment framework and tool, as well as the practical relevance of the assessments.

The research design follows a sequential and iterative logic. The first phase of the research was to conduct a SLR to identify appropriate digital technologies being used for manufacturing production, commonly used sustainability indicators, documented causal relationships, and existing measurement methods. The findings from this phase form the basis for the theoretical foundation for developing the assessment framework, as well as the identification of research gaps that are addressed by this research.

The second phase of the research synthesised findings from the SLR to develop a conceptual framework that links clusters of digital technology, enabling mechanisms, and dimensions of sustainability performance (environmental, economic, and social) to support the development of an assessment tool. The framework provided the basis for developing the assessment tool to operationalise the identified relationships and translate them into measurable and actionable elements for use at the production level. The third phase of the research is to empirically validate the assessment framework and tool. The purpose of this phase is not to measure sustainability performance; rather to assess the relevance, clarity, and practicality of the framework and tool from an industry expert and practitioner perspective. Feedback collected during this phase will be used to improve and refine the framework and assessment tool.

Overall, the research design ensures that the progression of the research from theory to application is coherent. By combining systematic literature analysis within the structured framework development and empirical validation, the study aims to provide a solid and practically relevant contribution to the assessment of sustainability impacts enabled by digital technologies in manufacturing production systems.

Figure 3.1: Research Design and Development Process

3.2. Development of the Sustainability Assessment Framework

Developing a framework for sustainability assessments was the 2nd phase of the research process and was built upon findings of the systematic literature review discussed in Chapter 3. This phase aimed to develop a conceptual structure for understanding how digital technologies utilized in manufacturing production systems can be linked to their sustainability performance. This conceptual structure creates a foundation for the future design of measurements and tools used to assess the sustainability impacts of digital technologies.

The sustainability assessment framework was developed using a theory- informed synthesis process consisting of 3 core components identified through literature review, specifically: (1) the use of digital technology in production systems; (2) different dimensions of sustainability performance; and (3) various enabling mechanisms through which digital technology impacts sustainability outcomes. Rather than adopting existing frameworks directly, these elements were reorganised and combined to address the specific research gap identified in the literature, namely the absence of a structured and operationalizable approach for assessing the sustainability effects of digital technologies at the production level.

3.2.1. Structuring of Digital Technology Clusters

The first step in this research was to group the digital technologies from the literature into a limited number of clusters based on their primary functional role in the manufacturing production system. The clustering was used to reduce complexity, improve the clarity of analysis and facilitate a structured assessment of the technology's contribution once all technologies were considered together rather than individually.

The clustering logic was based on functional similarity and the dominant function that the technologies performed within production usage; for example, data acquisition, connectivity, analytic tools, automation and/or system integration. Grouping the technologies based on their functional contribution rather than based on how they are technically implemented results in a higher, more abstract level of assessment that can be used for evaluation in multiple manufacturing contexts and at various levels of technology maturity.

3.2.2. Definition of Sustainability Dimensions

As has been documented in previous studies on sustainability in manufacturing, sustainability within the framework is based on the triple bottom line, which consists of environmental, economic, and social aspects. The literature indicates that manufacturing sustainability performance cannot be fully assessed using only one aspect, and therefore it is necessary to balance multiple aspects of sustainability performance.

Several different aspects of sustainability were selected based on how frequently they are addressed by researchers from previous studies, as well as how feasible it would be to measure them and use them in production operations at the production or shop floor level of manufacturing. The result of this was to create a theoretical framework that is also applicable in practice and has concepts related to sustainability that are too abstract to practically measure anywhere in manufacturing operations.

3.2.3. Identification of Enabling Mechanisms

The framework establishes a structure linking Digital Technology Clusters and Sustainability dimensions (i.e., Economic, Environmental and Social) via an intermediate layer of Enabler Mechanisms. Enabler Mechanisms provide the functional pathways through which Digital Technologies affect production processes and ultimately Sustainability Performance (e.g., in terms of improved Sustainability outcomes). Examples of such Enabler Mechanisms include Real-Time Visibility, Enhanced Transparency, Predictability, Process Automation, and Decision Support.

The two methodological purposes of including Enabler Mechanisms are as follows. First, it allows for a clear causal chain linking Technology Adoption to Sustainability Outcomes thereby addressing limitations associated with purely correlational approaches identified in the literature. Second, it facilitates differentiation between the various types of sustainability contributions provided by different Digital Technology Clusters, which is critical for developing an appropriate measurement design and operationalizing those measurements.

3.2.4. Framework Integration

The comprehensive sustainability evaluation framework brings all elements of digital technology cluster, enabling mechanism and sustainability dimension into one congruent conceptual structure. Digital technology clusters through enabling mechanism would have an indirect impact on sustainability performance, as opposed to having a direct/undifferentiated impact. Layered logic is used to provide the foundation to identify specific causal relationships, this way any sustainability impact attributable to any type of technology is done in a constant and analytically valid way.

It is important to note that the framework was developed as a conceptual framework, as opposed to a measuring framework, therefore at this time detailed sustainability indicators, measuring variables, and data sources will not be specified as they require further methodology considerations and will be addressed in the next phase of measurement and operationalisation of the framework.

3.3. Measurement Design

The Sustainability Assessment Framework establishes a conceptual model that identifies relationships between digital technology clusters, enabling mechanisms, and sustainability dimensions but does not provide measurable and operational elements to assess the relationships established in the framework. Therefore, it is necessary to conduct an additional methodological step that would result in the identification of measurement design and operationalisation which would define how sustainability effect can be assessed consistently and realistically at the production level. Operationalising the cluster-sustainability relationship focuses on converting the conceptualised causal pathways into measurement variables, measurement types, data sources, and calculation methods. Operational definitions of these variables form the analytical foundation of the Sustainability Assessment Tool discussed in Chapter 5.

Structured pairwise analyses between the digital technology clusters and sustainability performance indicators will be used for measurement design. Each technology cluster-sustainability KPI relationship will be examined individually to determine if a valid and reliable causal connection exists, rather than assuming that all KPI's are equally influenced by all clusters.

A guiding principle for this process is the notion of locked causality. Each cluster-KPI will have a dominant enabling mechanism that has been defined through a review of the literature to represent the primary pathway for which the clusters impact the KPI. Measurement variables are defined to measure this specific mechanism rather than aggregate or downstream sustainability impacts so that the cluster contribution is measured independently for each cluster/KPI relationship.

Operationalisation only occurs where there is a clear and identifiable direct causal relationship established between the technology cluster and KPI of interest. Therefore, if literature does not provide sufficient evidence of a direct causal pathway between the cluster and the KPI of interest, then the KPI will not be operationalised for that cluster. This exclusion facilitates analytical validity and avoids the forced or speculative quantification of the sustainability impact.

3.3.1. Definition of Measurement Variables

Clusters and related KPIs were defined with respect to each valid cluster-KPI pair to establish the measurement variable corresponding to the causal mechanism that had been established for that cluster. The measurement variables were established in such a way as to highlight the subjectivity of the immediate functional relationship between the given cluster and technology, rather than just the final sustainability performance outcome and/or the potential impact of other technology/organisational factors on such outcomes. Specific criteria were used in defining the measurement variables. First, the measurement variable must be mechanism oriented such that it reflects at least in part the enabling mechanism of the cluster being studied. Second, the measurement variable must relate specifically to that cluster, meaning it is a specific contribution that cannot be attributed in any other cluster in the entirety of the framework that is study. Finally, the measurement variable must be capable of being operationalised in a typical manufacturing production environment such that the necessary data can be collected for the performance measure to be completed.

To illustrate how this operationalisation process occurs relative to all clusters and environmental sustainability indicators, Appendix B presents a typical measurement design for one specific cluster of technologies and a selection of environmental sustainability indicators. The table indicates how the causal mechanisms were defined; how the cluster-specific measurement variables were defined; and whether the sustainability indicators were included or excluded from the cluster-specific measurement variable based on the degree to which the causal relationship was established. This same systematic approach was applied to all clusters and environmental sustainability indicators. The entire set of measurement design tables is included in the sustainability assessment tool and is presented in Chapter 5.

3.3.2. Measurement Types and Data Sources

As a result of the complexity of sustainability indicators and the limitations of data availability in manufacturing, the assessment tool will use various methods of measurement. Measurement variables will be classified into direct quantitative, semi-quantitative, and qualitative based on the type of indicator and the degree of feasibility for data collection.

Direct quantitative measurements will include ratio, count, or time-based data pulled from MES, EMS, and sensors. Semi-quantitative or qualitative measurements will be used when a direct measurement is infeasible (such as where indicators relate to either organizational practice or social aspects of sustainability).

To promote practical use of the assessment tool, measurement variables will be tied directly to realistic data sources typically present in manufacturing, such as shopfloor sensors, monitoring systems, operational databases, and expert evaluations if needed. This will allow the tool to function at varying levels of digital maturity without necessitating full automation or sophisticated data infrastructures.

3.3.3. Measurement Methods and Definitions

Each measurement variable has been paired with a measurement method to provide consistency and comparability between applications. Measurement methods will describe how the raw data are converted into indicator values using ratios, count data, time to event, or total change per product and using before and after comparisons. Measurement methods are defined and present operational definitions which clarify measurement context (i.e., non-normally distributed variables) and the normalization basis for each variable. For example, where applicable, the normalized variables will be defined as such (e.g., "per unit", "per batch", etc.), thereby reducing the impact of changes in production volume and/or changes in product mix on the measurement method and variables.

The tool is designed to use companies as baseline examples of operational history through operating monitoring systems. As such, all participating organizations will have utilized the appropriate systems to establish the baseline (the normal operation) of relevant variables. When the conditions that exist prior to a company creating the new operational baseline or production mix or process conditions are no longer valid and have deviated; then the deviation from the historical baseline is an abnormal event when referenced against their historical baseline of the establishment of their normal operation, as opposed to referencing from absolute threshold values.

Temporal components of the measurement method and duration for data aggregation intervals will provide certainty to how the measurements will be calculated based on real-time data (e.g., time to detection of event; or time to event) or based on periodic measurements for variables associated with process, automation or human-centred interventions.

Lastly, where a direct measurement will not be possible for the measured variable, proxy measurements or derived estimates will continue to be utilized based on the operations of that measure and, therefore, will have the necessary degree of transparency related to how the data will be used in each case. By having transparent measurement methods, normalization rationale for the measurement methodology and duration for each variable will aid in the reduction of any ambiguity in the interpretation of the measurement data and, therefore, support repeated, transparent, and contextually relevant evaluations of sustainability effects associated with digital technologies.

3.4. Empirical Validation Design

The goal of the empirical validation phase of the sustainability assessment framework is not to confirm the outcome of the assessment of sustainability performance, or to empirically validate the causal relationship with other variables; rather, it is to explore the conceptual soundness, understandability and usability of the framework and instrument when used in manufacturing production contexts.

Design Science Research provides a framework for validating artefacts considering their ability to solve the problems for which they were designed and assist with making decisions within real world contexts. An early form of this validation typically includes the use of expert opinion to assess the relevance, completeness, and usability of newly developed frameworks and instruments prior to their widespread empirical testing [85].

The empirical validation of the sustainability assessment framework was designed to provide qualitative expert-based evaluations, providing in-depth feedback regarding the structure of the framework, the logic of the measurement design, and the interpretability of the assessment tool. An expert-based validation is particularly appropriate for analytical tools intended to support decision-making at both the managerial and operational levels in complex socio-technical systems (e.g., manufacturing production environments) [86].

3.4.1. Validation Objective

Five evaluation objectives from recognised criteria for assessing design artefacts and decision-support systems defined the empirical validation phase. To evaluate the relevance of the proposed framework the first evaluation assessed if the selected digital technology clusters, sustainability dimensions and measurement variables capture the sustainability issues that are relevant and significant for manufacturing production systems. Relevance is a critical evaluation criterion in design science research; artefacts must provide value by addressing a real important problem [85].

The second evaluation assessed the completeness of the framework to determine if its contents accurately capture the essential components necessary to evaluate the sustainability effects of digital technologies, omitting no dimensions, mechanisms or perspectives. For sustainability assessment frameworks completeness is essential, since they evaluate multi-dimensional interrelated phenomena [87].

The third evaluation assessed the framework and assessment tool for clarity and comprehensibility by determining the extent to which the causal logic linking digital technology clusters, sustainability KPIs and measurement variables is comprehensible, and the extent to which the effect measurement methodology based on both relative percentage change and threshold-based classification enables practitioners to interpret the results transparently. Clarity is generally accepted as being a necessary precondition for the effective use and adaptation of analytical artefacts in practice [86].

Feasibility is the fourth parameter evaluated. Feasibility refers to the extent to which the data requirements, measurement methods and monthly assessment workflow required for using the framework and associated assessment tool are viewed as realistic and achievable within normal manufacturing environments. Feasibility is a primary issue in sustainability assessment research since tools are often not used in practice due to excessive complexity or data intensity, regardless of their strong conceptual basis, [87].

The final evaluation assessed the practical usefulness of the assessment tool by determining the extent to which the outputs generated are viewed as being helpful for internal reflection and decision-making regarding digital technologies and sustainability. Practical usefulness, indicates the extent to which an artefact satisfies its intended purpose as a decision-support tool, as opposed to being merely descriptive or analytical in nature [86].

The above five evaluation objectives provide a comprehensive evaluation of the framework and its assessment tool, ensuring that both are evaluated not only for internal consistency, but also for their suitability to be applied in real manufacturing environments.

3.4.2. Validation Method and Participant Selection

To confirm the evidence was true to reality, semi-structured interviews were performed with professionals in the industry with practical experience in areas related to manufacturing production systems, digital transformation initiatives, and/or sustainability. Semi-structured interviews have long proven effective for evaluating artefacts because they provide enough structure for all interviews to follow same pattern, while also providing room for respondents to elaborate on contextual information relevant to their situation [88]. Purposeful sampling was used to select participants and ensure that each participant had enough relevant expertise to be able to give critical feedback on both/each: the proposed framework and the assessment tool. To be included in the sample, respondents were required to be working in a professional capacity in the areas of production management, digital transformation, industrial analytics, and/or operations management, with an emphasis on experience within manufacturing organisations. The method of sampling used here is consistent with qualitative, design-oriented validation methods. The validation intention is not to produce statistically representative results from all expert respondents; the intention is to gather informed judgement from experts in a domain that would allow for critical analysis of the proposed framework and assessment tool [88].

3.4.3. Validation Procedure and Evaluation Criteria

During the validation process, the sustainability assessment framework and the assessment tool underlying it were explained to all participants. Participants were informed of the following components of the assessment tool; the digital technology clusters, sustainability KPIs, the causality logic, measurement variables and the effect measurement approach (percentage change using a 'before and after' comparison), a threshold-based classification system and a monthly assessment period. Interviews followed a predetermined structure of questions that addressed the overall evaluation criteria of relevance, completeness, clarity, feasibility and practical usefulness of the sustainability assessment framework. Participants were asked to indicate whether they believed the assessment framework represented, clearly presented and logically presented their organisation's sustainability impacts of digital technologies used in production, if they thought the measurement logic modelled was easily understandable and internally consistent, and whether there were realistic opportunities for the proposed assessment workflow process to be implemented through their organisation's operating environment. Qualitative analysis of the feedback provided allowed for the identification of themes and important observations across the collected data. The information obtained through the validation process was used to fine-tune both the sustainability assessment framework and assessment tool; the final product is documented, presented and discussed in Chapter 6. The results of the validation process in respect to the sustainability assessment framework and assessment tool are ultimately intended to be used to assess and improve the design quality of the two artefacts and not for conclusions about the sustainability performance of digital technologies within the scope of the study.

4 Proposed Framework for Sustainability Assessment Tool

4.1. Conceptual Framework Structure

The present section outlines the conceptual framework for a sustainable assessment framework. This framework establishes the analytical framework used to connect, in a systematic manner, the digital technologies implemented in manufacturing production systems and the resulting measurable sustainable consequences. In addition, this framework defines the structural logic of the sustainability assessment framework before it is operationalised into the sustainability assessment tool. The conceptual framework for the sustainability assessment framework is designed according to three central design principles. First, the digital technologies used in manufacturing are designed according to how they function to perform a certain role within the production system rather than according to their different levels of technological sophistication. Second, all sustainability consequences resulting from these technologies are determined using specified and defensible causal mechanisms. Third, only producing level impacts will be measured and composite sustainability scores, continuing to measure based on levels of maturity, will not be the basis of measurement.

There are four functional categories of digital technologies used in the manufacturing area: Monitoring & Visibility, Analytics & Prediction, Automation and Cyber Physical Execution, and Human Centred Digital Technologies. The basis for grouping digital technologies in this manner is to classify the primary operational contribution of each group of technologies to the production system. For example, Monitoring & Visibility technologies provide transparency into the flow of resources and the status of processes in real-time. Analytics & Prediction technologies use data to optimise performance and use predictive models to support decision making. Automation & Cyber Physical technologies translate digital intelligence into actual physical output, in addition to stabilising processes. Human Centred Digital Technologies provide operators with enhanced training and support in their interactions with digital technologies. The grouping of these digital technologies does not imply a hierarchy of technological advancement or technology maturity but is designed to segregate the various functions of the digital technologies and avoid confusion regarding the operational definition of each sustainable consequence. It is recognised that some functions may support or reinforce each other, such as the monitoring/visibility technologies providing the data needed for predictive analytics; therefore, each sustainable impact is measured based on the primary cause of the sustainability impact.

The sustainability perspective for the sustainable assessment framework is provided by the triple bottom line framework: environmental, economic, and social. However, sustainability impacts measured in the sustainable assessment framework will only include the impacts that can be observed at the production-level. This limitation will ensure that all indicators of measurement will be directly linked to manufacturing processes and will be operationally based. KPI selection was based on measurable, relevant to production, and with a defensible cause and effect relationship to the digital enabled technologies. The digital technologies designed to be used in manufactured goods will not, due to their existence, make all indicators of sustainability better. Instead, only the KPI relationships that can be explained through valid cause and effect relationships will be used to develop the sustainability assessment.

The framework's conceptual core is based on its Logic of Mapping Causality. Sustainability effects are not directly attributed to digital technologies themselves but rather to the enabling operational mechanisms provided by digital technologies. The analytical structure uses a layered logic where a digital technology cluster is used to activate a specific enabling mechanism that has an impact on a defined sustainability KPI. This structured causality prevents speculative/narrative-based sustainability claims from being made and requires conceptual justification for every relationship measured. Where the literature did not provide sufficient evidence or expert validation to identify a strong mechanism, the relationship was purposely excluded from the framework. Another defining attribute of the conceptual structure is that it avoids the use of composite sustainability indices to assess sustainability performance. Environmental, economic and social indicators are treated as separate and non-commensurable, meaning that they cannot be aggregated into one score without using normative weighting assumptions and thereby reducing the transparent nature of causal attribution. By evaluating sustainability effects separately at the KPI and cluster levels, the framework preserves the ability to interpret the results. The outcome is not a consolidated sustainability score, but rather a structured profile of effects which clearly shows where impacts are measurable and where they are not. The framework provides a coherent analytical foundation for quantifying the sustainability impacts of digitalisation on manufacturing systems by integrating functional technology clustering, production-level sustainability structuring and explicit causal theory. It changes the evaluation of digital sustainability from narratives based on assumptions to structured and measurable analytical models. The remaining sections of this document will operationalise this conceptual structure into the Sustainability Assessment Tool, providing baseline logic, effect calculation procedures and a practical workflow for application.

4.2. Operationalisation of the Sustainability Assessment Tool

Based on the conceptual framework outlined earlier, the sustainability evaluation instrument seeks to operationalize the conceptual structure by translating the causal-derived frame. Tool will allow users to measure the effects of digital technologies on sustainability at the manufacturer's operational level and will enable them to understand how these technologies are affecting their production operations. To achieve this end, the operationalization process will exemplify a central methodological criterion: All key performance indicators (KPI) must have a baseline determined before any evaluation of performance effects can be made.

The baseline is the value of the KPI against which the post-implementation performance will be compared; thus, the before-and-after logic used for the evaluation is being implemented consistently and uniformly by being structured into defined evaluation windows and based upon aggregated data collected over a period. The operationalization of the KPI within each of the clusters of the framework will use measurement variables defined at the causal mechanism level within the model; thus, these measurement variables will allow the causation of change (through observable measures) in production to be converted to the metrics (KPIs) defined within the framework.

The frequency of measurement for the KPI's has been determined to be monthly; this measurement frequency provides a sufficient level of detail to provide accurate measurement of change or improvement, while at the same time being practical for manufacturing environments to collect such data. While there are many other possible measurement frequencies for KPI's (e.g., weekly) it was determined that monthly would provide a sufficient level of measurement granularity without excessive fluctuations in data. KPI's to be measured will be established based on a continuous period of pre-implementation measurements of these KPI's in a stable operating condition; for valid baselines, pre-implementation measurements must be made for a minimum of three months.

However, to increase the validity of the reference level, baselines should be measured for six months; the average of the KPI values during the baseline period will then serve as the reference performance level for all future evaluations. Any significant operational disturbances that occur during the baseline period must also be documented to maintain their meaning during the implementation period as well.

Once the digital solution is implemented by the manufacturer, there will be a short transition or stabilization period (normally one to two months) that will not be utilized for the evaluation of effect due to the difficulty of measuring and defining effects and the presence of adaptation issues, learning curves, or temporary operational instability. After the stabilization of the digital solution, measuring will continue using the same measurement definition criteria used prior to implementation. All definitions will be kept constant to ensure comparisons between the periods before implementation and after implementation can be achieved consistently.

The monitoring system also requires the recording of product mix data (i.e. product share of each product produced in each period) as an additional means of control to help reduce the effects of structural variances in product mix on the KPIs. Where applicable, mix-adjusted expected values will be generated to ensure that changes in KPIs that are observed can be properly attributed to changes in production structure rather than merely arising from shifts in product structure. The mix adjustment does not change the underlying principle; it improves the integrity of the attribution of effect. To evaluate an effect, it is necessary to compare the average level of KPI performance observed during the defined post-implementation window with the established average level of KPI performance for the corresponding baseline period. The post-implementation evaluation window typically is 3 to 6 months in length, following the completion of stabilisation. The sustainability effect is the relative change between the post period average KPI performance and the baseline average KPI performance:

Whether an indicator suggests improvement or not will be based on how it is defined by KPI. If the KPI indicates that reducing something will help with sustainability (energy intensity, scrap rate, receiving and response), a reduction means a positive effect. If an indicator has a higher number meaning more sustainability (coverage rates, training), then a positive or negative translates back as an opposite. To ascertain how well the KPI is working will use pre-determined categories for the observed effect that values the size of the effect found in a way that does not create a composite score or provide a normed weighting system. The use of trend analysis should also be utilized to assist in providing an understanding of how the KPI performs. Ongoing tracking of actual KPI values, monthly, will help organizations to understand how KPI has evolved over time and whether improvement(s) are continuing. However, trend only captures one component of measuring sustainable impacts; sustainability impacts can only be formally measured through baseline averages versus post-implementation averages. Thus, operationally establishing baseline and maintaining consistency, controlling for variations in structure, and applying a transparent approach to determining effect, then all these elements (baseline establishment, keeping consistency measurement, controlling for structure)/ (assessing sustainable effects of production by utilizing digital content) will help you measure the sustainability of your organization. Details regarding evaluation logic and controls for robustness in evaluative process will be discussed in the next section.

4.3. Sustainability Effect Calculation and Robustness Controls

This Section defines the analytical mechanisms by which the sustainability impacts will be measured and validated using the assessment tool that will be used to quantify sustainability impacts (the Tool). In Section 5.2, operational requirements for the collection of data and establishing baselines were defined. This Section defines the way measurable changes to the performance will be assessed as sustainability impacts and ensures that there is a clear chain of attribution demonstrating the validity of sustainability impact. To establish the performance of an organisation prior to the digital intervention for purposes of measuring sustainability impact, organisation's historical performance will be evaluated against the post-implementation performance within a defined evaluation time frame using a structured comparison method. Specifically, sustainability impact will not be calculated based upon the variability of an organisation's performance in isolated months, but instead on aggregated averages that are calculated over stable time periods. This will decrease the amount of variability in calculating sustainability impact attributable to the digital intervention due to short term fluctuations in organisation's capacity to provide services.

After the completion of stabilising the organisation's performance, the post-implementation evaluation time frame will be established such that it occurs three to six months after the date of implementation of the digital intervention. During that evaluation time, the arithmetic mean of the values for each KPI will provide the estimated value for the post-implementation performance of the organisation. A sustainability impact will then be calculated by establishing the relative difference between the average of the post-implementation performance and the average of the pre-implementation performance for the same KPI. The relative change between the averages will provide the amount of improvement or deterioration in performance that can be attributed to the digital intervention and that occurred within the pre-defined boundaries. The direction of relative change will be evaluated based upon the nature of the KPI. For KPIs where lower values represent better performance with respect to sustainability (i.e., energy intensity, scrap rate, defects per unit, response time), a negative relative change will represent a corresponding positive sustainability impact. Conversely, for KPIs where higher values are representative of improved sustainability performance (i.e., coverage ratios, percentage of preventive actions, percentage of employees receiving training), a positive relative change will represent a corresponding positive sustainability impact. Each sustainability impact that is produced will be classified into pre-defined categories of negligible, moderate or strong sustainability impacts. This will help provide structure to the evaluation process without creating composite index measures. Since sustainability impacts will be calculated based on the current performance of organisations, organisations will not be compared against one another, nor will different/mixed KPIs be combined in providing a single measure of sustainability performance. In addition to directly measuring sustainability impacts, the Tool has controls that provide assurance as to the validity of the attributions of sustainability impacts. Because sustainability performance may be differentiated due to structural changes/events in manufacturing environments that are not attributable to digital interventions, there are three significant control mechanisms embedded within the evaluation process.

In the first step of verification, changes in the product mix are monitored. Any changes in the composition of the product from baseline to post-implementation period require an adjustment to ensure that changes in KPI measured performance reflect something other than the change in the structure of production, thus creating causal consistency with the original baseline comparison logic without changing the core logic of the analysis. Adjustments to production mix to make dynamics consistent creates additional miles for interpreting results in results influenced by cyclical demand or environmental variability. Use of rolling years of data or year-to-year comparisons of results may also aid in verifying observed improvements are not caused by the reliability of repeated seasonal events. Finally, parallel operating changes are similarly documented, if other major changes to processes, organisation restructuring or additional initiatives for improvement take place within the evaluation period that should be considered to mitigate the attribution of sustainability due only the digital intervention.

On completion of each verification step a qualitative confidence level is assigned to each evaluated effect (typically as high, medium or low). The confidence classification does not affect the calculated magnitude of the effect but provides context for understanding the reliability of attributing such effect. This creates analytical honesty but does recognise the complexity that is presented with multiple real production systems. The use of trend monitoring does not replace formal evaluation of effects. Monthly visualisations of actual results serve as continuous transparency from a production perspective so organisations can verify they are maintaining improved performance. Formal quantification of sustainability effects by this framework are only provided through structured comparisons of the baseline and post-implementation averages of effects. By following this evaluation logic, the tool provides a balance between analytical rigor and practical usefulness. It provides an open, consistent manner to quantify sustainability effects while providing safeguards against misrepresentations and over-attribution of effects. The next section will define how the tool will be structured as part of the implementation process in an operational environment.

4.4. Tool Structure and Application Workflow

The following section describes the practical implementation of the proposed sustainability assessment through the establishment of an operational assessment tool. Previous sections have defined the conceptual logic and analytical procedures; however, this section outlines how those conceptual and analytical elements are structured and applied to be of use to manufacturing organisations. The sustainability assessment tool is implemented in the form of a structured system based on spreadsheets. This spreadsheet-based system has been designed to provide transparency of the assessment, replicability of the assessment and practical usability of the assessment within a production environment. Three elements have driven the decision to implement the sustainability assessment using spreadsheets. The first reason for this selection is that manufacturing organisations use spreadsheet-based systems for their operational reporting, so the implementation can be performed without additional software. The second reason is that implementing the assessment using spreadsheets provides complete transparency regarding the calculation methods used within the sustainability assessment. Finally, the modularity of the spreadsheet system will permit adaptation to various production environments, without modification to the underlying principles of evaluation. The operational assessment will utilise a sequential workflow that aligns with the methodology described in Sections 5.2 and 5.3. The operational assessment process begins with the definition of the scope of the assessment. The organisation will identify the digital initiative(s) to be assessed, define the production boundary for their assessment (i.e. plant, line, product family), and select the appropriate sustainability key performance indicators (KPIs) from the predefined framework structure. The frequency of measurement will also be established, with a default frequency of monthly data collection.

After scope definition, the organisation will then enter the historical data for KPI indicators into the tool's baseline section, creating a baseline assessment of the selected KPIs through the collection of data for at least a three-month period (with the ideal collection period being six months when possible). As organisation's collect information related to their production mix and performance for the respective KPIs, they will enter that information into the tool the same way they did during the baseline assessment portion. The baseline average values of the selected KPIs will establish a reference point for the duration of the assessment cycle. After the organisation has collected the baseline performance data and implemented their digital initiative, they will continue monthly entry of their KPI performance data using the same definitions and processes used during the baseline assessment. A transition period will be defined using the tool to exclude the effects of early stabilisation from the formal assessment. Following the stabilisation period, the tool will automatically generate an aggregate of the selected post-implementation evaluation period and determine the relative percentage effect for each KPI based on the calculation formula defined in Section 5.3.

The internal structure of the tool has been designed so that the individual components (scope & parameter, data entry, calculation, and reporting) can be segmented away from other components to allow for logical coherence. Each of the components of the tool shall serve distinct functional purposes as follows: (1) the scope & parameter component will define the intended boundaries for the project, the length of the evaluation window and the period for the establishment of baseline data; (2) the data entry component will record the monthly values for the KPIs and production mix data; (3) the calculation component will calculate the assessed average KPIs, determine their relative change, classify the changes according to thresholds and establish positive or negative directional indicators; and (4) the reporting component will report sustainability effects by KPI and digital cluster through the use of tables and graphs that preserve transparency by not aggregating heterogeneous indicators into one composite score.

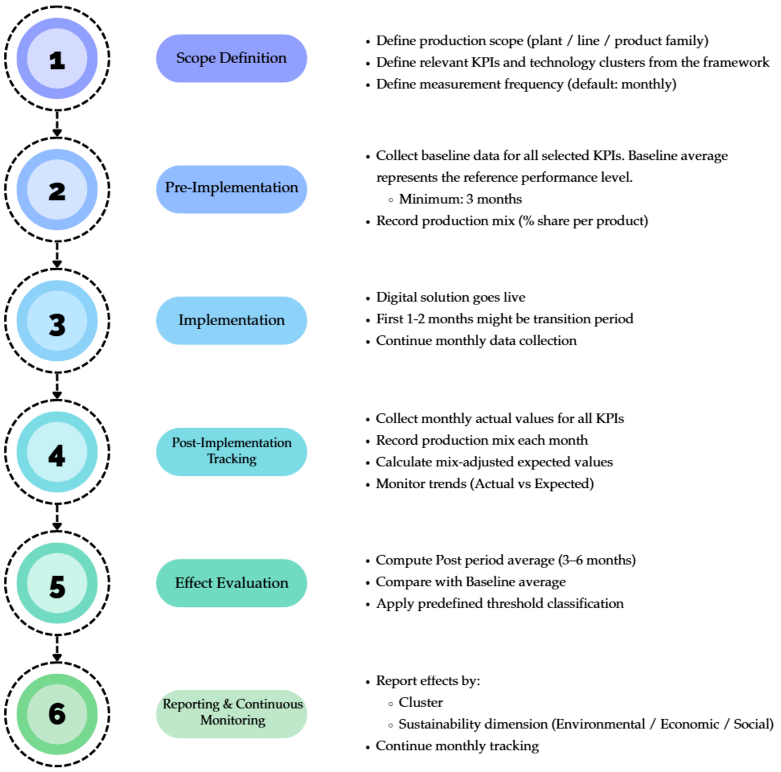

Figure 4.1: Assessment Tool Structure

The application workflow for the sustainability assessment tool follows a linear and systematic approach to its implementation. The scope and KPIs are defined by the organisation, before establishing baseline (or initial) performance data, then measuring actual performance each month for a specific post-implementation period and finally evaluating sustainability impacts at the end of the post-implementation period. Evaluation of actual performance also includes robust checks and confidence assignments, however, does not change the method for calculating performance before the implementation phase. Importantly, the tool does not serve as a benchmark or maturity model or performance rating tool. Therefore, it does not provide comparisons of organisations across different contexts, nor does it create weighted sustainability indexes. The sole purpose of the tool is to measure actual realised (or physical) sustainability impacts within a defined boundary of production, using a causation-driven and baseline-derived method of calculating actual performance impacts. In so doing, the tool takes the sustainability conceptual framework and translates it into a physical artefact that provides support for an evidence-based assessment of digital sustainability impacts for manufacturing systems. By combining methodical rigour with the practical feasibility of use, the tool provides organisations with the means to go beyond just descriptive statements and begin to do actual measurements of sustainability impact.

5 Empirical Findings and Discussion

5.1. Validation Outcomes

5.1.1. Overview of the Expert Panel and Validation Procedure

To empirically validate the proposed sustainability assessment framework and tool, semi-structured interviews were conducted with practitioner professionals in digitally enabled manufacturing environments. The expert respondents included plant leaders, prior and present production managers, operational excellence specialists, sustainability executives, and professionals in organisational development from large-scale industrial companies. Their expertise covers automation-intensive production systems, analysis-based optimisation initiatives, sustainability governance systems, and workforce capability development programs.

The variety of experts' expertise provided possible evaluations of the sustainability assessment framework through multiple complementing perspectives of shopfloor execution, digital infrastructure, sustainability, and human-centred organisational transformation. The purpose of the evaluation phase was to evaluate the developed framework artefact's conceptual robustness, internal coherence, and practical implement ability rather than empirical assessments of sustainability.

The semi-structured interview process used a structured interview protocol based upon the five defined evaluation criteria from Chapter 4 (relevance, completeness, clarity, feasibility, and practical usefulness). Experts were exposed to the framework's structure, including the four clusters of digital technologies, sustainability KPI architecture for environmental, economic and social dimensions, causal logic of the framework (technology → mechanism → KPI), cross-cluster enablement relationships, and relative change thresholds for before and after measurements.

For methodological transparency and replicability, the entire interview guide, individual evaluation questions, and related supporting documents for each expert participating in the validation process are provided in the Appendices. Thus, there is traceability between the evaluation design of the framework and the synthesised findings reported below.

Insights gained from participating experts were analysed through a thematic cross-expert synthesising methodology. Feedback was aggregated amongst expert opinions based upon the previously identified evaluation criteria rather than being reported in the order they were provided. Thus, converging evaluations, common challenges, and suggestions for improvements regarding the framework's design and utilisation were able to be established.

5.1.2. Relevance

Across all interviews, the overall architecture of the framework was constantly assessed as highly relevant to manufacturing production systems. The experts made the conclusion that the four digital technology clusters reflect the functional layering through which digitalisation unfolds in the industrial environment. The division between Monitoring and Visibility (Cluster 1) and Analytics and Prediction (Cluster 2) was operationally realistic. Data generation and data intelligence are often implemented in different stages, managed by different organisational units, and at different maturity levels, experts emphasised. Therefore, the framework's explicit distinction of these layers was perceived as production-reality-accurate. At the same time, experts cautioned that organisational actors frequently use umbrella terms such as analytics or digital solution.

Therefore, they suggested that the framework be reinforced with more explicit classification guidance to ensure that technologies are assigned to clusters based on their dominant causal mechanism, rather than system names. Enhancements included boundary examples and clarifying notes on what belongs to none of the clusters. The recommendations do not attack the conceptual structure but specify a need to improve operational reliability. Regarding sustainability KPIs, experts widely agreed that the selected environmental, economic, and social indicators capture aspects genuinely influenced by digital technologies at production level. The emphasis on operationally measurable outcomes, including energy consumptions, reduction in wastes, scrap, downtime, incidents of safety, ergonomics, and usage of digital work instructions, was considered justified and defensible. Avoiding corporate-level ESG metrics or loosely attributable sustainability KPIs was identified as a strength for guaranteeing credibility and causal integrity. Some experts observed that digital technologies can affect longer-term organisational learning, cultural changes, and work between different organisational functions.

Nonetheless, they concluded that it was impossible to isolate such effects within a before-after production logic. Therefore, the exclusion digital technologies' impact on longer-term organisational learning, cultural changes, and inter-functional organisational learning was a justified methodological boundary rather than a conceptual omission. However, it was suggested that the framework should make it clear that lack of measurement does not mean lack of value, particularly for human-centred technologies whose impacts may be measured across longer time horizons.

5.1.3. Completeness

Assessment of completeness entailed determining whether the framework can cover the relevant dimensions of digitalisation and sustainability in the context of the scope. The experts confirmed that the four-cluster structure can represent the operational technologies deployed on the shopfloor as well as the supporting digital systems that enable monitoring, analytics, automation, and human interaction.

The inclusion of enablement relationships between clusters was accurately validated as real DT pathways, whereby visibility conditioning analytics effectiveness, which, in turn, conditions and enables higher automation. Importantly, no expert suggested the addition of more clusters or sustainability main dimensions. On the contrary, it was argued that expanding the structure would risk unnecessary complexity and weaken the usability without improving the explanatory power. The existing scope was lastly seen to be balanced as it was wide enough to reflect meaningful digital sustainability interrelations but narrow enough to maintain causal clarity.

However, there were certain sustainability effects identified by experts that are real but fall outside the measurement boundaries of the framework. These include improvement in engineering problem-solving capability, speeding up root-cause analysis and organisational learning. Rather than proposing structural expansion, the experts recommended referencing these as unmeasured second round effects under the guidance of interpretation. However, this recommendation is not meant to compromise methodological rigour in assessing the outputs of the tool.

5.1.4. Clarity

The experts found that the conceptual framework's definitions and causal logic were clear and correctly organized. A common strength among these experts was the ability to successfully map the clusters of digital technologies to KPI's that relate to sustainable development through panels that specified the connections between these clusters and their respective KPI's. The expert commented on how they appreciated the thoughtful exclusion of clusters with weak relationships to KPI's as well as how the use of non-speculative references to sustainability was accomplished.

Several challenges were identified regarding the clarity of the operational elements of this work. The greatest area of concern raised by the experts was the potential for misclassification between the elements of Cluster 1 (Monitoring and Visibility) and Cluster 2 (Analytics and Prediction). Dashboards that have been enhanced with embedded alerts indicating threshold violations could potentially be labelled as "analytics" even though their primary function continues to be observance. Similarly, integrated MES capabilities could lead to confusion about separation of clusters if their classification is based upon vendor terminology instead of functional contributions.

A second area of boundary sensitivity discussed by the experts was that between Cluster 3 (Automation) and Cluster 4 (Human-Centric Technologies). High interest was exhibited within this discussion regarding robots that have been designed to assist employees in lifting by improving the ergonomics of the process. Experts emphasised that classification to a cluster should be based upon the prevailing sustainability mechanism, process control versus employee assistance, rather than technology. All experts agreed that several conditions must be satisfied to reduce uncertainty in classification of technology. Experts suggested enhancements to include more explicit operational safeguards such as, but not limited to, the use of short rules for decision making, examples of borderline case classifications, and identification of "what this cluster is not." Proposed improvements are targeted to help ensure each stakeholder (HR, Sustainability, IT, and Production) can consistently interpret classifications. Experts cautioned against the occurrence of post-hoc attribution bias. Experts expressed concern that improvements in KPI's after the introduction of digital technology will be mistakenly attributed to the technology itself unless all other factors, such as a change in production mix, shifts in staffing patterns and/or other related improvement initiatives, are thoroughly controlled. Therefore, all experts supported the incorporation of the contextual review tool embedded in the framework to be used as a rigid requirement rather than a procedural formality.

5.1.5. Feasibility

Experts largely agree, from a feasibility viewpoint, that most necessary operational data is accessible to most medium-to-large manufacturing firms (i.e. energy consumption, scrap rate, downtime, and incidents resulting in injury). However, data availability does not mean that they can be easily accessed or retrieved in a structured manner. Common feasibility challenges associated with operational data include the fragmentation of data ownership across functional boundaries, inconsistent baseline historical data, and limited structure surrounding social sustainability indicators. In some situations, companies may need to create their own unique metrics to assess metrics that have not traditionally been used in normal reporting.

Experts indicated that this further complicates the initial implementation of these tools by adding an additional workload. Experts did not advocate typification for measurement; however, they emphasized the need for analytical discipline to properly assess sustainable outcomes. Experts encouraged that an explicit governance framework be generated for the appropriate use of the tool, including cross functionally successful coordination among departments, clear assignment of data ownership, as well as obtaining appropriate support from ultimate authority.

Most experts believe that the monthly frequency of assessment would be appropriate, as increasing frequency would produce too much operational variation, and less frequency may make it more difficult to establish causal attribution. Experts also stressed that this tool should not be viewed solely as a tool for reporting but should be viewed as a structured learning tool that will require careful analysis to derive value.

5.1.6. Practical Usefulness

Experts consistently viewed the assessment tool as very valuable for managers as they implemented and stabilised their digital initiatives. The primary level of usefulness was the ability to verify if the assumed sustainability benefits had occurred, as well as to highlight any disparities between the expected and actual outcomes.

Many experts commented on the fact that the principle of non-aggregation was very helpful to provide insights specific to each unique cluster and to discourage users from comparing clusters without regard to their differences. Experts agreed that maintaining transparency at both the cluster level and KPI level was perceived as aiding decision-makers' ability to reflect on their decisions instead of hindering or reducing comparability.

Experts also stressed that misuse of the tool could occur if it were perceived as a ranking tool or a way to benchmark technology. To assist in avoiding misuse, the recommendations indicated usage guidelines should emphasise that the tool's purpose is to be a diagnostic and learning tool, rather than being utilised for competitive assessments. None of the experts believed the tool would be well suited to the early ideation or speculative stages of business case development. Most of the experts agreed that the greatest level of benefit would be achieved by organisations that already had operational digital technologies in place and were looking for a structured means of measuring the sustainability impact and determining where to make future investments.

5.1.7. Synthesis of Validation Outcomes

The validation shows that expert opinions are highly converged on the conceptual soundness, contextual relevance, and operational credibility of the framework, and the tool(s) used to assess it. All the core principles of design, such as explicit causal relationships, cluster separation, enablement logic, exclusion of weak relationships, and non-aggregation, were consistently validated by multiple experts as strengths.

All recommendations from experts indicate that there are no structural deficiencies but do indicate that improved operational guidance is necessary in the following areas: clearer boundary examples of clusters, explicit clarification of non-measured secondary effects, reinforcement of contextual controls to mitigate attribution bias, and articulation of governing requirements for successful implementation.

The validation confirms that the framework is theoretically sound and can be applied practically in manufacturing production settings. It also highlights that the successful implementation of the framework and the tool will depend on disciplined interpretation, cross-functional collaboration, and the protection of the tool from being used in an oversimplified way or for political motives. This information will contribute to the discussion and refinement of the framework in Section 6.2.

5.1.8. Discussion

The empirical validation findings give a solid basis for the theoretical strength and practical applicability of the sustainability assessment framework and tool presented. Expert input generally affirmed the theoretical soundness of the artefact and indicated the prerequisites necessary for its proper implementation; rather than suggesting a redesign of the artefact's basic structure, they delineated boundaries around the artefact and described how to implement it with discipline.

One major output of the validation exercise was unanimous expert endorsement for the framework's causation focus on its design. Specifically, experts regularly noted the value in the structured linkage established by the framework among digital technology clusters, enabling systems, and sustainability KPIs for each of the production, sustainability, digital and organisational functions. This outcome directly addresses the identified gap in the literature regarding digital sustainability models that either assume a positive impact or use maturity-based rating systems that do not isolate causes as the basis for measuring results. The validation showed that the credibility of sustainability assessments is enhanced when they are limited to cause-and-effect relationships that can be verified operationally. Experts interpreted the exclusion of weak, speculative cluster–KPI pairs as providing methodological protection against overstating sustainability.

Strong validation of the enabling logic linking the clusters was also obtained. Experts confirmed that the effectiveness of analytics is contingent on having foundational visibility capabilities, and that analytics influence the efficiency of the operation of automated systems. The layered inter-relation demonstrated by these behaviours accurately reflects the actual experience of the digital transformation in manufacturing. The framework provides for these inter-relationships without collapsing into a maturity model. It does not assume that technology will evolve in a linear manner and does not rank technologies hierarchically based on the level of their advancement. Rather, the clusters are delineated while also being recognised for their functional complementarity. Accordingly, the validation confirms that the framework is positioned as an effect-driven analytical model, as opposed to a capability ranking model.

An important interpretive finding of the validation related to the human-centred digital technology component of the framework; experts noted that while safety, ergonomics and digital work instructions are meaningful dimensions of sustainability, they also expressed caution that some behavioural and cultural impacts may not be observed through short-term before-and-after measurements. This does not lessen the validity of the framework but rather serves to define its epistemological boundary; the artefact measures sustainability impacts that can be attributed operationally to production systems, but while acknowledging that more comprehensive organisational transformation may require longer time frames and qualitative measures that are outside the artefact's purview. Therefore, the recommendation derived from validation is not to add measurements indiscriminately but rather to communicate clearly that the absence of quantification does not imply an absence of value.

A significant finding relates to the links between clarity of concept and how that concept is interpreted when applied. The majority of experts agreed that while the definitional frameworks are clear when viewed from a conceptual level; where concerns arise in regards to applying the concepts arise because of the way certain technologies are defined or seen within various contexts of vendors or organisations using those technologies and thus misclassified by way of how they are used; therefore, how you define a concept will help determine its practical application the proper classification of the technologies used based upon the dominant causal mechanism will enhance the strength of the framework. Therefore, the requirement of clear definitions, examples of boundaries of usage, and safeguards for interpretation applied to this framework will not only allow for more precise practical application of each of the respective concepts in the framework, but provide greater clarity of the framework as it relates to conceptually defining these methods for evaluation, thus will improve sustainability assessments within digital transformation across organisations.

The accompanying discussion of this study confirms there are several risks associated with the governance of organisations using the framework and the methodologies that comprise the framework, there are many of the same limitations that exist within the evaluation of sustainability by organisations in complex industrial settings. Within the governance of the organisation using the framework, experts provided examples include post-hoc attribution bias and/or pressure from external government entities or other politically motivated agendas to exaggerate their sustainability impacts, are found to have very low assurance of completion. The validity of the framework provides a level of assurance that the results provided by the framework are not aggregated and therefore mitigates the risks created by such circumstances. Consequently, the ultimate value of the framework will be established based upon cross-functional collaboration and demonstrated leadership of the organisation's use of the framework. From a managerial standpoint, the validated framework provides an answer to a problem that has been evident in the practice of digital transformation in manufacturing organisations. Many manufacturing organisations today justify their investments in digital technologies to enhance productivity or sustainability; however, they lack a structured mechanism for evaluating the actual outcomes of their investments. By providing a before and after structure for a KPI-related, cluster-specified evaluation process, the validated framework allows the transformation of rhetoric surrounding the benefits of a digital sustainability strategy into a tangible measurable benefit. In addition, not providing a composite score for each of the respective cluster evaluations has been praised by experts; because the absence of a composite score reduces the risk of oversimplifying complex issues related to sustainability and discourages the behaviour of organisations to benchmark their sustainability impacts without a causal understanding. In turn, this promotes the ability for organisations to reflect upon the use of the framework and determine the effect of sustainability within the organisation, the points within their sustainability supply chain where enablement has occurred, and where their expectations of sustainability impacts were not met.

However, the validation process provides further clarification regarding the life-cycle placement of the utilisation of the framework. The greatest value of the framework will arise during the post-implementation and stabilisation phases, when organisations will have been able to demonstrate tangible measurable outcomes of the digital initiatives. The utilisation of the framework for very early stages of ideation to substantiate a speculative business case in those timeframes limits the credibility of the utilisation of the framework. Validation has highlighted several restrictions within the validated framework. The framework is purposely limited to the impacts of sustainability at a production level only and does not include upstream supply chain situations nor how companies structure their ESG reporting. Availability and integrity of operation data is necessary; however, it varies significantly across different types of organisations. Additionally, it does not have any predictive abilities; it is parameter focused on realised performance. Contextual controls are built into the framework to try and eliminate confounding factors, but isolating causal factors is extremely difficult in an actual industrial setting. These restrictions of the validated framework do not diminish its contribution; they help define its parameters for use.

Within the larger context of the literature on digital transformation and sustainability, the validated framework provides a contribution by developing a causation-driven methodology for assessing digital sustainability, creating measures for sustainability at the production-system level, and structurally separating the digital functional components, while also acknowledging interdependencies that enable those functional components to work together. The empirical evidence gathered during the validation has provided support for this contribution by showing evidence of cross-role agreement regarding conceptual validity and functional reliability. Ultimately, it appears that the validated framework is structurally sound, and meets the criteria of being valid and reliable, according to expert assessments. The major variables that will determine success with the validated framework are discipline in the use of the framework, transparency regarding the scope of the framework, and open communication regarding the limitations of the framework. This insight will inform the section that follows, where recommendations from experts will be presented in terms of specific clarifications and/or reinforcement rather than structural modifications.

5.1.9. Framework and Tool Refinement

The empirical verification process revealed no underlying structural flaws in the proposed framework or assessment instrument. However, feedback from experts validated that the cluster architecture's conceptual soundness, the cause-driven KPI classification and the non-aggregation principle. As such, any refinements stemming from the validity process would not alter the rationale upon which the artefact is based. Rather, they provide clarity of operation, discipline of interpretation, and robustness of governance.

The first refinement relates to the clarification of cluster boundaries. Experts agreed that the four-cluster structure is conceptually separate; however, they expressed concerns regarding possible misclassification risk at the time of use, particularly between Monitoring/Visibility (Cluster 1) versus Analytics/Prediction (Cluster 2) and Automation (Cluster 3) vs Human-Centric Digital Technology (Cluster 4). These uncertainties are a result of practical tendencies of labelling technologies according to the name of their systems or the story of their organisation rather than due to similarities between these technologies. To mitigate this, additional classification guidance has been provided in the application documentation. The additional classification guidance includes explicit rules for making decisions based on the dominant causal mechanism, illustrative examples of borderline boundaries and statements of clarification as to what technology does not belong in each cluster. The additions to the classification guidance are designed to reinforce interpretational consistency, while not altering the cluster architecture itself.

The second refinement is the communication of non-measured secondary effect. Experts agreed during the validity process that digital technologies can produce broader organisational learning, changes in behaviour and the development of longer-term capabilities than what the measurement of short-term KPIs reflects. While the method of measuring KPI intentionally excludes such effects, it is recommended that an explicit articulation of this boundary be communicated in the framework to prevent misinterpretation of results. As such, the interpretative guidance has been enhanced to make explicit that the non-quantified impact does not equate to the absence of strategic value, especially with human-centric digital technologies, where the sustainability effect may take a longer period to materialise. This will add to the epistemological transparency of the interpretative guidance without sacrificing the causal rigor that was prescribed in developing the framework.

The final refinement relates to the prerequisites for effective governance. Experts agreed that the effectiveness of the tool is contingent upon discipline in its application; cross-functional collaboration across business functions; and support from senior leaders. At the validation meeting, experts identified three risk factors, post-hoc attributional bias; selective interpretations of results; and over-promising the sustainability impacts of digital technology, that are organisational rather than methodological challenges. To reinforce the original documentation associated with the framework with formal recommendations for governance, including explicit assignment of the responsibility for determining cluster classification, structured contextual verification steps prior to interpreting change in KPI, and a reaffirmation of the principle of no aggregation as a non-negotiable design principle. The contextual verification process is re-emphasized as a critical protection from the potential simplification or politicization of the framework in actual organizational settings.

A fourth refinement relates to the data preparation and measurement variables. While subject matter experts indicate that many required operational data will be available from medium- to large-size manufacturing organizations, they do indicate that some measurement variables related to specific clusters may not be calculated on a regular basis. Consequently, initial implementation may require additional structuring of existing data or the definition of new calculation protocols. The refinement is not to reduce the granularity of the measurements; rather it seeks to clarify the expectations of implementation. The framework distinguishes between conceptual measurement variables and organizationally available data. The initial implementation of the framework may involve a learning period with respect to establishing stability in data collection processes. This clarification does not simplify the existing measurement model, but it does align expectations with real-world implementation requirements. The clarification of the tool's position in the digital initiative lifecycle. During the validation process, it was confirmed that the highest value of utilization of the tool is in the post-implementation and stabilization periods, rather than in the early ideation or speculative business case development. This clarification has been explicitly incorporated into the use guidance of the framework to prevent misuse of the framework.

Therefore, the framework is reinforced as a diagnostic/reflective artifact and not as a predictive/promotional instrument. These refinements to the framework strengthen the operational robustness of the framework while retaining the core conceptual framework. The framework retains the four-cluster architecture, causality-locked KPI mapping, enablement logic, threshold-based effect classifications and non-aggregation principle. As a result, the validation process serves not as a corrective redesign of the framework, but as structured reinforcement of clarity, governance discipline, and transparency of scope within the original document. The refined framework is theoretically based, empirically tested, and operationally clarified. The remainder of this chapter summarizes the conclusions of the research and discusses future research opportunities associated with the framework.

6 Conclusions

6.1.1. Research Summary and Main Findings

The purpose of this thesis was to identify and address the central issue in assessing the effect of digital technologies on sustainability at the shop floor level within manufacturing production systems in the context of digital transformation. Despite the potential benefits of digitizing manufacturing through increased sustainability, many existing frameworks do not contain sufficient information to make accurate assessments of the relationship between technology and sustainability (e.g. lack of clear attribution logic, operational measurement guidance or delineation of technological capability versus realised sustainability). Thus, it has been difficult for companies to systematically understand if their investments in digital technology will produce environmental, economic, or social value in their production systems.

To fill this gap, the research developed a framework for assessing sustainability that is organised into four primary functional clusters of digital technologies: monitoring and visibility, analytics and prediction, automation and cyber-physical systems, and human-centric digital technologies. The framework specifically links these clusters to sustainability KPIs at the production level through clearly defined causal mechanisms. The framework was operationalised through an assessment tool that uses a before/after measurement logic, threshold-based classification of effects, and non-aggregation principles. This design allows for the assessment of sustainability effects to be made at both the cluster and KPI levels without collapsing heterogeneous effects into composite measures.

The framework underwent an empirical validation process with the assistance of experienced manufacturing and sustainability industry experts through a series of expert interviews to verify both the conceptual soundness and practical credibility of the framework. All the experts validated the clarity of the cluster architecture, relevance of the assessed KPIs, and the quality of the technology-mechanism-KPI linkages. Also, the relationships between the clusters were recognised by the experts as representative of actual digital transformation pathways within manufacturing organisations, and no structural redesign of the framework was recommended by the experts.

The validation process also revealed that the primary conditions for successful implementation of the framework are based on an organisation's disciplined implementation of the framework and not the conceptual redesign of the framework. Examples of potential risk factors for the successful application of the framework include misclassifying digital technologies, challenges of contextual attribution, and governance fragmentation. These factors indicate that organisations need to develop structured safeguards to mitigate these risks. These insights led to several targeted refinements to clarify classification guidance within the framework, improve interpretive transparency regarding the use of the framework, and enhance the governance prerequisites for the framework.

Overall, this research demonstrates that the effects of digital technologies on sustainability can be evaluated in a structured, causality-oriented manner at the production system level. The newly developed framework and tool provide an empirically validated mechanism for quantifying and interpreting actual outcomes of digital sustainability claims. The remaining sections of this thesis outline the theoretical and managerial contributions of the work, as well as limitations and avenues for future research.

6.1.2. Theoretical Contributions

This thesis seeks to provide a structured, causation-based approach for assessing the impact of digital technologies on sustainability at the production-system level as it relates to the larger discourse around the digital transformation of manufacturing or the digitalisation of manufacturing. The first contribution is creating a technology-mechanism-KPI logic framework that links enabling mechanisms associated with technology to production-level sustainability indicators, rather than establishing whether digitalisation leads to positive outcomes. The proposed framework restricts measurement to those instances that demonstrate a cause-and-effect relationship or some other identifiable relationship of significant causal rigour between technologies and sustainability indicators; thus, this creates enhanced conceptual rigour for evaluating digital sustainability. By linking mechanisms associated with technologies together, the framework delineates the differences between technology capabilities and the actual sustainability results achieved frequently observed in discussions of digital impact.

The second contribution is a functional organisation of digital technologies within manufacturing into four analytically distinct technology clusters, including Monitoring & Visibility; Analytics & Prediction; Automation & Cyber-physical Systems; and Human-Centric Digital Technologies. Each of these clusters contains enabling relationships to the other clusters reflecting the unique and divisive roles each plays in the manufacturing system and providing a systematic basis from which to evaluate how the different functional characteristics of technologies interact to impact sustainability performance. Through this functional division of technology roles whilst still capturing the inter-relationship between technology roles, the framework provides an enhanced degree of granularity for understanding the interaction of digital and sustainability in the production environment.

The third contribution is developing a means to operationalise the assessment of sustainability within the shop floor environment, where most sustainability assessments are discussed at the corporate or supply-chain level. The assessment of sustainability performance developed within the thesis provides measurable, quantifiable, production-level indicators of the environmental, economic and social dimensions of sustainability that digital technologies can directly impact. The proposed use of a before–after measure combined with a threshold classification of effect creates a direct correlation between conceptual sustainability goals and tangible production outcomes.

The fourth contribution is methodological through its principle of non-aggregation. The framework intentionally does not aggregate sustainability scores across technology clusters or dimensions, so it does not obscure heterogeneous impacts and retains interpretive clarity and supports cluster-level rather than total cluster learning. Ultimately, this methodological design choice reinforces analytical transparency criteria.

Finally, the validation process contributed by using expert evaluation to substantiate the conceptual design. The level of convergence that experienced professionals demonstrated across multiple perspectives lends evidence to the robustness of the structural framework design and provides clarity regarding the framework's boundary conditions. Therefore, validation of the framework provides evidence that disciplined causation and clearly defined scope are necessary to conduct defensible assessments of sustainability in digital-enabled production. Collectively, these five contributions advance a structured evaluation of the sustainability impacts of digital technologies within the manufacturing sector by demonstrating that analytical precision, functional differentiation, and explicit cause-and-effect attribution logic are essential elements of promoting both theoretical and practical clarity and applicability of digital sustainability assessment.

6.1.3. Managerial Implications

The findings of this research provide several important implications for manufacturing organisations seeking to understand and govern the sustainability effects of digital technologies within production systems.

First, the framework presented can provide managers with a way to evaluate how digital initiatives create measurable sustainability results at the shopfloor level. Digital investments in many businesses are made with little to no justification beyond anticipated productivity gains, or an expectation of environmental and social value; however, these same businesses typically perform limited or sporadic ex-post evaluations of the sustainability results that have been achieved. The assessment tool created in this dissertation will allow organizations to move from narrative-based assertions about the sustainability benefits of digital technologies to evidence-based reflections about their use by providing an explicit link between digital technologies and defined sustainability indicators using specified causal mechanisms.

Second, reconnecting clusters of digital technologies functionally within the evaluation process promotes a more transparent internal dialogue among Production, IT, Sustainability, and HR functions. By separating the digital layers, i.e. business processes or activities that could be classified as monitoring & control, analytical intelligence, automated processes, and the use of human beings as technology enablers, managers will be better able to evaluate how each of the four digital layers constitutes an effective contributor to a corporation's sustainability performance. This degree of definition helps to eliminate the simplification of the impacts of digital initiatives and will minimise the risk of attributing improvements solely to the abstract concept of "digitalisation", when more accurately reflecting on the unique contributions of the underlying causal mechanisms. Third, the evaluation process will help managers to understand the importance of evaluating the effects of digital sustainability through the non-aggregation principle built into the framework. Rather than providing organisations with a single measure of the total impact of a digital technology initiative, this framework will provide organisations with cluster-level and individual KPI profiles for evaluating the relative impact of each digital technology cluster on a corporation's sustainability.

This process will support a more focused discussion among managers as to where impact occurs, where it does not occur, and why or why not. This will enable managers to determine whether sustainability-related improvements are primarily attributable to enhanced visibility, predictive analytics, automated control, or support from human operators. Ultimately, this differentiation will facilitate informed prioritisation of future digital investments and the expansion of their use within a manufacturing organisation. Fourth, the evaluation process will reinforce the concept of governance discipline in the evaluation of digital sustainability initiatives. Consistent with the validation process of this research, logical classification of clusters, both organisational and functional, verification related to contextual variables, and cross-functional collaboration are essential to provide the requisite credibility with all parties involved with the digital sustainability initiative.

Therefore, as organisations adopt the discipline necessary to accurately evaluate digital sustainability through this framework, it should not only be used as an evaluation tool but will provide management a tool for enhancing the learning opportunities related to digital technology initiatives. By periodically examining and measuring the outcome of digital technologies from a before/after perspective, managers will be able to identify when the actual impact of a digital technology initiative does not align with prior expectations and make necessary adjustments to their digital strategies. Finally, this research will facilitate a shift in the mindset toward digital sustainability narratives being created from a more disciplined and conservative perspective. By mandating a clearly defined causal linkage between the digital technology and measurable performance-related benefits, this framework will mitigate the ability of any organisation to make excessive claims regarding the sustainability benefits achieved; thereby, increasing the credibility of any organisation making such claims.

Consequently, this will help to embed sustainable evaluation into operational management processes rather than exclusively being a reporting initiative. In summary, this study provides organisations with a framework to enable managers to establish a structured, transparent, and causality-based evaluation process for determining the sustainability impacts of digital technologies on their manufacturing production systems. Therefore, organisations that adopt a structured approach to evaluating digital sustainability will ultimately improve their decision-making capabilities and provide a higher level of accountability for sustainability performance.

6.1.4. Limitations

This thesis proposes a structured, cause-and-effect oriented framework for assessing how digital technologies impact sustainable manufacturing production systems; however, there are limitations regarding its scope and use. Firstly, this framework is very specifically focused on performing assessments of sustainability at the production level. It does not consider sustainability at other levels. The exclusive emphasis on technology implementations on the shop-floor results in cause-and-effect clarity but is likely to limit its use to enterprise assessments.

Future extensions to the framework would need to bridge production-level results to enterprise level sustainability assessments. Secondly, as the empirical validation was based on qualitative judgments, rather than the long-term implementation of the framework in manufacturing production settings, although the expert panel who evaluated the framework all provided strong consensus around its conceptual validity and operational reliability, no empirical testing of the long-term results and the behavioural dynamics of the implementation of the framework have yet been done across multiple manufacturing production sites for extended timeframes.

Thirdly, the effective use of the assessment tool will largely depend upon the use of reliable, consistent operational data. While most manufacturers have access to required production operations indicators (e.g. energy used, scrap produced or down-time), the use of aggregate production data very often is compromised due to, fragmentation of data, inconsistent baseline historical data and the challenge of ownership of production data across multiple departments/functions therefore limiting the practical implementation of the assessment tool. In many cases, the initial application of the assessment tool may require additional efforts in low-maturity, fragmented environments to stabilize the processes for data collection.

The assessment criteria for evaluating the effect of an improvement initiative is based on the logic of obtaining measurements taken before and after implementation of the initiative under the same contextual environment. Although the framework has been developed with contextual verification mechanisms, such as controlling for changes in production mix, variations in staff and concurrent improvement initiatives, it is difficult to completely isolate causal variables in complex industrial systems and thus, support only the use of structured attribution instead of experimental proof of causation.

The framework does not include long-term or diffuse sustainability impacts, such as those resulting from changes in culture, organizational behaviour or cumulative learning over time. Although an impact may be influenced by digital technologies, to apply a short-term quantitative measure to ascertain the attribution of such impacts is methodologically difficult. Hence the framework emphasizes measurable and operationally defensible sustainability impacts and therefore will limit itself to means of measuring directly observable production outcomes.

The limitations above do not lessen the contribution of the research but rather explain the parameters of analysis used to develop the framework. The framework has been created as a production-level, causality-driven sustainability assessment tool used in digitally enabled environments and provides structured attribution and interpretability of any assessed impacts, rather than a complete catalogue of all possible sustainable impact areas.

6.1.5. Directions for Future Research

The major area of research opportunity is longitudinal empirical applications. The framework has been validated through conceptual evaluation by experts; however, longitudinally applying the effect assessment tool at multiple manufacturing plants will verify how sustainability effect profiles change over time as digital technologies evolve, stabilise, and diversify. Additionally, longitudinal case studies may provide an understanding of how organisational learning dynamics affect ongoing use of the effect assessment tool.

Another research opportunity is conducting quantitative evaluations of the threshold-based classifications employed in the framework for assessing effects. Current threshold classification criteria applied in the framework assess the relative change in classifying sustainability effects as weak, moderate, or strong. Future research could statistically assess the sensitivity and reliability of these thresholds across multiple industry types, production types, and technology types. The availability of comparative data sets may provide some insight into possible improvements of the classification logic, or calibration to specific industry contexts.

Another possible extension of the research is through the integration of the effect assessment framework with existing environmental impact assessment methodologies. While the effects assessment framework focuses on production-oriented key performance indicators (KPIs), future areas of researchers can evaluate how assessed digital sustainability effects on the shop floor will affect LCA results and corporate sustainability reports. Through this integration, the relationship of digital operational effects to overall environmental performance can be evaluated.

Another opportunity for research is to further investigate how to better understand the social aspect of sustainability using human-centred digital technologies and its long-term behavioural sustainability effects. Qualitative and/or mixed qualitative methods could provide evidence of the long-term effects of digital work instructions, AR tools, or platforms providing digital transparency as it relates to safety culture, knowledge retention and skillset development. This research would further support the quantification of production level logic proposed through this research.

Another potential area of future research is the adaptation of the effect assessment framework for SMEs. Since the current framework was developed utilising moderate assumptions of data availability and organisational structure, future research may further explore simplified and phased strategies of implementation appropriate within organisations that are lower on the digital maturity spectrum while maintaining a focus on causal discipline.

A final opportunity for future research is to investigate the appropriateness of the four-cluster architecture in other industries, besides manufacturing, that were addressed in this dissertation. Research that evaluates the appropriateness of the framework for other process-related industries, types of discrete manufacturing and hybrid-processing systems will illustrate the contextual/delivery differences of the format while maintaining the overall underlying logic.

These various future research opportunities outline how original academic research will continue to be consistently built upon through this dissertation and the effect assessment framework, inclusive of the means and context of research, empirically applied research, and methods refinement. The provision of further academic insight into the sustainability performance of industrial systems due to the advent of digital technologies will continue to be developed as future research efforts.

6.1.6. Final Considerations

Digital transformation in manufacturing is frequently accompanied by strong sustainability expectations. However, without structured attribution logic and disciplined evaluation mechanisms, digital sustainability risks becoming a narrative rather than a measurable operational reality. This thesis has demonstrated that the sustainability effects of digital technologies in production systems can be assessed in a systematic, causality-oriented manner when technological functions, enabling mechanisms, and production-level indicators are explicitly linked.

By structuring digital technologies into functional clusters and connecting them to measurable environmental, economic, and social outcomes through a before–after logic, the research advances a transparent approach to sustainability evaluation at shopfloor level. The empirical validation confirms that such an approach is conceptually robust and operationally credible, if organisations apply it with interpretative discipline and governance rigor.

Ultimately, the value of digital technologies for sustainability does not lie in their technological sophistication alone, but in their demonstrable contribution to measurable improvement. Embedding structured, causality-driven assessment practices within digital governance can strengthen both managerial decision-making and sustainability accountability in manufacturing environments.

This research therefore contributes not only a framework and tool, but also a perspective: that digital sustainability should be evaluated with the same analytical precision as operational performance. In doing so, it supports a shift from assumption-based claims toward evidence-based understanding of how digital transformation shapes sustainability outcomes in industrial production systems.

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A Appendix A

A.1. DT Clusters-Environmental KPIs Causality Table

Technology Cluster	Environmental KPI	Causality	Description	Source(s)
C1	**Energy**	Real-time visibility	Real-time sensing and connectivity enable continuous measurement of machine- and process-level energy consumption, providing visibility into energy-intensive operations and consumption patterns. This visibility supports identification of inefficiencies and reduction of unnecessary energy use in manufacturing processes.	Contini & Peruzzini (2022); Huang & Badurdeen (2018)
C1	**Water**	Real-time visibility	Real-time sensing and connectivity enable continuous monitoring of water usage at machine, process, or facility level, providing visibility into water-intensive operations, abnormal consumption patterns, and water losses (e.g., leaks). This visibility supports identification of inefficiencies and reduction of unnecessary water consumption.	Contini & Peruzzini (2022); Huang & Badurdeen (2018); Ghobakhloo (2021)
C1	**Waste**	Real-time visibility	Real-time sensing and connectivity enable continuous monitoring of production processes and material flows, providing visibility into scrap generation, defects, and material losses at machine and process levels. This visibility supports identification of waste sources and reduction of production waste and scrap.	Contini & Peruzzini (2022); Huang & Badurdeen (2018)
C1	**GHG emissions**	*No strong causality identified*	Greenhouse gas emissions are calculated using activity data and emission factors rather than directly measured. While smart sensing and connectivity improve the accuracy and granularity of energy and material consumption data, the literature does not provide strong evidence of a direct causal relationship between these technologies and GHG emission reduction.	Contini & Peruzzini (2022); Huang & Badurdeen (2018)

C2	**Energy**	Predictive energy management	Predictive analytics models forecast future energy demand and consumption patterns based on production data, enabling proactive energy management actions such as load shifting, peak avoidance, and energy-aware production planning, leading to reduced energy consumption.	Cagno et al. (2025); Rojek et al. (2026)
C2	**Energy**	Simulation-based energy efficiency improvement	Simulation and digital twin models enable virtual testing of alternative production configurations and operating strategies to evaluate energy impacts before implementation, supporting selection of more energy-efficient solutions and reducing trial-and-error energy waste.	Billey & Wuest (2023); Khodadadi & Lazarova-Molnar (2024)
C2	**Water**	Data-driven water optimization & predictive management	Analytics and digital twin-based modelling of industrial water systems support continuous monitoring, prediction, and simulation of water use patterns, enabling identification of inefficiencies and proactive adjustments that reduce water consumption and improve water efficiency.	Emeka & Chikwendu (2025); Integration of Digital Twin Technology for Water Resource Management (2025)
C2	**Waste**	Predictive quality & process optimization	Data-driven analytics and machine-learning models predict defect formation and identify process conditions leading to scrap and rework. By enabling early detection of quality deviations and virtual testing of process adjustments, these models support reduction of material waste in manufacturing processes.	Contini & Peruzzini (2022); Wuest et al. (2019)
C2	**GHG emissions**	Carbon footprint modelling, assessment & optimization	Digital twin, simulation, and analytical models integrate energy and material consumption data with emission factors to quantify and analyse manufacturing carbon footprints. These models enable identification of carbon-intensive processes and virtual evaluation of lower-carbon production scenarios before implementation.	Digital Twin-driven carbon emissions management in manufacturing (2025); Billey & Wuest (2023); Cagno et al. (2025); *Systems* (2025)
C2	**GHG emissions**	Carbon-aware process planning & scheduling optimization	Optimization models explicitly integrate carbon emissions as an objective alongside traditional production objectives, enabling selection of process plans, machine assignments, and schedules with lower carbon impact, contributing to reduced production-related GHG emissions.	*Journal of Cleaner Production* (2023); *Sustainability* (2022); AIMS Mathematics / Sciences (2024/2025)

C3	**Energy**	Energy-efficient robotic execution	Industrial robotic systems can reduce energy consumption through optimized motion planning, task sequencing, and efficient execution strategies. Studies show that robot-level execution efficiency significantly influences energy consumption in manufacturing operations.	*ScienceDirect* (2023) – Energy-efficient industrial robotics
C3	**Water**	*No strong causality identified*	The reviewed literature does not provide direct empirical evidence linking robotic or automated execution systems to reductions in water consumption. Any potential impact is highly process-specific and indirect.	—
C3	**Waste**	Precision and repeatability of robotic execution	Robotic and automated execution systems improve process precision and repeatability, reducing variability-induced defects, scrap, and material waste compared to manual or less controlled execution.	*Springer* (2021) – Robotic automation and scrap reduction
C3	**GHG emissions**	Indirect emission reduction via energy-efficient automation	Lifecycle-based studies show that energy-efficient robotic automation can indirectly reduce production-related GHG emissions by lowering energy use per unit produced, though effects depend on system design and utilization.	*ScienceDirect* (2022) – LCA of robotic automation and CO_2 emissions
C4	**Energy**	Human-centric decision support for energy-aware operations	Human-centric digital systems provide energy-related information and feedback to operators and managers, supporting energy-aware operational decisions and improved energy efficiency through informed human judgment.	*Decision Support Systems* (2018)
C4	**Water**	Governance-enabled transparency and decision support	Digital governance and decision-support systems enhance transparency, monitoring, and coordination in water management, supporting more efficient water use through managerial and institutional mechanisms.	*Water Resources Management* (2024)

C4	**Waste**	Human-centric circular decision support	Human-centric Industry 4.0 tools support circular design and decision-making, guiding designers and engineers toward waste-minimizing design choices across the product lifecycle.	Emerald (2023) – *Industry 4.0 and the circular economy using design*
C4	**Waste**	Digital work instructions & error reduction	Digital work instructions and operator guidance systems reduce execution errors and material losses by improving task clarity and compliance, leading to reduced scrap and waste.	IEEE (2023)
C4	**GHG emissions**	*No strong causality identified*	The literature does not provide direct empirical evidence linking human-centric or governance-enabling digital systems to reductions in GHG emissions in manufacturing.	—

A.2. DT Clusters-Social KPIs Causality Table

Technology Cluster	Social KPI	Causality	Description	Source(s)
C1	**Occupational safety**	Real-time hazard detection and safety monitoring	Smart sensing, IIoT, and CPS-based monitoring systems enable real-time detection of hazardous conditions (e.g., unsafe machine states, abnormal environments, worker–machine proximity). This supports early warnings, accident prevention, and improved workplace safety through timely interventions.	World Scientific (2025); *Safety* – MDPI (2023)
C1	**Occupational health & ergonomics**	Continuous monitoring of physical and environmental exposure	Sensor-based and wearable monitoring systems enable continuous assessment of posture, physical load, vibration, noise, and environmental exposure. This supports identification of ergonomic risks and long-term health stressors, enabling preventive occupational health interventions.	*Sensors* – MDPI (2025); *Applied Ergonomics* – ScienceDirect (2017)
C1	**Staff training**	Data-driven identification of training needs	Real-time production and machine data from connected systems support identification of skill gaps and abnormal operating patterns, enabling targeted, data-driven training for operators and maintenance staff.	EBSCO / Google Scholar (training & digital manufacturing systems)
C2	**Occupational safety**	Predictive safety risk analysis and accident prevention	Analytics, machine learning, and predictive models analyse historical accidents and near-miss data to forecast safety risks and accident likelihood, enabling proactive safety interventions before incidents occur.	*Applied Sciences* – MDPI (2025); *Processes* – MDPI (2025)
C2	**Occupational health & ergonomics**	Predictive health risk and ergonomic modelling	Machine learning and simulation models assess ergonomic risks, workload, fatigue, and musculoskeletal disorder likelihood, enabling preventive occupational health and ergonomic improvements through scenario evaluation.	IEEE (2022); *Applied Sciences* – MDPI (2020)
C2	**Staff training**	Predictive skill gap and workforce capability analysis	Predictive analytics and workforce modelling identify current and future skill gaps based on job requirements, performance data, and technology adoption trends, supporting data-driven training and reskilling planning.	ResearchGate (2024): *Predictive Analytics for Identifying Skill Gaps and Future Workforce Requirements*
C3	**Occupational safety**	Risk reduction through controlled automation and HRI safety design	Robotic and collaborative systems improve safety by relocating workers away from hazardous tasks and by applying human–robot interaction safety mechanisms (e.g., collision avoidance, safe speed/separation monitoring).	HAL (2025); *Journal of Intelligent Manufacturing* – Springer (2025)

C3	**Occupational health & ergonomics**	Physical workload reduction and ergonomic risk mitigation	Cobots and robotic systems reduce physical workload and musculoskeletal strain by reallocating repetitive, forceful, or awkward tasks from humans to robots, supporting long-term occupational health improvements.	*International Journal of Human–Computer Interaction* (2022); *Safety* – MDPI (2021); Springer book chapter (2021)
C3	**Staff training**	Upskilling and competence development driven by automation adoption	Adoption of robotic systems increases demand for workforce training in robot operation, programming, supervision, and maintenance, requiring structured upskilling and reskilling initiatives.	*Procedia Manufacturing* – ScienceDirect (2025)
C4	**Occupational safety**	Immersive safety guidance and situational awareness	AR/VR, immersive, and wearable technologies enhance safety by improving situational awareness, providing context-aware guidance, and reducing human error through visual and interactive safety instructions.	ResearchGate PDFs (Alam et al.); WorldS4 (2023)
C4	**Occupational health & ergonomics**	Cognitive and ergonomic workload support via human-centric interfaces	Human-centric digital systems support occupational health by improving ergonomic evaluation, reducing cognitive workload, and supporting stress and fatigue management through improved task information and interaction design.	Springer (2025); University of Bologna CRIS; *Procedia CIRP* (2013)
C4	**Staff training**	Immersive digital training and experiential learning	AR/VR-based and immersive training systems enable interactive learning, safe practice environments, and improved knowledge transfer for complex or safety-critical tasks, supporting faster onboarding and higher competence.	*Applied Sciences* – MDPI (2020); ResearchGate PDF (Alam et al.)

A.3. DT Clusters-Economic KPIs Causality Table

Technology Cluster	Economic KPI	Causality	Description	Source(s)
C1	**Quality**	Real-time quality visibility and early deviation detection	Sensor-based and IIoT-enabled monitoring systems provide real-time visibility of process parameters and quality indicators, enabling early detection of deviations and timely corrective actions that reduce defects and scrap in production processes.	*Sensors* (2022); IEEE Conference Paper (2024)
C1	**Lead time**	Real-time production status transparency	Continuous visibility of machine states, work-in-progress, and production flow enables faster identification and resolution of disruptions and bottlenecks, reducing production and delivery lead time.	IEEE Conference Paper (2018); ResearchGate Study on Intelligent Scheduling (2025)
C1	**Productivity**	Downtime reduction through real-time monitoring	Real-time monitoring improves awareness of machine stoppages and performance losses, enabling quicker interventions that reduce unplanned downtime and increase throughput.	IEEE Conference Paper (2023); *Sensors* (2023)
C1	**Equipment utilization**	Utilization transparency and awareness	Continuous tracking of machine usage, idle time, and availability increases transparency, supporting better short-term operational decisions that improve equipment utilization.	IGI Global (2024); Springer Journal (2025)
C2	**Quality**	Predictive quality modelling and virtual process optimization	Analytics, machine learning, and simulation models predict quality outcomes under different process conditions, enabling proactive identification of defect drivers and virtual optimization of process parameters to improve quality performance.	*Processes* (2020); *Processes* (2022)
C2	**Lead time**	Simulation-based production flow and planning optimization	Digital models and simulations enable evaluation of alternative production configurations and planning scenarios, supporting identification of bottlenecks and selection of flow-efficient strategies that reduce lead time.	*Computers & Industrial Engineering* (2021); *Applied Sciences* (2025)
C2	**Productivity**	Performance modelling and throughput optimization	Simulation and analytical models evaluate system performance under different operating strategies, enabling data-driven decisions that improve productivity and throughput without physical trial-and-error.	ResearchGate (Simulation-based productivity study); *Machines* (2025)

C2	**Equipment utilization**	Model-based capacity and utilization optimization	Analytical and simulation-based approaches assess capacity usage and utilization under different scenarios, supporting planning decisions that improve equipment utilization and reduce capacity inefficiencies.	AJME (2024); *Journal of Manufacturing Systems* (2023)
C3	**Quality**	Execution consistency and automated quality control	Robotic and collaborative systems improve quality by reducing human variability, increasing execution repeatability, and supporting automated or assisted quality control activities, leading to lower defect and scrap rates.	*Journal of Intelligent Manufacturing* (2025); Puttero et al., ResearchGate
C3	**Lead time**	Cycle time compression through automation	Automation reduces processing and handling times and stabilizes production flow, decreasing waiting times and interruptions and thus reducing overall production lead time.	Teoh Bak Aun, ResearchGate (Industry 4.0 & Lead Time)
C3	**Productivity**	Throughput increase via task automation and human–robot collaboration	By reallocating repetitive or time-consuming tasks from humans to robots, automated execution systems increase throughput and output efficiency in production systems.	*International Journal of Human–Computer Interaction* (2022)
C3	**Equipment utilization**	Stable automated operation and reduced downtime	Automated systems enable more stable machine operation and, when combined with structured maintenance practices, reduce downtime and variability, supporting higher equipment utilization.	Robotic Systems & Intelligent Maintenance (2025)
C4	**Quality**	Error reduction and procedural compliance via digital guidance	Human-centric digital systems provide visual and contextual guidance that reduces human errors, improves procedural compliance, and supports standardized task execution, leading to improved quality outcomes.	*Procedia CIRP* (2024); *Future Internet* (2025)
C4	**Lead time**	Reduced rework and faster task execution	Digital work instructions and AR support improve task understanding and execution speed while reducing errors and rework, indirectly shortening operational lead time.	*Applied Sciences* (2023); Research Innovation Journal (AJSRI)
C4	**Productivity**	Improved operator efficiency and learning curves	Human-centric systems enhance productivity by reducing cognitive load, supporting learning and skill development, and improving operator efficiency in production tasks.	*Sustainability* (2025); *Manufacturing Letters* (2025)

C4	**Equipment utilization**	Improved human–machine coordination	Human-centric interfaces and scheduling support reduce setup errors and human-induced downtime, improving coordination between operators and equipment and indirectly increasing utilization.	ResearchGate (Human-Centric Scheduling Study)

B Appendix B

B.1. Environmental KPIs Measurement Variables

Technology Cluster	Environmental KPI	Causality	Measurement Variable	Measurement Method
C1	Energy	Real-time visibility	Share of machine energy consumption monitored in real time (%)	Ratio of monitored machine energy consumption to total machine energy consumption
C1	Water	Real-time visibility	Number of detected abnormal water consumption events per period	Count of abnormal water usage alerts over a defined period
C1	Waste	Real-time visibility	Time to detect scrap or defect occurrence (minutes)	Time difference between defect occurrence and system detection
C1	GHG emissions	No strong causality	—	Excluded from measurement for this cluster
C2	Energy	Data-driven optimization	Reduction in energy intensity after analytics-based optimization (%)	Compare energy per unit before vs after optimization model deployment
C2	Water	Process optimization	Reduction in water consumption per batch due to optimized parameters (%)	Before–after comparison of batch-level water usage
C2	Waste	Predictive quality & process control	Reduction in scrap rate attributable to predictive analytics (%)	Compare scrap rate before vs after predictive models
C2	GHG emissions	Energy & material optimization	Estimated GHG reduction from optimized energy/material use (kg CO_2e/unit)	Convert reduced energy/material use into CO_2e using emission factors
C3	Energy	Process stabilization through automation	Energy consumption variability per cycle (std. dev. of kWh/cycle)	Compare cycle-level energy variability before vs after automation

C3	Water	Automated process control	Water consumption variability per cycle (m^3/cycle)	Compare variability of water use per cycle
C3	Waste	Precision & repeatability of automated operations	Material waste due to execution errors (% of total waste)	Classify waste causes before vs after automation
C3	GHG emissions	Reduced execution-related inefficiencies	GHG emissions linked to execution inefficiencies (kg CO_2e/batch)	Convert reduced execution losses into CO_2e
C4	Energy	Human-centric decision support	Reduction in energy-related inefficiencies supported by digital tools (%)	Structured assessment of energy-related decisions before vs after
C4	Water	No strong causality	—	Excluded from measurement for this cluster
C4	Waste	Digital work instructions & error reduction	Reduction in operator-related production time losses (%)	Compare downtime/rework time before vs after digital instructions
C4	GHG emissions	No strong causality	—	Excluded from measurement for this cluster

B.2. Social KPIs Measurement Variables

Technology Cluster	KPI	Causality	Measurement Variable	Measurement Method
C1	Occupational safety	Real-time hazard detection & monitoring	Average response time between hazard detection and corrective action (minutes)	Compare alert timestamp with intervention timestamp
C1	Occupational health & ergonomics	Continuous exposure monitoring	Share of identified ergonomic/exposure risks triggering preventive actions (%)	Compare detected risks vs documented preventive actions
C1	Training	Data-driven training need identification	Share of training actions initiated based on production/machine data (%)	Compare data-triggered training actions to total training actions
C2	Occupational safety	Predictive safety risk analysis	Share of incidents preceded by predictive safety risk alerts (%)	Match incidents with prior analytics-based warnings
C2	Occupational health & ergonomics	Predictive health & ergonomic modelling	Share of predicted high-risk scenarios resulting in preventive actions (%)	Compare model-identified risks with implemented measures
C2	Training	Predictive skill gap analysis	Share of training/reskilling actions based on analytics-identified skill gaps (%)	Compare analytics-driven training actions with total actions
C3	Occupational safety	Automation-based risk reduction	Reduction in worker exposure time to hazardous tasks after automation (%)	Compare exposure time before vs after automation
C3	Occupational health & ergonomics	Physical workload reduction	Reduction in time spent on physically demanding tasks (%)	Compare task allocation before vs after automation
C3	Training	Automation-driven upskilling	Share of workforce trained for robot operation/supervision (%)	Compare trained workforce to total affected roles
C4	Occupational safety	Immersive safety guidance	Reduction in incidents or near-misses attributable to immersive guidance (%)	Compare incident frequency before vs after immersive systems
C4	Occupational health & ergonomics	Cognitive & ergonomic workload support	Reduction in reported cognitive overload or ergonomic risk	Structured assessment before vs after interface support
C4	Training	Immersive digital training	Reduction in time to achieve task proficiency via immersive training (%)	Compare onboarding/training duration before vs after AR/VR

B.3. Economic KPIs Measurement Variables

Technology Cluster	KPI	Causality	Measurement Variable	Measurement Method
C1	Quality	Real-time quality visibility	Share of quality deviations detected at source before process completion (%)	Ratio of deviations detected during execution vs total detected deviations
C1	Lead time	Real-time production status transparency	Time between disturbance occurrence and operator/supervisor awareness (minutes)	Compare disturbance timestamp with first system alert
C1	Productivity	Downtime awareness through monitoring	Share of unplanned downtime events detected automatically (%)	Compare automatic vs manual downtime detection
C1	Equipment utilization	Utilization transparency	Share of idle/underutilized time visible in real time (%)	Ratio of classified idle time vs total idle time
C2	Quality	Predictive quality modelling	Reduction in defects attributable to model-recommended parameter changes (%)	Compare defect rates before vs after parameter adoption
C2	Lead time	Simulation-based flow optimization	Reduction in lead time for simulated/reconfigured processes (%)	Compare lead time before vs after simulation-based changes
C2	Productivity	Throughput optimization via analytics	Increase in throughput linked to analytics-optimized policies (%)	Compare throughput under baseline vs optimized policies
C2	Equipment utilization	Model-based capacity optimization	Reduction in planned idle/buffer time after analytics-based planning (%)	Compare utilization plans before vs after optimization
C3	Quality	Execution consistency via automation	Reduction in defects caused by manual execution variability (%)	Classify defect causes before vs after automation
C3	Lead time	Cycle time compression	Reduction in manual handling/transfer time per unit (%)	Compare handling time before vs after automation
C3	Productivity	Task automation & HRC	Increase in output per automated workstation/robot (%)	Compare output per station before vs after automation
C3	Equipment utilization	Stable automated operation	Reduction in utilization losses from execution-related stoppages (%)	Compare stoppage-related losses before vs after automation
C4	Quality	Procedural compliance via digital guidance	Reduction in operator-induced quality defects (%)	Compare cause-coded defects before vs after guidance
C4	Lead time	Reduced rework via digital instructions	Reduction in rework time caused by instruction errors (%)	Compare rework time before vs after digital instructions
C4	Productivity	Operator efficiency & learning	Reduction in time-to-proficiency for complex tasks (%)	Compare learning curves before vs after digital support

C4	Equipment utilization	Human–machine coordination	Reduction in downtime caused by setup/operation errors (%)	Compare downtime causes before vs after human-centric tools

C Appendix C

C.1. Assessment Tool Validation Interview Questions

RELEVANCE

- Are the boundaries between the clusters sufficiently distinct to avoid conceptual overlap when applying the tool?
- Do you see any cluster whose sustainability relevance is overestimated or underestimated in the framework?
- Do the selected environmental, social, and economic KPIs capture the sustainability aspects that are genuinely influenced by digital technologies at production level?

COMPLETENESS

- Do the clusters sufficiently cover both operational technologies (shopfloor) and supporting digital systems relevant for sustainability assessment?
- Considering your experience, are there relevant sustainability effects of digitalization that are not captured by the current KPI set?

CLARITY

- Are the definitions of the technology clusters clear enough for different experts (e.g., production, IT, sustainability) to interpret them consistently?
- Are the causal links between technologies and KPIs sufficiently explained to understand why an impact is expected?

FEASIBILITY

- Based on your experience, is the data required by the tool generally accessible within manufacturing organizations?
- Is the step-by-step workflow realistic in terms of time, effort, and required expertise?

- Do you think the tool could be applied without external consultants, using internal company expertise only?

USEFULNESS

- How useful would the tool be for identifying priority areas for future digital or sustainability investments?
- At which stage of a digitalization initiative (planning, implementation, post-implementation) would this tool be most valuable?

IMPROVEMENT

- Which elements of the tool would you prioritize for refinement or simplification?
- Are there any KPIs, clusters, or workflow steps you would recommend merging, splitting, or redefining?
- If you were to apply this tool in your organization, what would be the main barrier to adoption?
- Overall, do you consider this tool sufficiently robust to assess the sustainability effects of digital technologies in production? Under which conditions would you trust its results?

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