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Digital Sustainability

Leveraging Digital Technology to Combat Climate Change

Edited by

Theo Lynn · Pierangelo Rosati · David Kreps · Kieran Conboy

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Kieran Conboy
Editors

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About This Book

Digitalisation and environmental sustainability are two of the megatrends impacting industry and society. This open-access Pivot is a timely exploration of some of the challenges and prospects related to digital sustainability from two main perspectives: how digital technologies can be used and maintained in a way that is environmentally sustainable over the long term (greening of digital technologies), and how digital technologies can be used to address climate change and improve environmental and sustainability outcomes (greening by digital technologies). The chapters included in this book are designed to provide some key definitions and concepts related to digital sustainability and its evolution, and more detailed insights on some of the key priority areas outlined in the European Green Deal, namely energy, mobility, buildings, food, and the circular economy. A critical review of these topics will summarise and present different perspectives that challenge old assumptions and highlight emerging trends and possibilities for digital sustainability. Industry and society face significant challenges in the twin transition to digital and green transformation, not least of which is the need to balance investment in digital technologies with environmental sustainability. This open-access book can serve as a primer for scholars, policymakers, and enterprise decision-makers, providing insights on navigating innovation ecosystems to support both green and digital objectives.

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Abbreviations

AGC	Automatic Generation Control
AI	Artificial Intelligence
AOT	Array of Things
AR	Augmented Reality
B2U	Battery Second Use
BEMS	Building Energy Management Systems
BoL	Beginning-of-Life
CAP	Common Agricultural Policy
CE	Circular Economy
CNN	Convolutional Neural Network
CO_2	Carbon Dioxide
DDoS	Distributed Denial of Service
DDPG	Deep Deterministic Policy Gradient
DDPP	Digital Decade Policy Programme
DER	Distributed Energy Resource
DESI	Digital Economy and Society Index
DL	Deep Learning
DPP	Digital Product Passport
DRC	Democratic Republic of Congo
DRL	Deep Reinforcement Learning
DT	Digital Transformation
EC	European Commission
EIA	Environmental Impact Assessment
EoL	End-of-Life
EPA	Environmental Protection Agency
ERDF	European Regional Development Fund

EU	European Union
EV	Electric Vehicle
EVB	Electric Vehicle battery
e-Waste	Electronic Waste
FAO	Food and Agriculture Organisation
GeSI	Global e-Sustainability Initiative
GHG	Greenhouse Gas
GIS	Geographic Information Systems
GNSS	Global Navigation Satellite Systems
GPU	Graphics Processing Unit
GWh	Gigawatt hours
HVAC	Heating, Ventilation, and Air Conditioning
ICT	Information and Communication Technology
IoT	Internet of Things
IS	Information Systems
IT	Information Technology
ITS	Intelligent Transportation System
ITU	International Telecommunication Union
LCA	Life Cycle Assessment
LCI	Life Cycle Inventory
LCIA	Life Cycle Impact Assessment
LLM	Large Language Model
LSTM	Long Short-Term Memory
ML	Machine Learning
MoL	Middle-of-Life
MT	Metric tons
OECD	Organisation for Economic Co-operation and Development
OEM	Original Equipment Manufacturer
PC	Personal Computer
PSS	Product Service System
RES	Renewable Energy Source
RFID	Radio Frequency Identification
RL	Reinforcement Learning
RNNs	Recurrent Neural Networks
SDGs	Sustainable Development Goals
SME	Small to Medium Enterprise
SPM	Sustainable Product Management
SSD	Solid State Drive
ST	Sustainability Transformation
SWM	Smart Waste Management
TBL	Triple Bottom Line
TWh	Terawatt Hours
UN	United Nations

UNEP	United Nations Environment Programme
V2G	Vehicle-to-Grid
VR	Virtual Reality
WEEE	Waste Electrical and Electronic Equipment
ZB	Zettabytes

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CHAPTER 1

Digital Sustainability: Key Definitions and Concepts

Pierangelo Rosati, Theo Lynn, David Kreps, and Kieran Conboy

Abstract Current market dynamics require organisations to compete in a hypercompetitive environment that is constantly reshaped by digital transformation. At the same time, organisations face growing pressure to implement more sustainable practices in their day-to-day operations and contribute to the UN Sustainable Development Goals. This has led to two

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discrete research fields in the wider sustainability domain, namely research that explores and addresses (1) the environmental impact of Information and Communication Technologies (ICTs) themselves (Green IT), and (2) the design and promotion of applications of ICTs to reduce adverse environmental impacts of ICTs (Green IS). While these fields have been typically explored separately in the academic literature, recent studies have proposed the idea of 'digital sustainability' which highlights the presence of potential valuable synergies between them. This chapter aims to define what we mean by digital sustainability and discusses some of the main trends, themes and concepts related to digital sustainability before discussing the different topics covered in the remainder of the book.

Keywords Digital sustainability · Digital transformation · Green IS · Green IT · Climate change · Twin transformation

1.1 Introduction

In recent years, the concept of sustainability has transcended its traditional environmental roots and extended into the digital realm. This chapter delves into the burgeoning domain of digital sustainability, tracing its evolution and providing comprehensive definitions. As the digital landscape continues to expand and evolve, understanding digital sustainability becomes imperative for ensuring responsible and resilient digital ecosystems.

The core ecological challenge of our era consists of three interlocking crises, namely energy, economic growth, and extinction (Kreps, 2018). While these challenges have been overlooked by corporations for a very long time, there has been a clear shift in recent decades. For almost thirty years, the awareness of the three 'Ps' (Profit, People, Planet) of the so-called Triple Bottom Line (TBL) model (Elkington & Rowlands, 1999; Savitz, 2013; Willard, 2012) has been reaching deeper and deeper into business consciousness. The main argument behind this model is essentially that organisations need to consider three distinct bottom-lines when evaluating their business performance. Firstly, of course, the bottom line of the profit and loss account. Secondly, the bottom line of a company's people account: a measure (and measuring this is not straightforward) of how socially responsible an organisation has been and is being throughout its operations. Corporate Social Responsibility and increasingly Corporate Data Responsibility are key elements of business practice for this people account. Finally, the third bottom line is the company's planet account: a measure of how environmentally responsible the organisation has been and is being. Thus, as Hart and Milstein (2003, p. 56) put it, "a sustainable enterprise is one that contributes to sustainable development by delivering simultaneously economic, social, and environmental benefits—the so-called triple bottom line", or as Savitz (2013, p. v) put it, TBL "captures the essence of sustainability by measuring the impact of an organisation's activities on the world; including both its profitability and shareholder values and its social, human and environmental capital". For Hart and Milstein (2003), there are four principal drivers for such a route, namely (1) resource efficiency and pollution prevention, (2) Internet-connected coalitions of non-governmental organisations (NGOs), (3) distributed technologies and (4) social development and wealth creation on a massive scale.

To enter a sustainable development pathway in accordance with the United Nations Sustainable Development Goals (SDGs) (United Nations, 2015), vast societal changes are required. Sachs et al. (2019) group such social changes into six main 'transformations': (1) education, gender and inequality; (2) health, well-being and demography; (3) energy decarbonisation and sustainable industry; (4) sustainable food, land, water and oceans; (5) sustainable cities and communities; and (6) digital revolution for sustainable development. This chapter, and this book more generally, aims to contribute to the discussion on the sixth of these transformations by exploring digital sustainability through the lenses of different perspectives and applications. The remainder of this chapter is structured as follows: Sect. 1.2 discusses the intersection between digital transformation and sustainability. Section 1.3 defines digital sustainability. Section 1.4 provides a summary of key themes in digital sustainability research and provides an overview of key terms and concepts related to digital sustainability that appear in this book and in the wider academy and industry discussion on this topic. Section 1.5 presents a summary of the topics discussed in the remaining chapters of this book. Finally, Sect. 1.6 presents some final remarks to conclude the chapter.

1.2 Tackling the Sustainability Challenge Through Digital Transformation

ICT and information systems (IS) are often presented as both a cause and a potential solution to the climate crisis. In fact, data centres and the wider communications sector are set to be responsible for 20% of the world's electricity use in the coming years (Andrae, 2017). Moreover, it has been argued that "the vast majority of information systems research is motivated and positioned as being of value to corporate stakeholders, often paraphrased by authors in their research contributions as 'managers'" (Davison, 2023, p. 1). Such a focus upon profit maximisation in IS discourse has been largely to the exclusion of social and environmental concerns. However, both IT and IS can play a critical role in supporting businesses to improve capabilities that deal with sustainability challenges (Hanelt et al., 2017). Korte et al. (2012) have pointed out that identifying and engaging all stakeholders in a sustainability focus in information systems management can be key to its success.

The response in respect of the climate crisis from research on digital technologies has, to date, been twofold: (1) attempts to address the carbon footprint of ICT themselves, sometimes referred to as 'Green IT' (e.g., Bose & Luo, 2011; Butler, 2011; Desautels & Berthon, 2011; Elliot, 2011; Watson et al., 2010; Zhang et al., 2011), and (2) research towards the design and promotion of applications of technology and systems (Elliot & Webster, 2017) to "reduce the adverse environmental impacts of business activities" (Nishant et al., 2017, p. 543) sometimes referred to as Green IS (Chow & Chen, 2009; Cooper & Molla, 2017; Gholami et al., 2016; Hedman & Henningsson, 2016; Loeser et al., 2017; Malhotra et al., 2013; Melville, 2010).

More recently, IS scholarship has turned also to other aspects of sustainability, including smart cities (Ismagilova et al., 2019), the circular economy (Zeiss et al., 2021), the high energy consumption of blockchain (Hughes et al., 2019), IS for the promotion of ecologically responsible behaviours (Corbett, 2013; Loock et al., 2013) and, last but not least, the importance of responding to the United Nations SDGs in the IS discipline (Corbett & Mellouli, 2017; Pan & Zhang, 2020; Watson et al., 2021). For Lawler (2012), however, for an organisation to truly embark on the sustainability journey, they should practice and integrate sustainability in all of their operations, which implies that sustainability is integrated into the very fabric of an organisation and everything that proceeds out of it. This is a key realisation for sustainability transformation.

An emerging strand of the academic literature spanning across multiple disciplines focuses on the interplay between digital transformation and sustainability and refers to this combination as 'digital sustainability' (George & Schillebeeckx, 2021; Pan & Zhang, 2020; Stuermer et al., 2017). Digital transformation can be defined as "a process that aims to improve an entity by triggering significant changes to its properties through combinations of information, computing, communication, and connectivity technologies" (Vial, 2021, p. 118). As such, it describes a firm-wide change which affects the way an organisation does business and impacts its value creation processes (Gölzer & Fritzsche, 2017; Verhoef et al., 2021). Traditionally, most of the interest in digital transformation has been driven by its potential to deliver financial benefits to the organisation through increases in sales or productivity, business model innovations, and novel ways to connect with customers and other stakeholders, among others (Downes and Matt et al., 2015; Nunes, 2013). Matt et al. (2015), for instance, present 'financial aspects' as one of the four essential dimensions of digital transformation strategies. More recently though, researchers have called for more attention to the non-financial benefits of digital transformation to include not only direct organisational non-monetary benefits but also societal and environmental benefits of these transformation initiatives (see, for example, von Kutzschenbach & Daub, 2020; Zimmer & Järveläinen, 2022). In addition to this, a growing number of studies discuss digital transformation and sustainability transformation as synergistic rather than competing phenomena within organisations (George & Schillebeeckx, 2021; George et al., 2021; Mair & Gegenhuber, 2021; Pan & Zhang, 2020; Zimmer & Järveläinen, 2022).

1.3 What is Digital Sustainability?

Bencsik et al., (2023, p. 3) refer to digital sustainability as "a nascent research strand with several blind spots". As it often happens in emerging research streams, one of such blind spots is represented by the lack of a unique shared definition of key concepts; digital sustainability is no exception. In fact, a number of definitions of digital sustainability have been proposed in various academic disciplines, from entrepreneurship (e.g., George et al., 2021) to marketing (e.g., Bencsik et al., 2023), information systems (e.g., Kotlarsky et al., 2023; Pan et al., 2022), and management (e.g., Falcke et al., 2024). Industry participants (e.g., Deloitte, 2023; KPMG, 2024) and international organisations (e.g., United Nations, 2024) have not shied away from this growing discussion either and have contributed to the growing debate on what digital sustainability means and the value it may potentially deliver for different stakeholders.

In the simplest way, digital sustainability can be defined as the convergence of digital transformation and sustainability transformation (also referred to as 'Twin Transformation' in Chapter 3 of this book) (Kotlarsky et al., 2023; Pan et al., 2022; United Nations, 2024). However, this definition does not communicate the whole breath of digital sustainability activities and their potential impacts and implications. Sparviero and Ragnedda (2021) argue that to better conceptualise digital sustainability it is important to understand where the concept of sustainability came from. While 'digital' sustainability has been under the spotlight in recent years, it is the result of an "on-going international interaction between new social movements, academia, politics and business" (Huber, 2000, p. 270) engaged in the so-called Rio process which has brought sustainability to the attention of industry participants, academic researchers, and the overall society more generally (Tulloch & Neilson, 2014). With this perspective in mind, digital sustainability builds on the same key values of sustainability (Sparviero, 2021; Sparviero & Ragnedda, 2021), namely:

- Equality: respect for equal rights of all without distinction for race, sex, language or religion, but also equality of opportunities for both present and future generations so they should all have access to the necessary resources to fulfil their needs (United Nations General Assembly, 2015).
- Harmony: the optimal end-state of a balanced and a collaborative process leading to better quality of life for everybody and to a common sense of shared responsibility (United Nations General Assembly, 2015).
- Self-determination: a sense of empowerment and of being in control of one's environment that not only characterises responsible citizens that are keen to participate in the protection of such an environment, but it also applies to social communities and countries that promote the respect for territorial integrity and political

independence (Tsosie, 2009; World Commission of Environment & Development, 1987).

In this context, digital sustainability may be defined as a set of values that "are the same values as sustainability, so that, if applied to the creation and adoption of new digital technologies, they contribute to a sustainable future" (Sparviero & Ragnedda, 2021, p. 221). This definition of digital sustainability, however, fails to highlight the three typical perspectives of sustainability, namely:

- Environmental sustainability: it mostly focuses on decreasing consumption of natural resources and engaging in practices aimed at improving the long-term health of the planet (Melville, 2010). Environmentally sustainable activities mostly aim to reduce greenhouse gas (GHG) emissions and prioritise the use of renewable resources to sustain all forms of life (Ekins, 2011; Melville, 2010).
- Economic sustainability: it relates to approaches that foster enduring economic prosperity while safeguarding natural resources and enhancing societal well-being (Anand & Sen, 2000; Foy, 1990; Spangenberg, 2005).
- Social sustainability: it involves nurturing robust societal advancements by fostering the growth of civil communities and fulfilling the present needs of society without jeopardising the well-being of future generations (Vallance et al., 2011). The main objective of social sustainability is to promote compatibility amidst cultural and social diversity while elevating individuals' standards of living and responsibly addressing the societal implications of business activities (UN Global Compact, 2024).

An alternative definition that somewhat overcomes such a limitation has been proposed by George et al., (2021, p. 1000) who define digital sustainability as "organisational activities that seek to advance the sustainable development goals through creative deployment of technologies that create, use, transmit, or source electronic data". As this definition points to the 'deployment' of digital technologies for advancing sustainable development, it mostly speaks to the concept of 'Green IS' or, to put it in different words, to sustainability *by* digital. As such, it essentially ignores the overall discussion around the sustainability *of* digital technologies which mostly focuses on the 'development' of more sustainable digital technologies (also referred to as 'Green IT'). More recently, Kotlarsky et al. (2023, p. 938) have defined digital sustainability as "the development and deployment of digital resources and artifacts toward improving the environment, society, and economic welfare".

This definition, although quite simple and concise, overcomes the outstanding limitations of other definitions that were proposed in the past however does not fully acknowledge the importance of sustainability across the lifecycle of the digital resources and artefacts. In some cases, shutting down or decommissioning digital artefacts and resources may be the most sustainable outcome. Furthermore, it does not underscore the need for adaptability in such solutions. Consequently, we propose an extension of this definition which we adopt as the main definition of digital sustainability in this chapter and, more generally, in this book:

> Digital sustainability refers to the design, development, configuration, deployment, and decommissioning of digital resources and artifacts toward improving the environment, and economic welfare.

1.4 Key Trends, Themes and Concepts in Digital Sustainability

Based on our discussion on the definitions of digital sustainability, it clearly emerges that this field of research is evolving rapidly and attracts significant attention from academia and industry alike. Interestingly, even though digital sustainability represents a relatively recent research area, it builds on concepts, values and theories that have already been developed in more established areas of the academic literature such as Green IS and Green IT (Kotlarsky et al., 2023). These provide digital sustainability researchers with robust theoretical and methodological foundations and will likely accelerate the development of this stream of research.

Most of the literature on sustainability generally and, more specifically, on digital sustainability focuses on environmental sustainability and climate change (Kotlarsky et al., 2023; Pan et al., 2022). This is somewhat unsurprising given the sustainability discussion at an international level was primarily established in response to growing concerns about the state of health of our planet and the detrimental long-term impacts of irresponsible use of natural resources (Sparviero & Ragnedda, 2021). Kuntsman and Rattle (2019) present a systematic review of the existing literature on digital sustainability and climate change and classify studies across four categories based on how digital and sustainability were conceptualised: (1) digital as a tool of sustainable innovation; (2) digital as a facilitator of change in people's behaviour through education; (3) digital as a facilitator of change in people's consumption patterns; and (4) digital as a material object. Articles framing digital as a facilitator of change account for the majority of the studies, followed by studies in on e-waste (digital as a material object) and studies picturing digital as a tool of sustainable innovation. More interestingly though, the authors highlight that a bias towards the positive outcomes of digital is commonly present across all categories. The authors refer to this phenomenon as 'digital solutionism' and call for "a systematic account of global and local material damages of devices, platforms and data systems adopted into sustainability research and practice [...]" and "[...] a reconceptualization and denaturalisation of the digital itself as a default solution" (Kuntsman & Rattle, 2019, p. 579). Overall, this suggests that, even though environmental sustainability has attracted most of the research effort so far, significant research opportunities still exist in this area particularly in relation to the potential environmental impact of the transition from old to new technologies, and development and large-scale deployment of energy-demanding digital technologies such as artificial intelligence (AI), cloud computing, blockchain and quantum computing.

Moving beyond the narrow view of environmental sustainability to include the economic and social perspectives of sustainability, Guandalini (2022) summarises existing literature across four key themes, namely (1) digitalisation strategies for sustainability purposes, (2) applicability of digital sustainability to specific industries or sectors (e.g., smart agriculture, industry 4.0, etc.), (3) applicability of digital sustainability to different types of organisations (e.g., public *vs* private sector, large *vs* small to medium enterprises, etc.) and stakeholders (e.g., communities, consumers, etc.), and (4) sustainability through specific digital technologies or functionalities (e.g., big data, digital twins, Internet of Things, etc.). Despite the relatively large number of studies considered in this review (given the emerging nature of this literature), several research gaps still remain. In this context, potential avenues for future research may include, for example, the implementation of multidisciplinary approaches looking at the implementation of digital sustainability from both a technical (e.g., computer science) and non/less technical domain (e.g., management, organisational behaviour, etc.) (Guandalini, 2022), the investigation of organisational strategies for digital sustainability that may provide more transferable findings across different sectors and contexts (Falcke et al., 2024), cross-country comparisons of digital sustainability practices and outcomes in different empirical contexts (Delgosha et al., 2021), the mapping of value capturing strategies and business model blueprints for digital sustainability (Bencsik et al., 2023), and the design of performance measurement frameworks for digital sustainability initiatives that take into account various business and societal stakeholders (Kotlarsky et al., 2023). Finally, some key terms and concepts in the digital sustainability that appear in this book and in the wider digital sustainability discussion are presented in Table 1.1.

1.5 Perspectives on Digital Sustainability

The other six chapters of this book offer varied viewpoints and valuable insights that contribute to our comprehension and interpretation of digital sustainability. They illustrate that, despite considerable intellectual endeavours in conceptualising digital sustainability, we are still at an early stage of theoretical development and empirical research. More importantly, they emphasise the necessity for actionable outcomes that can inform and guide practical applications and support both organisational and individual decision-making. They are presented as follows.

Chapters 2 and 3 are dedicated to sustainability of digital technologies and the interplay between digital transformation and the sustainability challenges that organisations face in the current market environment. More specifically, Chapter 2 discusses the evolution of Green IT and how organisations have embedded this concept into their activities along the entire value chain in response to growing environmental concerns associated with ICT. The chapter then highlights the environmental challenges posed by emerging technologies such as AI and blockchain, and the growing emphasis on circular economy principles (repair, reuse and refurbish). Overall, the authors suggest that the growing interest in these emerging issues may be interpreted as a renewed focus on mitigating the negative impacts of ICT within Sustainable ICT.

Chapter 3 introduces the concept of 'Twin Transformation', a combination of digital and sustainability transformation that enables organisations to leverage the strengths of digital technologies to reach sustainability objectives and vice versa. The authors put particular emphasis

Table 1.1 Key terms and concepts in digital sustainability

Term	*Definition*
Carbon footprint	Carbon footprint represents the total greenhouse gas (GHG) emissions produced directly or indirectly by an activity or accumulated over the lifecycle of a product (Shi & Yin, 2021)
Carbon offsetting	Carbon offsetting refers to "an activity when a company or other actor purchases carbon credits, retires them, and claims the climate benefit as part of its climate action" (Helppi et al., 2023, p. 925)
Circular economy	Circular economy refers to an economic system aimed at minimising waste and maximising the reuse, recycling and repurposing of resources, including digital devices and components that is enabled by an alliance of stakeholders (e.g., industry, consumers, policymakers, researcher) and their technological innovations and capabilities (Kirchherr et al., 2023)
Deep renovation	Deep renovation is a renovation that captures the full economic energy efficiency potential of all improvement works to existing residential buildings that leads to a very high energy performance and significant energy savings (Lynn et al., 2021)
Digital divide	Digital divide refers to the gap between individuals and communities that have different access to digital technologies often due to socioeconomic factors, geographical location or infrastructure limitations, leading to disparities in opportunities and outcomes (Lynn et al., 2022; Philip et al., 2017)
Digital literacy	Digital literacy refers to the ability to access, evaluate and effectively use digital technologies and information resources for personal, social and professional purposes (Martin & Grudziecki, 2006)

(continued)

Table 1.1 (continued)

Term	*Definition*
Digital transformation	"A process that aims to improve an entity by triggering significant changes to its properties through combinations of information, computing, communication, and connectivity technologies" (Vial, 2021, p. 118)
Electronic waste (or e-waste)	Electronic waste refers to discarded electronic devices and components, such as computers, smartphones and appliances, that pose environmental and health risks (Amankwah-Amoah, 2016)
Environmental impact assessment	Environmental impact assessment (EIA) refers to a multi-stage assessment framework for identifying and systematically evaluate the environmental, social and economic impacts of significant developments (Northmore & Hudson, 2022)
Environmental monitoring	Environmental monitoring refers to the systematic collection, analysis and interpretation of data concerning various environmental parameters, such as air and water quality, noise pollution, temperature and humidity, using advanced technologies and IoT devices (Catlett et al., 2017)
Green computing	Green computing refers to the practice of designing, manufacturing and using computer systems and IT resources in an environmentally sustainable manner therefore minimising energy consumption, reducing electronic waste and promoting the use of renewable energy sources in computing operations (Kurp, 2008)
Green IT	Green IT refers to the practice of designing, manufacturing, using and disposing of information technology in an environmentally responsible manner (Murugesan, 2008; Molla, 2013; Thomas et al., 2016)

(continued)

Table 1.1 (continued)

Term	*Definition*
Green IS	Green IS refers to the use of technology to achieve environmental objectives while maintaining or improving the performance and functionality of digital infrastructures and services (Hedman & Henningsson, 2016; Leidner et al., 2022; Loeser et al., 2017; Malhotra et al., 2013)
Intelligent transportation systems or smart (transportation)	Intelligent Transportation Systems or Smart Transportation refers to the application of advanced sensor, computer, electronics, and communication technologies, and management strategies in an integrated manner to improve the safety and efficiency of the surface transportation system (McGregor et al., 2003)
Life cycle assessment	Life cycle assessment is a systematic analysis of the environmental impacts associated with a product, service or process throughout its entire life cycle, from raw material extraction to end-of-life disposal (Finnveden et al., 2009)
Smart building	Smart building refers to cyber-physical solutions able to support and aid the daily routines of users and/or to optimise the management of the building (Vale et al., 2023)
Smart city	Smart cities leverage digital technologies to enhance efficiency, sustainability and quality of life for residents, often incorporating initiatives related to energy management, transportation and public services (Albino et al., 2015; Batty et al., 2012)

(continued)

Table 1.1 (continued)

Term	*Definition*
Smart grid	Smart grids leverage digital technologies, such as sensors, connected meters and analytics, to optimise the generation, distribution and consumption of electricity, enabling efficiency improvements, demand response and integration of renewable energy sources into the power grid therefore contributing to sustainability and resilience in the energy sector (Tuballa & Abundo, 2016)
Smart waste management	Smart waste management (SWM) is the use of enabling ICTs for more efficient, effective and sustainable operations of waste management (Zhang et al., 2019)
Sustainability transformation	It refers to the comprehensive and systemic changes in societal, economic and environmental systems aimed at achieving long-term sustainability goals. This involves, for example, shifting towards more sustainable practices, policies and behaviours to address pressing global challenges such as climate change, biodiversity loss and social inequality (Elliot, 2011; Melville, 2010)
Sustainable design	Sustainable design involves creating products, services and systems with minimal environmental impact throughout their lifecycle, from conception to disposal (He et al., 2018; McLennan, 2004)
Sustainable innovation	Sustainable innovation involves developing novel solutions, products and business models that address societal and environmental challenges while creating long-term value for stakeholders, fostering resilience and competitiveness in the economy (Cillo et al., 2019; Tello & Yoon, 2008)

on the use of AI to foster twin transformation initiatives thanks to its ability to leverage ever-increasing data flows to deal with complex and multi-faceted challenges which are typical of sustainability. The chapter concludes with the presentation of a framework for AI-enabled Twin Transformation and a call for more studies at the intersection of AI-enabled systems, information systems for environmental sustainability (Green IS and Green IT) and digital transformation to provide more theoretical and practical insights on how to best harness the potential of both digital transformation and sustainability transformation.

The second part of this book focuses on four of the eight priority areas for sustainability identified in the European Green Deal (European Commission, 2019), namely energy (Chapter 4), sustainable mobility (Chapter 5), sustainable food (Chapter 6) and the circular economy (Chapter 7).[1] Chapter 4 discusses the role of digital transformation in enhancing efficiency, sustainability and resilience in power generation, transmission and consumption. More specifically, the chapter focusses on how deep learning and reinforcement learning can be used to enable smart grids and better manage the production, storage and usage of electricity from renewable sources, and to protect the energy infrastructure for malicious cyberattacks. The author argues that, if implemented correctly, these technologies can act as catalysts for the transition to smarter, more efficient, resilient and sustainable energy systems.

Chapter 5 is dedicated to the implementation of sustainable practices in the urban environment, whether in cities or towns. The chapter discusses four key research themes relating to digital sustainability in smart cities and towns, namely smart transportation systems, building energy optimisation, smart waste management and environmental monitoring. As such, it encompasses a wide range of the European Green Deal's priority areas. The authors conclude highlighting that the road leading to the realisation of smart cities and towns is not without challenges. These can only be overcome implementing an inclusive, long-term and multi-stakeholder collaborative approach which will provide us with the opportunity to create a more digital, sustainable and liveable future for generations to come.

[1] Other priority areas have been discussed in other publications. See, for example, Lynn et al. (2023) for an in-depth discussion on the role of digital technologies in the context of building renovation.

Chapter 6 is dedicated to implementation of digital sustainability within food systems. More specifically, this chapter focusses on smart farming technologies and discusses how these technologies can lead to the development of more sustainable farming practices and to more resilient food systems. The authors provide an overview of the main barriers and drivers to the realisation of sustainable digital agriculture and discusses international visions of future food systems as proposed by international agencies such as the United Nations (UN), Food and Agriculture Organisation (FAO), the Organisation for Economic Co-operation and Development (OECD), the World Bank, and European Union (EU).

Finally, Chapter 7 discusses the principles of the circular economy and of sustainable product management (SPM). The authors focus on the application of four key technologies (AI, analytics, the Internet of Things and blockchain) for SPM and on how they can be applied in the context of Life Cycle Assessment (LCA) and Product Service Systems. Finally, the authors present the use of digital product passports in an SPM context using electric vehicle batteries as an exemplar use case.

1.6 Conclusion

Digitalisation creates unique opportunities for organisations to prosper but it also poses significant threats to how they transact and interact; climate change is a significant threat to society. To survive, organisations and society need to balance both a digital and sustainability transformation. Extant literature clearly differentiates between research on the environmental impact of digital technologies and the potential of digital technologies to contribute to reducing the adverse impact of business and societal activities on the environment. These should not be viewed as mutually exclusive activities but rather as interrelated and inter-dependent, a twin transformation that mutually motivates and accelerates the other. Notwithstanding this, digital sustainability is a relatively new term in scholarly literature whose definition remains nascent. In this chapter, we discuss current conceptualisations of digital sustainability and define it as the design, development, configuration, deployment and decommissioning of digital resources and artefacts towards improving the environment and economic welfare. The remainder of the book presents snapshots of research on key themes in digital sustainability both on Green IT and Green IS, separately and together.

The transition to a society that builds on both digitalisation and sustainability provides us with substantial opportunities and significant challenges. We face the challenge of transitioning to an 'information society' permeated by digital technologies without not only compromising environmental values but actively contributing to the reversal of the adverse effects of climate change. Yet despite the potential of digital technologies and the existential threat of climate change, our progress is retarded by a lack of awareness, access, adoption and use of digital technologies to achieve sustainable outcomes. Accelerating digital sustainability requires addressing these issues in a coordinated and integrated way. Reframing and refocusing enterprise strategies to accelerate climate action and sustainability through better designed and purposeful digital technologies is a good start.

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CHAPTER 2

Green IT: The Evolution of Environmental Concerns Within ICT Policy, Research and Practice

Per Fors, David Kreps, and Ann O'Brien

Abstract This chapter delves into the environmental concerns associated with Information and Communications Technology (ICT) along its value chain, understood as the series of activities that need to be undertaken to produce, use and dispose of ICT. These activities have their

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respective challenges in terms of environmental sustainability, including greenhouse gas (GHG) emissions, pollution and waste. Furthermore, the chapter offers an overview of practices and discourses, particularly within the realm of information systems (IS), since the 1960s and onwards. It traces the evolution of the Green IT, a concept that originated in response to mounting environmental concerns and the widespread integration of ICT into various facets of society around the mid-2000s. The chapter explores the translation of Green IT, which was mainly concerned with the negative environmental impact of ICT, into Sustainable ICT, a broader concept imbued with more optimistic narratives about the environmental impact of ICT. Drawing from this extensive review, the chapter highlights emerging issues, such as the energy consumption of ICT with the advent of AI and cryptocurrencies, and a growing emphasis on repair and refurbishment. The authors then interpret the interest in these emerging issues as a renewed focus on mitigating the negative impacts of ICT within Sustainable ICT.

Keywords Sustainable ICT · Green IT · Sustainable development · ICT · Evolution of Green IT

2.1 Introduction

Since the introduction of the first microprocessor in the 1970s, the pervasive influence of Information and Communications Technology (ICT) has reshaped the fabric of society. With regard to the environment, it is often assumed that ICTs can potentially be used to promote sustainability (Gholami et al., 2016; Malhotra et al., 2013), e.g., through the dematerialisation of the economy, optimisation of industrial processes and promoting sustainable behaviours and practices (Fors, 2019; Zapico, 2013). However, currently ICTs are predominantly used for other reasons, such as to boost economic performance, thereby intensifying the environmental impact of the technology (Lennerfors et al., 2015). Therefore, it is vital that the technology itself is sustainable in its production, use and disposal, which is currently not the case. On the contrary, ICT presents a variety of challenges concerning environmental sustainability, including the generation waste and carbon dioxide (CO_2) emissions (Forti et al., 2020; Koot & Wijnhoven, 2021; Kreps & Fors, 2020; Perzanowski, 2022). While the potential for using ICT as green tech (greening *by* ICT) is by far greater in theory and often emphasised in contemporary discourse, we advocate for maintaining a strong focus on the greening *of* ICT itself and its value chain(s).

This chapter provides an overview of the environmental concerns of ICT and a historical narrative of these concerns in research and practice since the 1960s. The review methodology is inspired by the hermeneutic approach (Boell & Cecez-Kecmanovic, 2014). We argue that the battle to consider even a human environmental context for information systems (IS) took so long, and other developments such as the advent of the Internet took up so much of scholars' attention, that the impact of ICT on the non-human environment only began to be appreciated in the IS literature after the turn of the millennium. We chart the change in conceptualisation of Green IT from being concerned largely with energy efficiency and cost-effectiveness, to a Green IT that emphasises user behaviours reflecting the changing perception of digital sustainability. The remainder of this chapter is structured as follows. Section 2.2 presents the current environmental challenges of the ICT value chain. Section 2.3 provides a historical narrative of environmental concerns within the ICT industry since the advent of ICT. Section 2.4 turns the attention to emerging trends, and to those concerns we deem likely to be of most significance in the field of Green IT in the coming years. Finally, Sect. 2.5 concludes the chapter with some final remarks.

2.2 The Environmental Impact of ICT Along Its Value Chain

Producing, using and disposing of ICT will always cause some level of environmental harm, due to the physical nature of these products. The impacts of these activities may range in their degree of harm and, at best, be climate neutral, but they can never contribute positively to environmental sustainability (Aebischer & Hilty, 2015; Berkhout & Hertin 2021). Greening *of* ICT—or simply Green IT in its original formulation (Murugesan, 2008)—primarily focusses on minimising the environmental impacts associated with ICT across the entire value chain. The value chain of ICT products refers to the distinct phases of extraction of raw materials, design, manufacturing and transportation, use and disposal (Fors, 2019). The following subsections summarise the more harmful impacts associated with ICT along its value chain.

Extraction of Raw Materials

ICT devices are known for their complex material composition. A single smartphone requires 75 different elements to produce, ranging from plastic and copper to 16 of the 17 known rare earth elements (REEs) (Humphries, 2016). While one device weighs approximately 128 grams (Merchant, 2017), its production necessitates the extraction of 34 kilograms of ore from the earth. This implies that roughly 99.97% of the material extracted ends up as waste even before the device is disposed of. Many ICT companies like to point out that their products consist of recycled materials. Intel, which is one of the more outspoken ICT companies in terms of their sustainability efforts, often talks about the circularity of their products and business models (Intel, 2022). Apple (2022), often described as the industry leader in terms of sustainability, proudly presented in a recent sustainability report that they used up to 20% recycled materials in their products, meaning that 80% of the material used in the 225 million iPhones and the 26 million MacBooks they sold in 2022 were virgin materials. The waste generated from mining activities can be toxic and pollute the land, air and water supplies in areas where the ore is mined. Furthermore, industrial-scale mining activities often make use of machinery powered by fossil fuels, which contribute to climate change.

When ore is refined into useful materials, there are other environmental issues that need to be taken into consideration. Refining ore is a water-intensive process that threatens local supplies of drinking water (Meißner, 2021). Furthermore, it creates various by-products that, if not properly handled, can seep into nearby surroundings, leading to environmental damage and posing health risks to individuals exposed to the waste (Perzanowski, 2022). The fact that many of the materials used in ICTs are extracted in developing countries, while the products themselves are mainly used in developed countries, results in an unequal exchange of resources and environmental impacts between rich and poor nations (Hornborg, 2001; Lennerfors et al., 2015).

The ICT industry is heavily reliant on conflict minerals, such as tin, tantalum, tungsten, gold (3TGs) (Fitzpatrick et al., 2015) and to some extent coltan (Bleischwitz et al., 2012). These minerals are often sourced from the Democratic Republic of Congo (DRC), where ICT companies run the risk of funding militarised groups that control artisanal mines in conditions akin to modern-day slavery. Many ICT companies have claimed that to stop sourcing from the DRC is not a viable alternative (Patel, 2016), and instead the region has been described as a laboratory for various sustainable supply chain initiatives. However, the widespread corruption in the country prevents transparency, leading researchers to assume that these companies may still be indirectly supporting the conflicts (Aula, 2020). While the problem of conflict minerals is mainly a social issue, it may also have some implications for environmental sustainability, since the corruption and the political fragility and instability of the areas prevent policies and frameworks for environmentally conscious extraction (Rhode, 2019).

Design, Manufacturing and Transportation

Designing and manufacturing ICT devices is both electricity and water intensive, and will always result in various streams of waste and by-products that need to be handled (Arushanyan, 2016). In the case of most devices, particularly smaller ones such as laptops and smartphones, the bulk of their carbon footprint has already been generated before they reach the hands of the consumer (Perzanowski, 2022). For an iPhone, approximately 81% of its total emissions stems from processes involving the extraction of raw materials, production, manufacturing and the transportation of the device (Greenly Institute, 2023), depending on the electricity mix where the iPhone will later be used and the length of its useful life. While the total figure is quite modest—approximately 70kg of CO_2 throughout its lifecycle—the immense number of units sold globally translates to a significant overall environmental impact. A laptop, which generally lasts longer than a smartphone but generates more emissions in the use phase, emits approximately 200–500kg of CO_2 emissions as it is manufactured (Belkhir & Elmeligi, 2018). Freitag et al. (2021) suggest that for most user devices (e.g., laptops and smartphones), approximately half of the emissions are 'embedded', meaning that they occur in the extraction and manufacturing phase. Today, especially the production of Solid State Drives (SSDs) is extremely carbon intensive compared with conventional mechanical hard drives (Tannu & Nair, 2023).

Because of the complex material composition of ICT devices, materials need to be sourced from all around the globe, leading to increased emissions from transportation both upstream and downstream in their supply chains. Intel, for instance, contracts more than 9000 suppliers located in 89 different countries to, among other things, supply the materials for their manufacturing process (Intel, 2021). Most materials and components are transported using oceangoing ships that emit not only CO_2 but other pollutants such as sulphur dioxide and nitrogen oxides (Stathatou et al., 2022). Although oceangoing vessels are known for their substantial pollution, their capacity to transport large loads results in per-unit emissions that are nearly negligible. Still, devices must be delivered to homes and offices, and this is often done using medium-duty freight vehicles that are much less efficient on a per-unit basis (Perzanowski, 2022). Amazon, a prominent player in the delivery of such devices, was responsible for a substantial 19 million metric tons of carbon emissions in a single year, primarily attributable to their logistics operations (Ivanova, 2019).

Use

ICTs in their use phase contribute to an increasing portion of CO_2 emissions globally. Freitag et al. (2021) conclude that the global CO_2 footprint of ICTs, in the use phase, contributes to somewhere between 1.8 and 2.8% of the global emissions, which is in line with early estimates by Gartner Institutes (Mingay, 2007). The emissions from most user devices have been lowered substantially over the past 20–25 years due to technological innovation and new legislation and policy, such as the Energy Star[1] and the TCO Certified[2] certifications. Still, as the total number of devices in use is constantly increasing, the overall emissions from ICT in this phase are still on the rise (Allianz, 2023).

While some research suggests that the overall emissions from ICT in the use phase might plateau due to energy-efficient servers and renewable energy sources (Malmodin, 2019), emissions from data centres currently contribute to a substantial portion of the overall CO_2 emissions from ICT (Andre & Edler, 2015; Belkhir & Elmeligi, 2018). This is mainly attributed to the usage phase, as these devices are energy intensive and typically remain operational at all times (Freitag et al., 2021). Media streaming contributes to the increased demand of data centres, and emerging streaming-related practices and technologies, such as ultra-high definition (UHD) streaming (Schwarz, 2022), 'media multitasking' (Widdicks et al., 2019) and streamed video games (Marsden

[1] https://www.energystar.gov/

[2] https://tcocertified.com/

et al., 2020), may well result in increased emissions from data centres. Emerging technologies like Artificial Intelligence (AI) and blockchain are currently consuming immense amounts of electricity, with AI, in particular, expected to be a major driver of the rising electricity consumption within the ICT sector in the foreseeable future (Ferré, 2023). In a recent report, it is projected that, given current trends but assuming a relatively unchanged electricity mix, ICTs could generate emissions exceeding 830 metric tons (MT) of CO_2 by 2030 (Allianz, 2023), surpassing even those of the airline industry. Nevertheless, there is a silver lining since the emissions from ICT usage are intricately linked to the composition of the electricity mix, implying that successful transitions to more sustainable energy systems by countries could substantially mitigate the adverse environmental effects of the ICT industry.

Disposal

ICT devices consist of complex material compositions, but also software, that make them difficult to repair, refurbish or recycle properly (Kreps & Fors, 2020). ICT companies also have very little incentive to produce long-lasting devices, as the business imperative is to have customers replace their devices with new ones as quickly as possible (Perzanowski, 2022). According to the European Commission (2023), ICT products are often disposed of prematurely, leading to 35 million tons of waste, 30 million tons of resource depletion and 261 million tons of GHG emissions within the European Union (EU) annually. For many decades, electronic waste (e-waste), which includes but is not limited to disposed ICT devices, has for a long time been the fastest-growing waste stream globally (Cucchiella, 2015). The waste is often toxic and can contain arsenic, lead, mercury and other toxins, and only approximately 15% of this waste undergoes proper recycling (Ruiz, 2023). The problem is also unequally distributed among the world system (Lennerfors et al., 2015). Despite measures to prevent illegal export of e-waste, much of the waste accumulated in the Global North is exported to the Global South as second-hand goods (Umair et al., 2016). Here, e-waste is informally recycled without proper tools or protective equipment, leading to workers being exposed to mercury fumes, dioxins and cadmium dust and pollutants released into both the air and water reserves (Prakash et al., 2012; Umair et al., 2016).

E-waste contains a significantly higher percentage of valuable materials compared to ore (Kreps & Fors, 2020). For example, one metric ton of circuit boards may hold between 40 and 800 times the quantity of gold and 30–40 times the amount of copper obtained from one metric ton of ore (Bizzo et al., 2014). Still, 'urban mining' has not yet become economically feasible in the developed world, primarily due to the low cost of sourcing virgin materials. This is just one of the many challenges that currently prevent circularity within the ICT industry. Traditionally, the focus has been on increasing the recycling rate, but as Perzanowski (2022) shows, the sheer amount of new e-waste accumulated each year greatly exceeds the capacity of the existing recycle infrastructure. It may therefore be more sensible to reduce the rate of e-waste accumulation by designing products with longer lifespans that can be easily repaired and upgraded. As expressed by Patrignani and Whitehouse (2014, p. 84), promoting environmentally friendly ICT necessitates embarking on a 'quest to slow down the ICT lifecycle'.

2.3 The Evolution of Green IT and Sustainable ICT

Since the dawn of the environmental movement and the widespread adoption of ICT, in parallel with the emergence of the field of IS in the mid-twentieth century, the core ideas of Green IT have emerged—slowly, and at times against the odds—in research, practice, and policy. Furthermore, once established, there has been a gradual shift from Green IT to the more optimistic discourse of Sustainable ICT. The early days of ICT coincided with the rise of the environmental movement in the 1960s, and while global environmental concerns such as climate change were not yet on the agenda, these first two decades saw first an increased awareness of concerns such as electronic waste and toxic chemicals used in the production processes. Later, primarily due to the oil crisis, attention shifted to problems associated with the energy consumption of the large mainframes adopted by organisations worldwide (see Table 2.1). Some ICT companies during these decades implemented power-saving features and even recycled the heat from their data centres into the central heating system, or to heat nearby offices in order to save oil and money (Fors & Lennerfors, 2018). The focus on decreasing energy consumption of ICT continued in the 1980s and 1990s due to the rapid adoption of ICT, not least personal computers (PCs) with over dimensioned power supplies

(Norford et al., 1988). An important realisation during these decades was that most ICT products consumed almost as much power in stand-by mode as when they were fully operational, and in particular in the 1990s, the reduction of stand-by losses became the leitmotif of policy activities in the field of ICT (Aebischer & Hilty, 2015), with examples such as Energy Star and TCO Certified. The increase in power consumption of ICT eventually gave rise to the concept of Green computing. Simpson (1996) noted computers as the fastest-growing electrical load in business, with a fivefold increase in energy consumption over a decade. E-waste policy was also becoming more refined during these decades, with the Basel Convention[3] being adopted in 1989, which among other things banned the export of e-waste to developing countries. Given the growing concern for environmental sustainability within practice and policy in the 1980s and 1990s, surprisingly little attention was devoted to these issues within the academic field of ICT during this time. In the ensuing decades, public awareness grew regarding the significant contribution of the ICT industry to global CO_2 emissions.

While energy-conserving features and strategies had been implemented earlier for cost-saving purposes, it was in the 2000s and 2010s that the link between ICT and global warming became widely recognised. Melville (2010) highlights that environmental sustainability was notably absent from the contents of the 'basket of 8' IS journals until as late as 2003, and in 2007—when Elliot (2007, p. 109) suggested that 'environmental sustainability of ICT should be seen as a sustainable topic in the mainstream of IS research'—the concept of Green IT emerged. One could say that it originated as a response to diverse environmental issues associated with ICT, encompassing concerns like e-waste and the widespread use of various chemicals in the industry. However, its primary emphasis and key selling point were addressing the climate impact of ICT, which at the time was estimated at two percent of the global emissions (Mingay, 2007). This marked a sudden realisation for the IS field where positivist approaches, for many decades, had in various aspects been complicit in the ICT-related factors contributing to climate change (Kreps, 2018). The introduction of the concept grouped pre-existing strategies for fostering environmentally sustainable ICT practices under the umbrella of Green IT (Murugesan, 2008). While mitigating the negative effects of ICT was

[3] https://www.basel.int/.

Table 2.1 Evolution of Green IT

Time period	*Highlights from practice*	*Highlights from IS research*
1960s and 70s	• Establishment of the US Environmental Protection Agency (EPA) (1970) • First UN Conference on the Human Environment, Stockholm (1972) • Enactment of the US Resource Conservation and Recovery Act (RCRA) (1976)	• Hirschheim and Klein's (2012) 'First Era' • Exclusively technological imperatives in Management of Information systems (MIS) • Scant mention of the impact of ICTs upon human beings, let alone the non-human environment • Gradual inception of sociotechnical approaches (Bostrom & Heinen, 1977) • 1st IFIP Human Choice and Computers conference (1974) • Technical Committee 9 on ICT and Society (1976)
1980s and 90s	• Energy efficiency drives in response to rise in personal computers and related energy use—particularly in 'stand-by' mode • Basel Convention on the Control of Transboundary Movements of Hazardous Wastes and Their Disposal (1989) • US EPA began addressing e-waste informally (1990s) • Continued rising electricity consumption of ICT equipment promotes notion of Green computing • Promotion of user participation in system development processes	• Hirschheim and Klein's (2012) 'Second' and 'Third Eras' • 1st International Conference on Information Systems (ICIS) (1980) • Founding of Association for Information Systems (AIS) (1994) • Journals recognised later as the 'Basket of 8' begin to become established • Positivism challenged by reference disciplines arriving in Information Systems: *Philosophy of Technology* (e.g., Kuhn 1962), *Sociology of Technology* (e.g., Mackenzie and Wajcman 1985), *Science and Technology Studies* (e.g., Bijker, 1993), *Foucault studies* (e.g., Discipline and Punish 1975) and *Bourdieu studies* (e.g., Logic of Practice 1990) • Emphasis on user 'acceptance'

(continued)

Table 2.1 (continued)

Time period	*Highlights from practice*	*Highlights from IS research*
2000s and 2010s	• Notion of Green IT (2007) • Publication of the EU Waste Electrical and Electronic Equipment (WEEE) Directive (2003 then revised in 2012) • Notion of Circular Economy promoted by the Ellen MacArthur Foundation (2013)	• Ethical goals and critical approaches (Walsham, 2012) gain traction in IS • Responsible research and innovation (Stahl, 2012) • Genuinely useful research (Rai, 2017) • Green IS tracks at AIS conferences • Sustainability-related special issues in the premier journals

the main objective for Green IT initiatives in the early days, the potential of ICT to be used to promote sustainability in other areas of society, for example through the use of videoconferencing and telepresence technologies, or through carbon accounting and tracking (Mingay, 2007), was soon recognised.

Although this facet was initially associated with Green IT, subsequent perspectives generally classify it under Green IS or Sustainable ICT. This more optimistic discourse grew rapidly after the introduction of Green IT, not least with the help of the Global e-Sustainability Initiative's (GeSI) inaugural SMART series reports. Well-received by industry professionals, policymakers and scholars, these reports highlighted the potential of the ICT sector to enhance the sustainability of society as a whole, suggesting that ICT-based solutions decrease CO_2 emissions by up to 20% globally by 2030 (GeSI, 2015). A few years later, UNEP's International Resource Panel published a comprehensive report outlining steps for achieving sustainable development. The report emphasised the role of ICTs and technological solutions in decoupling economic growth from carbon emissions, promoting environmental sustainability alongside maintained economic growth (Hilty et al., 2011; UNEP, 2011). We argue that this optimistic discourse about the relation between ICT and sustainability took over in the late 2000s. However, in the 2020s—perhaps due to reports of massive emissions stemming from data centres worldwide as the result of video streaming, training AI models and maintaining cryptocurrencies—the main arguments of Green IT are regaining relevance.

2.4 The Relevance of Green IT Today and in the Future

Here we present a sample of contemporary issues that are currently emphasised in research, practice and policy. The majority of these aspects are not new per se, but interest in them has been renewed due to recent events such as the COVID-19 pandemic, the war in Ukraine, the rise of emerging technologies and the (un)availability of raw materials resulting from various geopolitical tensions.

The Environmental Effects of Emerging Technologies

Since the late 2010s there has been a rapid development of AI, blockchain, Augmented and Virtual Reality (AR and VR). These technologies alter how we engage with and navigate the boundaries between the virtual and the physical, and find applications across gaming, entertainment, education, healthcare and production. It is assumed that these technologies may help to further sustainability efforts in various ways in the future (Davis et al., 2023), including minimising the necessity for travelling (Krupnova et al., 2020; Talwar et al., 2022). However, they also present new sets of environmental challenges (Leffer, 2023).

AR and VR devices pose environmental challenges including the demand for rare and critical materials, and specifically new e-waste challenges due to device repair difficulties. This is because wearable devices need to be light and extremely compact, which limits the possibilities of repair (Perzanowski, 2022). For instance, it was recently found in a review of Apple's new VR headset Apple Vision Pro by the Phone Repair Guru (2024) that the device is currently unrepairable.

While AI has seen extensive use in certain industrial sectors and in finance, healthcare and education, the general public started to encounter and actively engage with AI with the release of Large Language Models (LLMs) and various image generating applications. The penetration of these applications in society has given rise to discussions concerning ethics and sustainability. Van Wynsberghe (2021) and Crome et al. (2024) argue that research tends to focus on the potential of AI to solve various sustainability-related problems and overcome sustainability-related challenges in various sectors, including agriculture, banking, healthcare and energy. Coeckelbergh (2021), for example, argues that AI has the potential to help mitigate climate change and various other environmental concerns, and Ludvigsen (2023) shows how using AI models to write or to generate images could potentially save energy compared with manual labour. Still, as both Coeckelbergh (2021) and Van Wynsberghe (2021) show, the impact of AI on environmental sustainability is predominantly negative at present, since AI contributes to increased energy consumption. OpenAI has disclosed that it used 25,000 Nvidia GPUs (Graphics Processing Units) for 100 days, consuming approximately 50 Gigawatt hours (GWh)) of energy, in the process of training a single LLM, GPT-4 (Patel & Wong, 2023). Lai (2023) concludes that the energy used to train the specific language model is equivalent to the energy consumption of 1000 average US households over five-to-six years.

Blockchain technologies are perceived as potentially beneficial in supply chain management, voting systems and healthcare. Davis et al. (2023) present positive applications of blockchain for environmental sustainability, demonstrating instances such as utilising excess heat from data centres for wood drying and incentivising clean energy production. Today, the technology is mainly used to enable cryptocurrencies, most notably Bitcoin. Much research has focussed on the immense electricity consumption of this currency, which has been compared to that of a small country. The Cambridge Centre for Alternative Finance (2024) recently estimated that the power demand of Bitcoin in 2023 was approximately 121.13 Terawatt hours (TWh). Limiting the negative climate impact of this immense electricity consumption, for example through transitioning towards more energy-efficient consensus algorithms, is therefore considered a high priority (Saleh, 2021; Varavallo et al., 2022).

The Environmental Impacts of the Data-Driven Digital Revolution

There is a widespread assumption that digitalisation generally will play a pivotal role in contributing to several of the United Nations' (UN) Sustainable Development Goals (SDGs). Initiatives to improve education, healthcare and clean energy production often rely heavily on ICT, especially on efficient transmission of data. Globally, the volume of data generated, captured, duplicated and consumed has increased almost exponentially, especially since the pandemic, from 41 zettabytes (ZB) in 2019 with a projected growth to 181 ZB in 2025 (Statista, 2023). While the growth in data generation and transmission can be attributed mainly to cloud computing and media streaming, we must now also take into account the high-performance computing power required to analyse the vast amounts of data generated by the Internet of Things (IoT) as more devices in both industries and households contribute to data generation and transmission (Gray, 2018). While access to new information provided by this data can identify important insights for decision making, the impact of this energy consumption is said to be in the region of 23% of the total CO_2 emissions from ICT (Ganesan et al., 2020). Mitigating this huge increase, virtual machine consolidation in green cloud software engineering has been used to support energy-efficient cloud infrastructure (Ganesan et al., 2020). As the number of data centres multiplies to accommodate increasing demand, the use of cloud computing becomes ubiquitous, the greening of the cloud becomes even more important; this includes resource allocation mechanisms that aim to efficiently use and distribute cloud resources (Kumar et al., 2022).

While energy efficiency in data centres has increased significantly, the need for data transmission is increasing even faster, leading to increased climate impact in absolute terms (Andrae & Edler, 2015). Policy initiatives that aim to support data-driven initiatives are just starting (Lucivero et al., 2020). Organisations heavily dependent on data centres are often hesitant to disclose data on their environmental impact, as there are limited incentives for them to make such information publicly available (Crawford et al., 2019). In order to exploit the sustainability-related potential of the data-driven digital revolution, it is essential to address the escalating energy consumption of data centres globally. Therefore, the European Commission (2020a) has recently decided that energy-efficient cloud computing should be a top priority in Europe, and sets out to achieve climate-neutral data centre operations no later than 2030.

Circularity of ICT: Refurbishing and the Right to Repair

Perzanowski (2022) shows how manufacturers of technological devices have deliberately created obstacles, including design, business and legal barriers, to impede repairs, thus compelling consumers to buy new devices rather than extending the lifespan of their current ones. In 2020, the European Commission (2020b) adopted the new Circular Economy Action Plan (CEAP) that introduces initiatives along the value chain of different products, including ICTs. It targets how these products are designed and produced, used, reused and discarded. As part of the CEAP, European Commission (2023) recently adopted a new proposal aiming to promote the repair of electronic products. The proposal seeks to encourage more sustainable business models among manufacturers by instituting more extensive obligations. Various similar laws have been enacted in US states such as Minnesota, Massachusetts and New York.

Another related trend is refurbishing of ICT products, which refers to the practice of restoring pre-owned ICT devices to a like-new condition, often including repairs, upgrades and quality assurance checks. In recent years, companies have emerged in the EU and in the US that collect smartphones, laptops, servers and other ICT products that they refurbish and resell to both companies and private consumers. According to the French Environment and Energy Management Agency (ADEME, 2022), choosing a refurbished smartphone reduces, on average, waste by 89%, while also reducing water usage and CO_2 emissions significantly. The demand for refurbished ICT increased during the COVID-19 pandemic as people transitioned to remote work and study, and had to acquire new laptops, headsets and webcams. Simultaneously, production challenges in China resulted in a decreased supply of newly produced ICTs, leading people to search for alternatives. Even before the pandemic, there was a shortage of certain components, particularly GPUs, attributed to the growing interest in Bitcoin mining (Lim & Wibowo, 2022). Given the continued volatility in the market due to various geopolitical concerns, it is safe to assume that the market for refurbished devices will continue to rise in the foreseeable future. In a recent report, CMI (2022) assessed the refurbished device market at about USD 52.34 billion in 2021 and anticipates it to rise to USD 64.10 billion in 2022, with a projected increase to roughly USD 146.43 billion by 2030.

2.5 Conclusion

Despite the environmental movement gaining momentum as early as the 1960s, the ICT industry largely avoided the level of criticism directed at other polluting sectors, at least until the mid-2000s (Lennerfors et al., 2015), when the concept of Green IT was first introduced and the field of IS started to emphasise these issues. Yet the topic of energy efficiency in ICT was a subject of discourse as far back as the 1970s during the oil crises (Fors & Lennerfors, 2018). The e-waste problem also started to gain increased attention in the 1970s, focussed on the hazardous substances that posed threats to human health and wildlife. Discussion of the human environment around ICTs in the 1970s and 1980s in the IS literature laid the groundwork to expand into consideration of the environment. Thus, in the historical narrative in this chapter we have presented how initiatives promoted by Green IT to improve the environmental sustainability of ICT had already been implemented and discussed to some extent within policy, research and practice albeit, usually, for economic, political or regulatory reasons or to promote social sustainability. Improved environmental sustainability played a relatively small part in the endeavours employed to make ICT green, until the mid-2000s, when environmental concerns began to be used to promote change. Even then, relatively few genuinely new solutions were developed or invented; instead, existing ideas were often repurposed, repackaged or recontextualised as Green IT (Fors, 2019).

For a relatively short period of time, Green IT focussed almost exclusively on mitigating the negative effects of ICT production, use and disposal (Murugesan, 2008). However, the concept acted as a bandwagon towards new understandings of and discourses about the intersection of ICT and environmental sustainability (Fors, 2019). This led to an eventual shift in discourse where ICT was described as having relatively minor negative impacts on the environment during production, use and disposal, but could contribute substantially to furthering environmental sustainability during its use phase (GeSI, 2015). This more favourable perspective on ICT and sustainability prevailed until new discussions about emerging technologies such as AI, blockchain, video streaming and cloud computing once again put the focus on the negative environmental impact of ICT due to its electricity use. Recent policy initiatives that prioritise the promotion of the circular economy emphasise extending the lifespan of ICT devices and encouraging repairability, with a specific emphasis on e-waste reduction (European Commission, 2023). We interpret that the pendulum is once more swinging towards a more active consideration of the negative impact ICT has on the environment.

To conclude, we argue that the potential for ICT to contribute to environmental sustainability remains mainly theoretical. Truly Sustainable ICT, with the power to greatly reduce the negative environmental impact of other polluting sectors of society, has, as of yet, not been deployed on a large scale, and it is difficult to say whether this potential will be unleashed (Börjesson Rivera, 2015). The long-term effects of certain technologies are difficult to foresee (Hallonsten, 2023), not least since their true impacts (or lack thereof) will reveal themselves only in decades to come, oftentimes in unexpected ways and contexts (Mazzucato, 2021). Therefore, we cannot be sure whether these emerging technologies will prove beneficial for environmental sustainability purposes or not. What we do know is that they currently pose a direct threat to the environment, today. We must therefore ensure that their direct negative effects along their respective value chains are mitigated, now.

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CHAPTER 3

Integrating Digital and Sustainability Transformation Through Artificial Intelligence: A Framework for AI-enabled Twin Transformation

Carlotta Crome, Valerie Graf-Drasch, Anna Maria Oberländer, and Stefan Seidel

Abstract "Twin Transformation" is characterised by synergistic leveraging of efforts towards digital and sustainability transformation. It relies on digital transformation to develop digital solutions that can improve sustainability and on sustainability transformation to provide the goals and insights that are required to design these digital solutions. This integrated approach uses data streams and the predictive and generative capabilities of systems enabled by Artificial Intelligence (AI). These systems help to overcome the boundaries of human rationality in addressing the complex

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problem space that exists at the intersection of digital and sustainability transformation. This chapter provides a framework for AI-enabled Twin Transformation and calls for a joint discourse to master what are arguably the two key transformations of this and the following decades.

Keywords Digital transformation · Sustainability transformation · Twin transformation · Artificial intelligence · AI-enabled systems

3.1 Introduction

Digital transformation (DT) and sustainability transformation (ST) are dominant transformational forces. In the past few years, DT has been driven by rapid advancements in digital technologies and has had profound impacts on individuals, organisations, and society (e.g., Vial, 2019; Wessel et al., 2021). Emerging digital technologies, such as digital platforms and Artificial Intelligence (AI), are advancing the ability to collect and process ever-larger volumes of data, make predictions based on that data, and generate solutions. Current DT research mainly focuses on such technological progress changing value creation paths and related positive and negative impacts on different levels of analysis (Hanelt et al., 2021; Vial, 2019). At the same time, concerns about environmental

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degradation, social inequality, as well as economic instability shape market dynamics and have accelerated discussions about digital sustainability and digital resilience (Boh et al., 2023; Kotlarsky et al., 2023). ST depends on the vital role of digital technologies such as AI-enabled systems in addressing environmental and societal challenges to facilitate the development of innovative solutions and systemic changes (Lehnhoff et al., 2021; Watson et al., 2010). AI-enabled monitoring and analysis of data like CO_2 levels and forecast data of extreme weather events play major roles in environmental concerns of ST.

Given the need to pursue both key transformations simultaneously, some businesses and regulators (e.g., European Commission, 2022) have identified a synergistic relationship between DT and ST. Businesses that use an integrated approach to deal with both transformations at once appear to be more successful than those that focus on one at a time (Ollagnier et al., 2021). The European Commission (2022) identifies several applications for an integrated DT and ST approach, including systematic management of supply chains and financial flows, developing monitoring frameworks that measure well-being beyond economic goals, and advancing secure data-sharing frameworks.

Despite these potential synergies, the academic discourse on DT and ST has evolved in relative isolation. Only recently information systems (IS) research started to discuss the potential of an integrated transformation of DT and ST, using the label *Twin Transformation* (e.g., Christmann et al., 2024; Graf-Drasch et al., 2023). Christmann et al., (2024, p. 7) characterise Twin Transformation as "a value-adding interplay between digital and sustainability transformation efforts that improve an organisation by leveraging digital technologies for enabling sustainability and leveraging sustainability for guiding digital progress." Thus, Twin Transformation leverages DT to develop digital solutions that improve ST to provide the goals and insights that are required to design those digital solutions.

In this chapter, we argue that IS researchers and practitioners can play a role in further integrating DT and ST to capitalise on their synergistic potential, acknowledging that IS are embedded in larger systems where human action affects and is affected by the natural environment (Christmann et al., 2024). Specifically, we highlight how AI—the ever-evolving frontier of computational advancement (Berente et al., 2021)—will play a pivotal role in realising Twin Transformation. We develop a framework for AI-enabled Twin Transformation to show how AI-enabled systems can help to overcome the boundaries of human rationality in addressing the complex problem space that exists at the intersection of DT and ST.

The remainder of this chapter is structured as follows. Section 3.2 outlines the Twin Transformation concept and highlights how the problem spaces of DT and ST overlap. Section 3.3 describes the role of AI-enabled systems in contributing to DT's and ST's joint solution space. Finally, Sect. 3.4 concludes the chapter with a discussion of our framework's implications for IS research and practice.

3.2 Twin Transformation: Converging the Problem Spaces of Digital Transformation and Sustainability Transformation

Twin Transformation integrates DT's and ST's problem spaces providing a joint solution space at their interface. These problem spaces comprise the respective challenges of the individual transformations, while they are addressed in an integrated manner in the Twin Transformation solution space. Such integration may appear contradictory at first, as DT initiatives typically focus on economic concerns (e.g., efficiency improvement, sales increase) (Vial, 2019), whereas ST initiatives are motivated by social and environmental concerns (Schoormann, 2020; Seidel et al., 2013).

The DT problem space refers to digital innovations that transform aspects of private and professional lives, organisations' value propositions (Wessel et al., 2021), and society's interconnectedness (Mousavi Baygi et al., 2021). At the individual level, digital technologies redefine communication, collaboration, workplace design, and work practices (sometimes referred to as the future of work). At the organisation level, DT affects processes, products, services, and business models (Vial, 2019). At the societal level, an interconnected techno-society unfolds in which digital technologies create and shape reality instead of only representing it (Baskerville et al., 2019). At all levels, DT involves continuous change and causes significant tensions between the 'old' and the 'new' (Drechsler et al., 2020), requiring flexibility and acceptance of a new culture (Svahn et al., 2017). As a result, the success of DT is often only partial—but the partial success is also because its complex drivers and effects are still poorly understood (Gurbaxani & Dunkle, 2019).

The ST problem space refers to social, environmental, and economic sustainability issues related to individuals, organisations, and society. Individuals can have a positive impact on sustainability by making sustainable consumption choices, while organisations can contribute by empowering individuals to make sustainable consumption choices and to use their power to improve global sustainability. The effect of organisational behaviour should not be underestimated, as, for example, the energy sector in the European Union (EU) is responsible for two thirds of the greenhouse gas (GHG) emissions of the EU (European Parliament, 2023). At the societal level, legislators use regulations to steer individuals' and organisations' behaviour and support intergenerational justice by mitigating biodiversity losses and natural disasters to ensure that future generations can continue to live in a world worth living in (Ekardt et al., 2023). Overall, ST uses the underlying mechanisms and links among the three levels of sustainability to shape and guide its means and ends.

Building on insights from IS research on DT and ST problem spaces, recent publications focus on the intersection where solutions address DT- and ST-related problems simultaneously. Zimmer and Järveläinen (2022), for instance, apply the triple-bottom line of economic, environmental, and social sustainability to DT research and provide a framework for sustainable and digital co-transformations. Graf-Drasch et al. (2023) analyse Twin Transformation on various organisational levels using an integrative work system perspective to describe the interplay of DT and ST and guide organisations in their Twin Transformation. Christmann et al. (2024) examine dynamic capabilities of making DT sustainable and enabling the digitalisation of ST processes to realise Twin Transformation. In this context, particularly because of their learning abilities, AI-enabled systems are recognised as the current technological frontier for developing dynamic capabilities in transformational DT and ST, and the specific role of AI in Twin Transformations warrants our attention.

3.3 A Framework for AI-enabled Twin Transformation

Twin Transformation is rooted in two complex and overlapping problem spaces, each rife with multidimensional problems that are too complex and too large for humans to navigate. DT and digital technologies like AI-enabled systems open many opportunities to address the multi-layered challenges of sustainability, which are often characterised by uncertain interdependencies and nonlinearities (Malhotra et al., 2013; Schoormann, 2020; Watson et al., 2010;). The complexity that results from DT's almost infinite opportunities and ST's multidimensional dependencies make it difficult for humans to evaluate the value of a (digital) solution design (Rai, 2017), so Twin Transformation is a prime example of problems that require application of AI-enabled solutions' predictive and generative capabilities to overcome the boundaries of human rationality (Berente et al., 2021). Through their capacity to learn, make predictions, support decision-making, and generate new solutions, AI can help to build socio-technical systems that have the requisite variety (Ashby, 1991) needed to address complex economic, environmental, and social concerns simultaneously.

The interplay between DT and ST is enabled by networks of sensitised objects, which generate the data streams that provide fodder for AI-enabled systems. AI-enabled systems can process large amounts of data that form the basis for their ability to *learn* (i.e. improve through data and experience) and to be autonomous (i.e. having the ability to act without human intervention) in an expanding range of contexts (Agrawal et al., 2018; Berente et al., 2021). Moreover, AI-enabled systems can provide predictions and *generate design options* that can inform design decisions and lead to new data streams. They can find patterns in large amounts of unstructured data and generate novel artefacts (e.g., through generative AI), thus helping to clarify phenomena related to sustainability and informing appropriate design interventions (Padmanabhan et al., 2022). ST requires AI-enabled systems to learn about a transformation's consequences, such as the gains that are likely from implementing aspects of the Circular Economy (Zeiss et al., 2021).

In the AI-enabled Twin Transformation solution space, AI-enabled systems facilitate identification of patterns and structuring of pertinent data (streams), thereby catalysing Twin Transformation efforts (Christmann et al., 2024). AI-enabled solutions for Twin Transformation *learn* from incoming data streams from DT, while the ST aspect is reflected in providing goals and occasions for generating that data, thereby guiding the *design* of new solutions (Graf-Drasch et al., 2023). Figure 3.1 captures the dual dynamics that underlie AI-enabled Twin Transformation, including the role of data streams and AI-enabled systems.

We conceive of the AI-enabled Twin Transformation solution space as being realised through AI-enabled solutions at the individual, organisational, and societal levels. AI-enabled Twin Transformation solutions

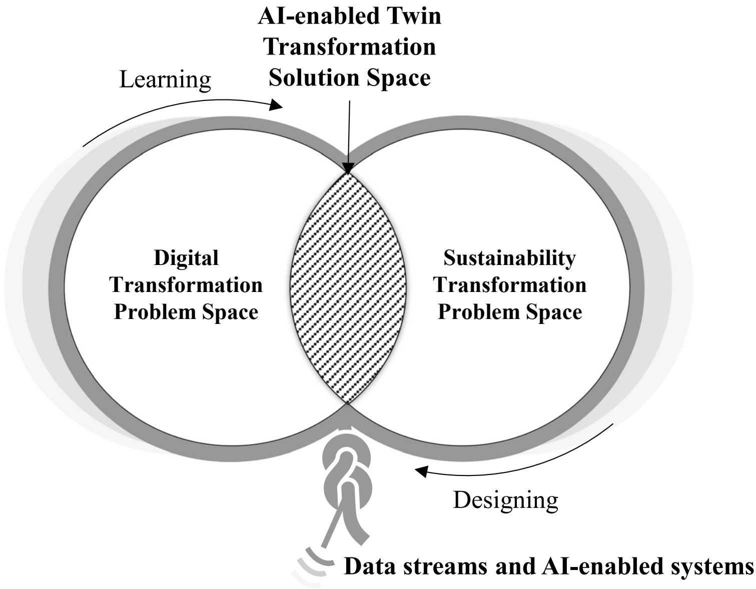

Fig. 3.1 Framework for AI-enabled Twin Transformation

are based on the capabilities of AI-enabled systems, while their design is guided by sustainability principles or purpose. Table 3.1 highlights examples of such AI-enabled solutions for Twin Transformation at these three levels of analysis. The examples show that DT and ST interact synergistically, which results in contributions to sustainability objectives as well as a positive impact on digitalisation.

Recognising that AI-enabled Twin Transformation is a boundary-spanning, holistic transformation, questions for research, and practice arise at the three levels of analysis (Fig. 3.2). First, individual-level behaviour represents the basis for change on all other levels. Individual-level Twin Transformation involves both leveraging data streams and AI to learn about individual behaviour's impacts on sustainability, and designing digital applications to guide individuals towards sustainability-oriented behaviour (Bashir, 2022) while ensuring technology acceptance (Venkatesh et al., 2016). Organisation-level research and practice should

Table 3.1 Examples of AI-enabled solutions for twin transformation

Level of analysis	*Example*	*Description and exemplary impact*
Individual level	Plant Jammer[1]	Plant Jammer helps individuals to reduce food waste in everyday life through providing users customised recipes based on the ingredients they have at home. By leveraging AI-enabled systems, Plant Jammer personalises recipes by understanding users' eating habits and preferences ***Digitalisation impact*** Smarter and more versatile cooking with available ingredients ***Sustainability impact*** Decreasing individuals' food waste
Organisational level	The Climate Choice[2]	The Climate Choice Platform facilitates AI-driven screenings of suppliers to decrease an organisation's negative impact on climate and encourage suppliers to improve their own climate-related performance ***Digitalisation impact*** Data-based assessment of suppliers' (sustainability) performance ***Sustainability impact*** Identifying GHG emitters in the supply chain and reducing emissions
Societal level	Rainforest Connection Guardian Platform[3]	The data- and AI-powered Guardian Platform helps to protect the rainforest from illegal logging and poaching by using solar-powered acoustic streaming devices to monitor and analyse the sounds of the rainforest for abnormalities ***Digitalisation impact*** Guiding rangers more effectively in the search for poachers ***Sustainability impact*** Safeguarding the rainforest and global biodiversity

use AI-enabled systems to explore pattern identification and the impact of organisational activities on sustainability to support the design of cost and resource-efficient digital processes, products, services, and business models (El Hilali et al., 2020). Societal-level Twin Transformation integrates DT's impact on sustainability and ST's impact on digitalisation

[1] https://www.plantjammer.com/empty-your-fridge/inspiration.

[2] https://theclimatechoice.com.

[3] https://rfcx.org/guardian.

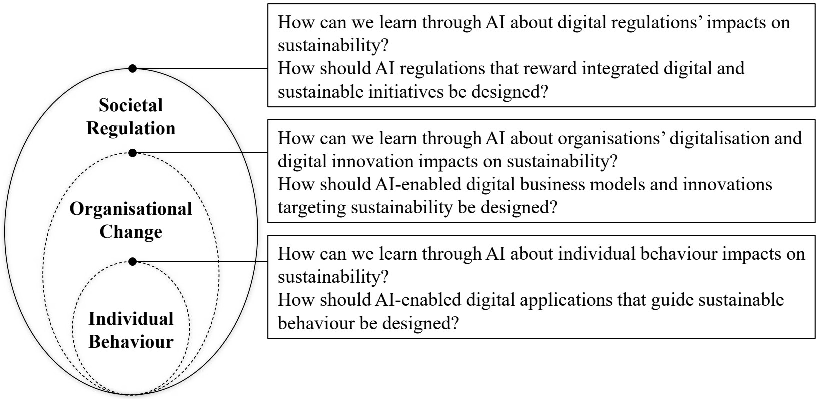

Fig. 3.2 Key questions about AI-enabled twin transformation on three levels of analysis

to influence regulations that measure and reward integrated DT and ST initiatives (European Commission, 2022).

3.4 Implications for Information Systems Research and Practice

To foster leadership and develop mitigation strategies related to the current challenges for DT and ST, such as how to motivate individuals to use new digital technologies or how to enable organisations to measure their impact on climate change, IS researchers and practitioners should focus on AI-enabled Twin Transformation. We identify three implications of such a focus that emerge from this view.

First, Twin Transformation that builds on AI-enabled systems and data streams requires capitalising on the learning and designing cycles simultaneously. Predictions facilitate better designs that can produce new streams of economic, environmental, and social data. Bringing together DT and ST perspectives can result in a virtuous cycle of learning and design activities. Not every IS study has to do both, but we suggest that they at least build on each other cumulatively. Twin Transformation is complex, and complexity can be dealt with through decomposition (Baldwin & Clark, 2000; Simon, 1996). For instance, learning that a particular digital component achieves a particular goal in a particular system (e.g., sensors that monitor the operation of production processes) can provide the foundation for further, more complex designs that produce more complex data streams (e.g., for assessing and certifying the GHG emissions generated in the supply chain). Managing AI-enabled systems in Twin Transformation requires managing the learning and designing cycles that alternate or blend.

Second, Twin Transformation research integrates DT and ST problem spaces, thus opening a new solution space at their intersection, where AI-enabled systems catalyse Twin Transformation solutions that learn from DT to foster sustainability and exploit ST's guidance for DT design (Christmann et al., 2024; Graf-Drasch et al., 2023). However, using AI-enabled systems can be resource-intensive (e.g., energy consumption) and subject to social biases (e.g., gender bias), thus negatively affecting environmental and social sustainability. Hence, practitioners and researchers must account for address, and improve the sustainability of AI-enabled systems across their entire lifecycle to exploit all of Twin Transformation's potential (van Wynsberghe, 2021).

Third, our research offers an outlook on the future of AI-enabled systems and Twin Transformation's interplay in practice. Individuals, organisations, and society deal with the infinite possibilities of AI-enabled solutions. Our framework supports individuals, organisations, and society in connecting AI-enabled solutions and the objectives of Twin Transformation to leverage digital and sustainable advantages. By highlighting the role of data streams and AI-enabled systems in Twin Transformation, our work presents practitioners with a fresh strategic perspective on integrating DT and ST problem spaces.

In conclusion, we argue that Twin Transformation is the pivotal transformation for this and the coming decades. Joint discourse grounded in research on AI-enabled systems, IS for environmental sustainability (i.e., Green IS, Green IT), and DT can help to clarify the relationship between the two transformations, namely digital and sustainability transformation, and explorations of the AI-enabled Twin Transformation solution space to unearth digital and sustainable results.

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CHAPTER 4

Digital Transformation and AI in Energy Systems: Applications, Challenges, and the Path Forward

Eric Olson

Abstract The integration of digital technologies like Machine Learning (ML), Artificial Intelligence (AI), and the Internet of Things is transforming energy systems. This digital transformation aims to enhance efficiency, sustainability, and resilience in power generation, transmission, and consumption. A key focus is developing smart grids that leverage real-time data and intelligent algorithms to optimise operations. In response, deep learning and reinforcement learning techniques are being applied to bolster cybersecurity in the energy sector. Deep learning excels at detecting threats by identifying patterns in large datasets. Meanwhile, reinforcement learning can simulate attack scenarios to train adaptive defence strategies. However, cybersecurity threats pose a major risk as energy infrastructure becomes more interconnected. The Colonial Pipeline ransomware attack in 2021 demonstrated the vulnerabilities of

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critical infrastructure to cyberattacks. Despite great potential, challenges remain regarding model transparency, ethics, and data availability. Overall, realising the promise of AI in the energy sector requires navigating technical complexities and prioritising explainable, trustworthy systems. If implemented thoughtfully, these technologies can catalyse the transition to smarter, more efficient, resilient, and sustainable energy systems.

Keywords Digitisation · Smart grid · Machine learning · Artificial intelligence · Cybersecurity

4.1 Introduction

In the coming years, digitalisation is set to revolutionise energy infrastructure (Kang et al., 2023). Broadly, digitalisation denotes the increasing integration of information and communication technologies (ICTs) across various sectors of the economy. This transformation is driven by advancements in data processing and analytics, Machine Learning (ML), and Artificial Intelligence (AI). Central to this transformation is the confluence of data, AI/ML, and the Internet of Things (IoT). The affordability of sensors, coupled with expanded data storage capabilities, has spurred rapid advancements in analytical techniques to better forecast energy demand as well as predict outages (Potdar et al., 2018). The smart grid represents a transformation in power system operations, driven by integration of renewable energy, deployment of advanced sensors and communication systems, active consumer participation, and increased digitalisation (Dileep, 2020). However, conventional optimisation and control techniques struggle to manage the complexity, dynamics, and uncertainty inherent in modern smart grid operations. In fact, traditional model-based methods rely on accurate system models and knowledge of parameters, which are challenging in complex, stochastic environments (Glavic, 2019). This has motivated growing interest in AI and ML techniques for smart grid applications.

Historically, the energy sector has been a pioneer in adopting technological innovations. For instance, during the 1970s, power utilities were early adopters of technologies that bolstered grid management (Gross et al., 2018). Similarly, oil and gas companies have consistently integrated innovative digital tools to simulate exploration assets and curtail maintenance costs. The energy sector's adaptability and forward-thinking approach have positioned it to harness the full potential of digital advancements. A significant portion of the potential for digitalisation in the energy sector stems from its capacity to synchronise energy demand and supply more effectively (Baidya, 2021). The real-time data relay capabilities of the IoT can substantially minimise energy wastage, thereby curtailing carbon emissions and helping to mitigate climate change.

This chapter examines applications of deep learning (DL) and reinforcement learning (RL) across major smart grid operations (domains including optimal dispatch, electricity markets, and emerging areas like cybersecurity and privacy). For each area, key papers are analysed to provide an overview of implementations, results and limitations. Challenges and future directions are also discussed. The review illustrates that while DL shows immense potential, further research is needed to address issues like cybersecurity, scalability, and stability before large-scale deployment. Overall, DL models represent an important innovation for realising the vision of efficient, reliable, and resilient smart grid operations. The remainder of this chapter is structured as follows: Sect. 4.2 provides a brief description of the smart grid and DL and RL; Sect. 4.3 provides a description of DL applied to the batteries and the smart vehicle grid; Sect. 4.4 examines DL and RL in the context of cybersecurity while Sect. 4.5 provides some concluding remarks.

4.2 The Smart Grid and Deep Learning

The smart grid represents a significant advancement in contemporary energy management. The integration of affordable sensors and monitoring devices has significantly improved the grid's ability to monitor and adjust processes. This gives operators the tools to analyse and leverage data from sensors throughout the grid. As such, the smart grid is able to minimise losses during energy transmission and distribution, thereby improving resource utilisation and overall system efficiency (Wang et al., 2023). The smart grid also improves grid reliability. In real-time, it can respond to disruptions and outages. This is particularly important due to the increased use of renewable energy sources such as solar and wind (Wang et al., 2023). It effectively manages the intermittent nature of these resources, balancing supply and demand, storing surplus energy, and ensuring grid stability. This is instrumental in achieving a cleaner and more sustainable energy future. However, conventional modelling, optimisation, and control techniques encounter substantial challenges in managing the massive amount of data that comes from the smart grid. As such, AI and ML have emerged as crucial components in advancing the smart grid (Massaoudi et al., 2021). AI in the energy space primarily refers to the creation of algorithms capable of performing tasks that traditionally demanded human intelligence, such as real-time monitoring, fault detection, and load forecasting (Cheng & Tao, 2019). ML, a subset of AI, empowers machines to learn from data and adapt without explicit programming, making it particularly valuable for the smart grid. By processing vast amounts of data from various sensors and sources, these models can optimise the grid's operation, reducing transmission losses and improving resource allocation. Additionally, they facilitate real-time monitoring, enabling rapid detection and response to grid disruptions, ultimately minimising downtime, and ensuring uninterrupted power supply.

Two particularly important types of ML have emerged as useful for the smart grid: DL and RL (Zhang et al., 2018). Both fall under the broader category of ML and came from the development of multi-layer neural networks. While DL can encompass a broader range of applications, the term is commonly associated with neural networks with a large number of layers. In RL, the core elements consist of an individual, an overall environment, rewards or pay-outs, and actions. The goal within RL is to optimise the accumulated rewards through a sequence of actions depending upon how the environment changes. Both types of learning have been studied in the academic literature for a while but have only recently been applied to energy sector. Deep Reinforcement Learning (DRL) combines DL and RL, leveraging neural networks for perception and RL for sequential decision-making (Arulkumaran et al., 2017). This enables DRL agents to learn control policies directly from data through interactions with the smart grid, without requiring an explicit system model (Cao et al., 2020).

Models, such as Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks, excel at forecasting tasks due to their ability to process sequential data and learn from it. In integrated energy systems, accurate demand forecasting is crucial. The fluctuating nature of renewable energy sources like solar and wind presents a significant challenge to their integration into the energy mix. DL can mitigate this issue by analysing consumption trends and predicting generation patterns by combining different data sources (e.g., weather forecasts and commodity prices), thus enabling grid operators to balance intermittent renewable resources with natural gas, coal, and other hydrocarbons (Wang et al., 2019). This balance is critical for maintaining grid stability and ensuring a constant energy supply. Additionally, DL can optimise energy storage systems, deciding when to store excess energy and when to release it back into the grid, based on predictive models that take into account future energy generation and consumption. Yang et al. (2021) used an improved Deep Deterministic Policy Gradient (DDPG) framework for lowering operation costs. Zhou et al. (2020) introduced DRL strategy for the economic dispatch of combined heat and power. The improved DRL algorithm (i.e., distributed proximal policy optimisation or DPPO) demonstrated better performance in handling a variety of operating situations compared to conventional methods, all while providing real-time optimal control strategies.

DRL also offers opportunities for enhancing demand-side management by providing systems that can learn and adapt to dynamic energy consumption patterns (Lissa et al., 2021). In demand-side management, DRL agents are trained to optimise energy usage within a grid or a local system by considering real-time variables such as current demand, pricing, and the availability of renewable energy sources. The technology can manage the operation of interconnected devices and systems, from residential HVAC (heating, ventilation, and air conditioning) units to industrial machinery, adjusting their operation to align with changes in the price as well as changes in the source of the energy being used. This capability ensures that energy consumption is not only more economical but also more responsive to the intermittent nature of renewable energy sources. As such, emissions may fall if individuals or manufacturers can adjust production depending on the type of electricity used. For example, Zhong et al. (2021) applied DRL to dynamically optimise incentives for electric heating integration and found cost savings for users and companies, increased wind power consumption, and a more intelligent system for regenerative electric heating by considering user behaviour and differences.

Maintaining the equilibrium of electricity supply and demand is a pivotal role of automatic generation control (AGC), which modulates the power output from various generators. The synergy of ML and AI with such devices equips AGC systems with the foresight and agility to more effectively fine-tune the interplay between generation and demand, thereby bolstering the grid's flexibility and operational efficiency. DRL has been leveraged for AGC to enhance the tracking of unpredictable renewable energy sources and to augment system adaptability (Vijayshankar et al., 2021). Li et al. (2020) employed hierarchical multi-agent DRL to showcase its capability to adjust to fluctuating scenarios and to perform economic optimisations. Despite these advancements, challenges like system instability, hyperparameter sensitivity, and the complexity of sample handling persist.

4.3 Deep Learning, Batteries, and Stabilising the Smart Grid

Batteries will play an integral role in smart grid stability and emissions reductions. Batteries are not merely storage devices; they are the cornerstone of a sustainable, efficient, and reliable power system (Chang et al., 2018). Their role in facilitating the transition to a low-carbon future is becoming increasingly apparent, marking them as indispensable tools in achieving global environmental goals. The future of energy is inextricably linked to the advancement of battery technology, heralding a new era of greener power and more sustainable living. Over the past decade, the cost of lithium-ion batteries dramatically fell which significantly changed the economics of energy storage and electric vehicles (EVs). Since 1991, the price of lithium-ion batteries has dropped by approximately 97% (Ziegler & Trancik, 2021). This steep decrease is largely attributed to improved manufacturing processes, larger production facilities, and advancements in the chemistry and design of the batteries themselves, which have increased energy density and prolonged lifespan (Ziegler & Trancik, 2021). Their ability to store surplus energy from renewable sources like wind and solar is invaluable in mitigating the inherent intermittency of renewables. Moreover, DL and RL learning ensures a more consistent and reliable power supply, crucial for maintaining grid stability. By storing energy during periods of low demand and releasing it during peak consumption times, batteries effectively manage load balancing (Muralitharan et al., 2016). This process, known as peak shaving, reduces the burden on the grid and lessens the dependency on carbon-intensive, peaking power plants, which are typically activated during high demand periods. Moreover, the integration of batteries into smart grids leads to more efficient grid operations. Modern smart grids, equipped with advanced battery storage systems, optimise the use of renewable resources and minimise dependence on outdated, less efficient power generation facilities. Beyond grid stabilisation, batteries are instrumental in the broader context of emission reduction. They optimise power plant operations by reducing the need for plants to run in less efficient, more emissive standby modes. Batteries enable power plants to operate more steadily and efficiently, thus diminishing greenhouse gas (GHG) emissions (Jafari et al., 2022). Batteries also support the growth of Distributed Energy Resources (DERs), such as residential solar panels. By storing energy generated locally, these batteries reduce transmission losses and reliance on centralised power generation, which is often more carbon-intensive. This localised energy production and storage model enhances the efficiency of the power system and contributes to emission reduction.

In the transportation sector, batteries are key to the electrification of vehicles, which is a major avenue for cutting down emissions. EVs not only contribute to cleaner air but may also serve as dynamic energy storage units that can supply power back to the grid when needed. This Vehicle-to-Grid (V2G) capability allows EVs to act as mobile energy reservoirs, further stabilising the grid and promoting the use of renewable energy (Theissler et al., 2021). DL algorithms are also transformative for the energy sector in the realm of EVs, especially for battery management and monitoring. By processing historical battery performance data, DL models can detect signs of battery degradation, thus enabling pre-emptive maintenance actions to be scheduled (Theissler et al., 2021). This pre-emptive model helps in devising intelligent battery management systems; these then dynamically change charging protocols to safeguard battery health while concurrently meeting the energy demands of EV owners. DL contributes to the enhancement of state-of-charge and state-of-health estimation models (Tian et al., 2021). These models are great at forecasting the dependable range of EVs and are instrumental in extending the overall lifespan of the battery. The accuracy of these predictive models is critical, as they directly influence the trust that users place in the EV's operational reliability. Moreover, DL models can integrate environmental variables, such as temperature fluctuations, to refine the battery management process. In fact, temperature is a salient factor that significantly impacts battery performance, efficiency, and safety. Extreme cold can hinder battery chemical reactions, leading to reduced range and slower charging rates, while excessive heat can accelerate battery degradation and pose safety risks (Jaguemont et al., 2016). Thus, DL models can anticipate and adjust to temperature-related battery performance variations, thereby optimising charging strategies and operational guidance according to real-time and forecasted weather conditions (Koohfar et al., 2023). RL presents opportunities to incentivise owners to properly maintain their vehicles. RL agents can be trained to maximise long-term rewards like improved safety and reliability. Owners can receive cost savings or other benefits for proactively maintaining their vehicle based on diagnostic alerts. This positive feedback loop ensures owners prioritise maintenance, vehicles operate optimally, and costs are reduced for manufacturers who avoid warranty claims. RL models may also get smarter by incorporating maintenance data, refining alert triggers and personalised incentives to shape driver behaviour.

City planners can estimate how increased EV adoption will strain the electrical grid under different charging behaviours (Deb, 2021). Utilities can identify locations likely to require grid upgrades to meet new EV load. With computational scenario modelling, DL provides the necessary intelligence to scale infrastructure appropriately. It also aids macro-level energy management and renewable integration by revealing charging patterns. Intelligently expanding charging infrastructure relies heavily on DL (Tuchnitz et al., 2021). High-dimensional spatial datasets describing vehicle populations, existing stations, power grid capacity, and land use can be utilised to determine ideal new charging locations. DL algorithms can pinpoint placement that maximises accessibility and utilisation based on current EV owner charging habits derived from surveys and public data. Compatible sites can be proposed at parking garages, retail centres, and other high-traffic locations where drivers tend to stop for 20 minutes or longer. DL may ultimately provide a way to implement a data-driven approach for strategic infrastructure growth, ensuring charger availability keeps pace with EV adoption. DL also presents ample opportunities to enhance electric vehicle (EV) infrastructure through data-driven modelling and optimisation (Deb, 2021). A key application is creating accurate models of EV energy consumption based on driving conditions. Again, by analysing historical data, DL algorithms can learn to predict future energy needs during a planned trip based on inputs like road type and condition, traffic patterns, driving style, and weather. Models can be personalised by learning from an individual driver's past trips to account for variations in acceleration, braking, and speed. With granular energy consumption forecasts, DL provides a major improvement over simplistic range estimation that relies on battery size alone allowing EV drivers to better (and more accurately) plan routes and charging stops.

Finally, DL enables robust V2G systems whereby EVs bi-directionally transmit power between their batteries and the grid (Vadi et al., 2019). DL optimises the timing and volume of energy flow in either direction. By analysing usage patterns, a DL model can predict upcoming charging demand during peak times. EVs can then be incentivised to delay charging by a few hours to ease grid strain, or discharge energy back to the grid if requested. Meanwhile, during periods of excess renewable generation, EVs can absorb surplus clean energy to charge batteries. This avoids curtailing sustainable power and uses EVs as dynamic storage assets. DL can combine historical data with real-time grid and vehicle signals to orchestrate V2G energy transfer. This balancing act reduces grid volatility introduced by variable renewable sources, benefiting all ratepayers. It also compensates EV owners for energy services that support the overall system. An RL agent can monitor factors like electricity prices, renewable energy availability, and individual user patterns to determine optimal charging. By receiving feedback on outcomes like minimising costs and maximising battery lifespan, the system learns when and how much to charge each vehicle. This personalised charging ensures efficient energy use while satisfying individual mobility needs. Additionally, RL enables intelligent demand response systems, where EVs interact with the grid to balance supply and demand. The RL agent learns strategies for charging or discharging vehicles in response to real-time grid conditions. For instance, EVs can soak up excess renewable energy during sunny middays when solar production peaks. Later in the evening when electricity demand spikes, those same vehicles can discharge power back to relieve grid strain. By optimising bi-directional energy flow, RL helps stabilise an electrical grid incorporating more variable wind and solar generation while compensating EV owners. At a broader level, RL can optimise traffic signals in real-time to improve EV efficiency and reduce emissions. An RL agent controlling traffic lights learns adaptive signalling strategies based on traffic conditions. This dynamic approach reduces congestion and keeps vehicles moving at steadier speeds compared to fixed timing plans. Maintaining consistent speed enhances an EV's energy efficiency, as frequent starts and stops drain more battery charge. Smoother traffic flow also diminishes brake wear and emissions. Additionally, optimising traffic flow allows existing charging infrastructure to support more EVs.

Battery technologies, pivotal in enhancing grid stability and powering EVs, offer notable environmental benefits but also face certain challenges. On the upside, they enable the integration of intermittent renewable energy sources into the grid, facilitating a stable, continuous energy supply and thus reducing reliance on fossil fuels. This integration is instrumental in lowering GHG emissions, both in the energy sector and in transportation, as EVs replace traditional, emission-heavy vehicles. Batteries also promote energy efficiency by allowing for energy storage during low-demand periods and usage during peak times, which diminishes the need for carbon-intensive peaking power plants. However, these advantages come with challenges, including the environmental impact of battery production and disposal, which involves resource-intensive processes and potential issues with recycling and waste management. There is also the concern of sourcing raw materials, often linked to ecological and human rights issues. Moreover, the lifespan and energy density of batteries are areas requiring ongoing technological advancements to ensure long-term sustainability and practicality. Therefore, while battery technologies are central to a more sustainable future in grid management and transportation, addressing these production, disposal, and material sourcing challenges is essential for maximising their environmental benefits.

4.4 Cybersecurity and the Smart Grid

As we move towards smart grids, the critical issue of cybersecurity emerges prominently. Cybersecurity is crucial for ensuring the environmental sustainability of our energy systems, as threats can significantly hinder the adoption and efficiency of smart grids. This indirectly impacts our ability to integrate renewable resources and reduce emissions. A notable example is the Russian cyberattack on Ukraine's electricity grid, which illustrates the potential for widespread disruption in critical energy infrastructure.[1] The integration of renewable resources and the proliferation of IoT devices into the smart grid have significantly enhanced the efficiency and reliability of energy distribution and consumption, but they also introduce complex cybersecurity challenges (Kimani et al., 2019; Gunduz et al., 2020). The threats range from data breaches

[1] https://www.csis.org/analysis/responding-russian-attacks-ukraines-power-sector.

and privacy violations to coordinated attacks on energy infrastructure, potentially causing widespread disruptions. For example, the Colonial Pipeline hack, which occurred in May 2021, was a significant cyberattack that targeted one of the largest pipeline operators in the United States (Hobbs, 2021; Tsvetanov & Slaria, 2021). The pipeline carries gasoline, diesel, and jet fuel along a 5,500-mile route from the Gulf Coast to the New York metropolitan area. The perpetrators deployed ransomware that successfully infiltrated and encrypted the pipeline's computer systems (Dudley & Golden, 2021). This did not just threaten data integrity; it held the company's operational capability at ransom, demanding a significant payment in cryptocurrency to provide the decryption key necessary for recovery. Colonial Pipeline took decisive action to halt all pipeline operations, triggering a supply shock across the Eastern United States and leading to fuel shortages, panic buying, and heightened public anxiety about energy security. The US Government declared a state of emergency to ensure the continuation of fuel deliveries. The incident inflicted significant economic damage and underscored the urgent necessity for more robust cybersecurity defences and strategies tailored to the unique challenges of the energy sector.

DL and RL have become imperative for enhancing cybersecurity in this context. DL models are well-equipped to identify complex patterns that could signify cybersecurity threats (Dixit & Silakari, 2021). In fact, DL algorithms can process and analyse the data points generated by smart grids and identify potential attacks before they manage to breach the system. For example, Convolutional Neural Networks (CNNs) can be trained on network data to recognise the signatures of malware or intrusion attempts, while Recurrent Neural Networks (RNNs) can monitor system logs for suspicious activities over time (Wang et al., 2019). Moreover, DL models can be used for anomaly detection, learning the normal operational patterns of an energy system and then flagging deviations that may indicate a cyber threat. This capability is crucial for early detection, allowing for immediate containment and mitigation of potential breaches.

RL is particularly suited to help cybersecurity where the threat landscape is dynamic, and the attackers continually evolve their strategies (Nguyen and Reddi 2021). By simulating cyberattack scenarios on the smart grid, RL algorithms are trained to recognise patterns of intrusion and react in real-time to neutralise threats. This simulation-based learning allows the algorithms to experience a wide range of attack vectors, ensuring a comprehensive defence strategy. In energy systems, where infrastructure resilience is critical, RL's ability to adapt to rapid changes is invaluable. During an attack such as a Distributed Denial of Service (DDoS), RL can efficiently manage resources and re-route traffic to ensure minimal disruption. Over time, as the RL algorithm encounters more attacks, its strategy becomes more refined and robust, thereby enhancing the overall security of the system.

The implementation of DL and RL in securing the smart grid comes with its set of challenges. One of the primary concerns is the demand for large volumes of high-quality training data, which can be difficult to procure, especially in scenarios simulating sophisticated cyberattacks. The computational intensity required for training and running these advanced models also poses logistical and financial challenges. Additionally, there is the risk of adversarial ML, where attackers may intentionally feed misleading data to corrupt the learning process. The opaque nature of these models, often referred to as 'black boxes', complicates the understanding of their decision-making processes. This lack of transparency can be a significant hurdle in sectors like cybersecurity, where trust and accountability are paramount. To address this, the development of explainable AI/ML tools is crucial. Ensuring that these systems adhere to ethical guidelines and regulations is essential to maintain public trust and to safeguard against the misuse of technology. While DL and RL offer transformative potential for cybersecurity in the energy sector, realising this potential requires navigating technical complexities, ethical considerations, and the need for explainable and trustworthy AI systems. As these technologies continue to mature, their integration into the cybersecurity infrastructure will play a pivotal role in securing the future of energy systems against the ever-evolving landscape of cyber threats.

4.5 Conclusion

The digital transformation underway in the energy sector holds immense potential to enhance efficiency, sustainability, and resilience. Integral to this evolution is the integration of AI and ML, underpinned by proliferating data and advanced analytics. The convergence of these technologies unlocks new capabilities that were previously unattainable. A good example of this potential is the smart grid, which leverages real-time data and intelligent algorithms to optimise generation, transmission, and distribution. Another pivotal application relates to EVs, where AI can improve battery management and charging patterns. But thin data in nascent areas like predictive maintenance necessitates careful training to avoid problems. As with smart grids, transparency and ethics are vital to steer AI towards the public good. The path forward must also address data availability and quality, as training robust models requires vast datasets. Public–private partnerships could help overcome proprietary barriers to data sharing and sharing computing power and energy demands also warrant consideration given AI's intense computational needs.

As outlined, DL and RL enable myriad grid enhancements spanning forecasting, control, and cybersecurity. However, substantial obstacles remain before large-scale adoption. Ensuring the safety and stability of AI-based systems is paramount, as failure could trigger cascading blackouts. Rigorous testing and validation are critical. The opacity of complex neural networks also engenders concerns about accountability and ethics. Developing explainable AI models to elucidate the rationale behind autonomous decisions will be crucial for stakeholders' trust.

As underscored by the Colonial Pipeline attack, cyber threats represent the dark side of connectivity. AI-powered defence systems show promise, but underestimating how nefarious actors may use AI adversary invites failure. Adversarial ML could corrupt training data or exploit blind spots in models. Ultimately there are no silver bullets in cybersecurity. Overall, while AI enables step-changes in the energy sector, it is not a panacea. Technology is only one piece of the puzzle. Realising a sustainable energy future requires holistic thinking across policy, business models, culture, and infrastructure. AI should augment human capabilities, not supplant them. AI is a powerful tool, but not a replacement for human ingenuity, ethics, and leadership. Moving forward, striking the right balance between innovation and regulation will be crucial. Effective governance can steer AI towards the public good while giving it space to evolve responsibly. Beyond technology, truly sustainable energy demands integrating social science, especially economics, and humanities perspectives into solution design. A shared vision for the future and willingness to adapt will determine if AI lifts the energy sector to new heights or leads it astray.

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CHAPTER 5

From Concrete Jungles to Smart Cities and Digital Towns: Deploying Digital Technologies for Environmental Sustainability

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Abstract Urban areas account for most of the world's energy consumption and greenhouse gas emissions, and struggle to cope with the pressure of ever-growing urbanisation and an ageing infrastructure. This issue is likely to become even more prominent in the future due to current trends in population migration that see more people moving from rural to

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urban agglomerates. Luckily, research shows that digital technologies have clear potential for mitigating some of the negative environmental effects of urbanisation while making the urban environment more liveable and enjoyable for citizens. This chapter discusses four key themes discussed in the literature on 'smart cities' directly related to the deployment of digital technologies in the urban environment to support greater environmental sustainability—smart transportation, building energy optimisation, smart waste management, and environmental monitoring.

Keywords Smart cities · Digital towns · Smart transportation · Energy efficiency · Waste management. environmental sustainability · twin transition

5.1 Introduction

Forecasts suggest that up to seven out of ten of the world's population will live in urban areas by 2050 (World Health Organization, 2021), a shift bringing both economic opportunities and substantial challenges for governments and municipal authorities. Urban centres are major consumers of energy, accounting for more than two-thirds of global consumption, and they are responsible for up to 70% of greenhouse gas emissions (GHG) (World Bank, 2023). This intensification of urbanisation not only exacerbates environmental issues but also poses significant health risks, including those related to road traffic injuries, pollution, and limited access to safe physical activities (World Health Organization, 2021). Concurrently, many cities and indeed towns are grappling with the pressures of urbanisation on ageing infrastructures (KPMG, 2012).

In response to these challenges, the concept of the 'smart city' has evolved and gained significant popularity over the past thirty years. A number of definitions of smart city have been proposed and, despite some differences, they share a common conceptualisation of leveraging information and communication technology (ICT) to enhance the functionality of urban subsystems, thereby fulfilling the needs of inhabitants and communities (Albino et al., 2015; Batty et al., 2012). Despite the promise of smart city technologies, these projects often face governance, economic, and technological hurdles that have negatively affected their widespread adoption and implementation (Del Real et al., 2023; Rana et al., 2019). Additionally, the concept of 'smart city' creates a disproportionate focus on large-scale urban agglomerations (i.e., cities) and neglects the needs of smaller and more rural–urban areas and communities which may be affected by similar challenges but have less resources. In response, concepts relating to digital towns and smart streets have been developed to address the needs of both urban and rural areas (Hosseini et al., 2018; Lynn & Wood, 2023; Lynn et al., 2022).

In this chapter, we explore four key themes in research relating to digital sustainability in smart cities and towns, namely smart transportation systems, building energy optimisation, smart waste management, and environmental monitoring. Each of the following sections provides a high-level overview of these themes including the benefits of and challenges to adoption. Finally, Sect. 5.6 concludes the chapter with some final remarks.

5.2 Smart Transportation

Smart transportation, sometimes referred to as intelligent transportation systems (ITS), refers to the integration of advanced information and communication technologies (ICTs) into the transportation infrastructure and vehicles. In contrast, while often conflated with smart transportation and ITS, smart mobility as a concept encompasses all types of transport users including cyclists and pedestrians (Chen et al., 2017). In this chapter, we focus on smart transportation systems as the targets of these systems (e.g., cars, etc.) are those who contribute most to adverse environmental impacts in cities and towns.

Smart transportation systems aim to improve traffic and transit management, manage road use and behaviour, enhance safety, reduce energy and environmental impact, and increase the efficiency of transportation networks (Lynn & Wood, 2023; McGregor et al., 2003). At an infrastructural level, smart transportation systems are enabled by advances in sensor technologies, mobile communication networks, the Internet of Things (IoT), smart transportation communication protocols, and novel computing architectures that expand from the cloud to the edge (Oladimeji et al., 2023). As such, smart transportation can leverage a wide range of technologies including but not limited to:

- Smart traffic signalling, traffic demand management, and control systems to support and actuate decision-making (European Commission, 2020b);
- Automated street bollards, licence plate recognition, and embedded road lighting to prioritise users and manage transportation, change street use, and record infringements (Ghaemi, 2017; Lynn et al., 2020; Dabrowska-Zółtak et al., 2021);
- On-street parking sensors for identifying vacant spots, charging, recording usage, and signalling pricing (Christensen et al., 2021);
- Autonomous vehicles to support public transportation, freight, and micro-mobility (Iclodean et al., 2020; Sell et al., 2021);
- Road anomaly and incident detection (Santosh et al., 2020; Amandio et al., 2021); and,
- Route optimisation, driver, and vehicle information systems (Rammohan, 2023).

Chen et al. (2017) outline the potential ways in which the adoption of smart transportation systems can contribute to energy efficiency. Firstly, the adoption of smart transportation systems can have a number of short-term benefits. These include energy savings related to changes in transport mode (e.g., to public transport), reductions in travel times (e.g., route optimisation and traffic management), and associated reductions in energy consumption per vehicle (Chen et al., 2017). Secondly, smart transportation systems may enable or catalyse other initiatives or interventions that may result in energy efficiencies and ultimately behavioural change (e.g., change in vehicular ownership, residential location, or activity pattern) (Chen et al., 2017). Jianwei et al. (2010) similarly note that ITS and other smart transportation systems may result in significant reduction in traffic-related costs and socio-economic benefits. Specifically, they note that such systems can result in reduced economic losses due to road construction costs, traffic congestion, environmental pollution, road injuries, and fatalities (Jianwei et al., 2010).

Despite the opportunities presented by smart transportation systems, there are significant challenges. Waqar et al. (2023) identify six distinct categories of barriers to the adoption of smart transportation systems—technical, resource, interoperability, management, economic, and personal challenges. In their analysis, interoperability challenges received the highest mean score, followed by economic and technical challenges.

Waqar et al. (2023) identify a wide range of barriers within these categories. Significant barriers included the need for efficient traffic management procedures (technical), inadequate infrastructure for smart transportation systems (resource), guaranteeing compatibility across a range of intricate transport systems and technologies (interoperability), managing, and administering a complex smart transportation system (management), cost of implementation and maintenance (economic), and privacy and security concerns (personal). Both Golub et al. (2019) and Waqar et al. (2023) identify the need for smart transportation systems to be accessible to all users, regardless of ability or money. Golub et al. (2019) caution that while smart transportation systems may have environmental benefits, they may exclude disadvantaged members of the community who do not have access to private vehicles, banking, credit, internet, and mobile phones. Chen et al (2017) highlight three categories of challenges which could equally be viewed as critical success factors in the successful adoption and implementation of smart transportation systems—institutional conditions (including organisational, legal, and policy aspects), technical conditions (concerning technology and analytics), and physical conditions (infrastructure, equipment, and devices). It is important to note that these conditions will be contingent on the development stage of the city or town and the country in which it is located. Consequentyly, the conditions, approach, and prioritisation for smart transportation systems adoption and implementation should reflect local needs and constraints (Chen et al., 2017). In all instances, smart transportation initiatives should involve a wide range of stakeholders and be as transparent as possible (Chen et al., 2017).

5.3 Building Energy Efficiency

85% of buildings in the European Union (EU) were built before 2000; 75% of which have a poor energy performance; over a third of the EU's GHG emissions come from buildings (European Commission, 2024). As over 80% of the energy used in households is consumed for heating, cooling, and hot water, it is unsurprising that a significant element of EU policy focuses on solutions for these areas by 2050. As the overwhelming majority of the European building stock will continue to be in use by 2050, the goal is to increase the energy efficiency in new and existing building stock dramatically by 2050 (European Commission, 2020a). To achieve this, EU policy seeks to ensure new builds are designed to higher standards of energy efficiency and that the existing building stock is refurbished to reduce building energy consumption by significant levels, so-called deep renovation (European Commission,).

Vale et al., (2023, p. 431) define a smart building as "cyber-physical solutions able to support and aid the daily routines of users and/or to optimize the management of the building". They are cyber-physical as they combine ICTs such as building energy management systems (BEMS) and advances in materials and engineering such as pre-fabricated envelope components, biomass insulation, and energy harvesting and renewable energy source (RES) technologies (Lynn et al., 2021). In the context of digital sustainability, the twin goals of smart buildings are efficient energy management combined with a comfortable environment (Zhou et al., 2018). In their review, Al Dakheel et al. (2020) identify four main functions of smart buildings:

1. Climate response: the buildings' capability to respond to actual and expected external climate conditions to minimise energy consumption and maximise renewable energy generation;
2. Grid response: the building's capability to respond to actual and expected data from the energy grid(s) to which it is connected to maximise energy and/or economic efficiencies.
3. User response: the capability of a building to respond to user behaviour and priorities.
4. Monitoring and supervision: the capability to monitor the operational aspects of the building including technical systems and user behaviour and take corrective action to support efficient operation and minimise energy consumption.

As mentioned earlier, these functions are delivered through smart energy management systems including meter data management systems, BEMS, and building automation and control systems (BACS), their connection to IoT-enabled hardware and devices (e.g., sensors and actuators) throughout the building and integrated into key systems (e.g., lighting, heating, etc.). Advanced smart energy management systems can monitor energy supply from the grid and building consumption and through analysis (increasingly enabled by machine learning and deep learning) identify actual or potential inefficiencies, and automatically adjust settings to reduce energy waste. For instance, smart lighting and

HVAC (heating, ventilation, and air conditioning) systems can be dynamically adjusted based on the energy grid supply, user behaviour, occupancy, and anticipated weather patterns to ensure comfort is maintained in an energy-efficient or cost-efficient way (Bhutta, 2017). Similarly, RES and other energy storage systems can be programmatically controlled to manage storage, use, or sell excess electricity back to the grid (Al Dakheel et al., 2020).

While the integration of smart technologies into buildings offers significant potential for energy savings, their implementation is not without challenges. Al Dakheel et al. (2020) note that these challenges differ depending on whether the smart building project is a new build or a retrofit. Research suggests that in new builds significant challenges include the high cost of initial construction, lack of guidelines to manage smart building construction, lack of government incentives and policy, planning issues, lack of properly trained energy efficiency professionals and construction workers, and associated resistance to change from using traditional technologies, techniques and designs, external (grid) and internal system interoperability, amongst others (Al Dakheel et al., 2020; Ejidike & Mewomo, 2022; Lynn et al., 2022). For retrofits, the barriers are more complex. Lynn et al. (2022) identify four categories of barriers to smart building technologies including human, organisational, technological, and external environmental barriers. Buildings involve a wide range of stakeholders including owners, managers, residents, and other users. Research suggests that human barriers including social norms and habits, lack of instruction on how to use new technologies, a lack of information on energy consumption and energy saving opportunities, short-termism, and disturbance of daily routines (Lynn et al., 2022). Technological barriers include those mentioned earlier with new builds with the added complexity that existing buildings often have legacy mechanical systems that have not been designed for digital connectivity and therefore these systems need to be optimised and integrated for modern smart energy management and control systems (Al Dakheel et al., 2020). In deep renovation, again many of the challenges listed for new builds apply. Financial barriers, including high upfront investment costs, funding, the duration, and payback period of deep renovation financial investments, are widely cited in the literature (Lynn et al., 2022). While all smart building projects experience some degree of planning and regulatory challenges, retrofitting existing building stock faces additional challenges, not least where buildings may be protected on historical or cultural grounds. External environment barriers, particularly funding, can be compounded for social housing where local authorities have significant financing and account controls (EMBuild, 2017). Furthermore, while there are significant deep renovation incentives, these may be poorly designed (e.g., split incentives) or complex to draw down (EMBuild, 2017; Lynn et al., 2022).

5.4 Smart Waste Management

Increased urbanisation has a direct and significant impact on waste generation and management challenges. Unsurprisingly, the greater population densities in cities and towns result in a higher waste generation than rural and sparsely populated areas, but also different types of waste including increased volumes of electronic, chemical, and plastics waste which are more difficult to dispose of and recycle. This issue is exacerbated by legacy waste management systems leading to even greater environmental impact.

Smart waste management (SWM) refers to the use of enabling ICTs for more efficient, effective, and sustainable waste management operations (Zhang et al., 2019). Extant research and applications range across the entire waste management lifecycle leveraging technology across various stages of waste management, including collection, sorting, recycling, and energy recovery. Digital technologies, including IoT-enabled bins, geographic information systems (GIS), Radio Frequency Identification (RFID), and advanced analytics, are transforming how waste is collected, transported, and tracked through the waste management lifecycle (Hannan et al., 2015; Rada et al., 2013; Shyam et al., 2017; Sosunova & Porras, 2022). For example, waste collection is increasingly digital and sophisticated. IoT-enabled solar-powered waste receptacles with built-in compactors, such those provided by Bigbelly,[1] cannot only perform multiple functions but notify waste management services of the need to be collected as well as collecting data on volume, fill rate, and collection activity for analysis and chargeback. Similarly, automated vacuum-based systems, such as those offered by ENVAC,[2] are being developed and used to capture different types of waste through standardised inlets connected to an underground pipe network in buildings

[1] https://bigbelly.com/

[2] https://www.envacgroup.com/

or the public realm. Waste receptacles are emptied at pre-programed times or when sensors indicate that the units are full. There is also increasing research and application for autonomous robots for sweeping and steaming pavements or emptying and transporting waste receptacles from smart bins amongst other applications (Roche Cerasi et al., 2020). Once waste is collected new decision support systems are being developed using digital twinning, machine learning and deep learning that optimise waste collection routes dynamically, saving time and fuel but also reducing inconvenience (Yang et al., 2022; Barth et al., 2023; Cardenas et al., 2023).

Once waste is collected, it must be sorted and segregated to support both energy recovery and recycling. Robotic sorting systems (see, e.g., Wilts et al., 2021) and automated segregation techniques based on machine vision can significantly improve the efficiency and accuracy of waste separation, essential for effective recycling (Flores & Tan, 2019; Mohammed et al., 2023; Sanathkumar et al., 2021). Santti et al. (2020) sought to use digital technologies to incentivise and change consumer behaviour with respect to waste sorting. By gamifying waste sorting and segregation, they were able to dramatically increase recycling activities within student residencies. In their experiment, the recycling rate of biowaste increased from 76 to 97% and the recycling rate of plastic from 25 to 85% (Santti et al., 2020).

At the later stages of the waste management lifecycle, intelligent systems are being integrated for real-time monitoring and waste-to-energy frameworks, highlighted in studies by Vlachokostas (2020), Curtis et al. (2021), Kaya et al. (2021), and Shu et al. (2022). These advancements not only improve the operational efficiency of waste processing facilities but also bolster the sustainability of energy recovery methods.

In their survey of public and private waste management services, Borchard et al. (2022) find a wide range of motivations for digitalisation of the waste management value chain including efficiency and quality gains, faster payment transactions, cost optimisation, increased process quality, and increased competitiveness. Interestingly, environmental objectives are reported as the least important objective for the services surveyed (Borchard et al., 2022). They may reflect the digital maturity of the sector and associated solutions. For example, it is far easier to adopt digital technologies in the administrative aspects of waste management than in parts of the value chain which require capital investments and significant changes to infrastructure.

Zhang et al. (2019) identify 12 main barriers in their study of the barriers to SWM adoption and implementation, namely lack of SWM knowledge, lack of regulatory pressures, lack of innovative capacity, difficulties in technologies and applications, lack of market pressures and demands, cost and other financial challenges, lack of environmental education and culture of environmental protection, lack of stakeholder cooperation, including service provider co-operation, short termism, lack of cluster effect, lack of leadership commitment, and finally, lack of proper standards of waste management. They note that the relative importance of these barriers may vary across different stakeholders (e.g., government, technology provider, or technology user). In all cases, there was agreement that lack of knowledge of smart waste management, lack of regulatory pressures, and lack of environmental education and culture of environmental protection were important causal barriers (Zhang et al., 2019). However, Zhang et al. (2019) identify other stakeholder-specific barriers. For example, technology users rated lack of innovation capacity, difficulties in technologies, and their applications higher than the technology providers (Zhang et al., 2019). This study provides insights into the need for cities and towns to consider a wide range of stakeholder needs in the design of any SWM initiative.

5.5 Environmental Monitoring

Environmental monitoring in smart cities and towns refers to the systematic collection, analysis, and interpretation of data concerning various environmental parameters, such as air and water quality, noise pollution, temperature, and humidity, using advanced technologies and IoT devices (Catlett et al., 2017; Kennedy, 2023). As we discussed earlier in Sect. 5.3, data on the external environment can determine sustainability decisions within buildings (e.g., external weather changes impact heating and cooling requirements in buildings). However, environmental monitoring can also play a significant role in enhancing public health, and residents' quality of life by identifying pollution sources, monitoring urban environmental trends (e.g., traffic, regulatory compliance), and facilitating data-driven decision-making for urban planning and management. By leveraging real-time environmental data, smart cities and digital towns can proactively manage environmental risks, reduce pollution, and ensure a healthier, more liveable urban environment for their inhabitants. This approach not only addresses current environmental challenges but also contributes to the resilience and adaptability of urban areas in the face of climate change and rapid urbanisation.

The University of Chicago's Array of Things (AOT) was an experimental urban measurement system based on Waggle, an open platform for edge computing and intelligent, wireless sensors developed at Argonne National Laboratory (Catlett et al., 2017). AOT provided programmable, modular 'nodes' with sensors and computing capability so that one can analyse data at the edge and then periodically send this data to fog nodes or the cloud for analysis (Catlett et al., 2017). For example, it included functionality for measuring climate, air quality, noise levels, flood and water levels, as well as counting the number of vehicles at an intersection (and then deleting the image data rather than sending it to a data centre). Use cases identified by the project included consumer recommender systems for healthiest and unhealthiest walking times and routes, real-time detection of urban flooding, and micro-climate measurement and analysis (University of Chicago, 2021). AOT was designed to be attached to existing street infrastructure (e.g., lampposts), and provide insights at a city or municipal level. A follow-on project, Eclipse, sought to provide increasingly granular insights at a neighbourhood level (Esie et al., 2022; Daepp et al., 2022). For example, results from Eclipse were able to identify environmental-related social inequities across neighbourhoods, e.g. particulate matter levels were notably higher in neighbourhoods with larger compositions Hispanic/Latinx and Black populations at different times. In Gorey, a small town in rural Ireland, a similar 'box of things' has been put in place, through a collaboration between Dublin City University and Wexford County Council, to collect data on air quality, noise pollution, temperature, humidity, and traffic flow (Kennedy, 2023). One of the benefits of the 'box of things' project is to create a critical mass of open data for use by the public, researchers, or industry. However, as Janssen et al. (2012) note open data on its own has little intrinsic value; its value is created by its use.

When combined with other smart city systems and sources of data, the value of environmental monitoring data is significantly enhanced. These systems include traffic control and demand management systems, energy demand response systems, neighbourhood, and district energy management systems, as well as mobile applications for citizens (Lynn & Wood., 2023). In all these instances, environmental data can be used to enhance predictive capabilities and provide insights to actuate change. Furthermore, environmental data can augment and be augmented by data from government socio-economic data on focal populations, public service and utility usage, climate, etc., but also new street-based technologies. For example, there are numerous examples of smart lampposts, street furniture, and smart kiosks that include environmental sensing for data collection (Gomez-Carmona et al., 2018; Baumgartner et al., 2019; Nassar et al., 2019).

Environmental monitoring is not without challenges. From a technological perspective, the availability and scale of enabling infrastructure and technologies, and the associated funding to finance such infrastructure is a significant constraint (Biber, 2013; Lynn & Wood, 2023). Additionally, any public ambient monitoring, on the environment or otherwise, raises concerns regarding trust, data protection, and data security (Lopresti & Shekhar, 2021; Lynn & Wood, 2023). Biber (2013) also notes a number of institutional, political, and legal constraints including the need for institutional continuity, inter-agency conflict, lack of transparency on how data is being used or whether it is effective or not, and lack of skills to analyse and use the data effectively.

5.6 Conclusion

We are witnessing an unprecedented level of urbanisation combined with accelerated climate change. Urban areas, whether cities or towns, have a disproportionate impact on the environment. This chapter discusses the potential impact of digital technologies to proactively manage environmental risks, reduce pollution, and ensure a healthier, more liveable environment. Through smart transportation systems, cities and towns can alleviate congestion, improve and promote eco-friendly modes of mobility, and thereby significantly reduce carbon footprints while increasing safety. Smart buildings, on the other hand, offer a pathway to sustainable urban living by ensuring energy efficiency and fostering healthier indoor environments through intelligent design and operational practices. Furthermore, smart waste management practices enabled by digital technologies not only aim to reduce waste generation but also support and maximise recycling, reuse, and energy recovery, all of which contribute to a circular economy. Lastly, we discussed the critical role of environmental monitoring in identifying, analysing, and mitigating environmental risks through data-driven insights. Realising smart cities and towns is not without challenges however an inclusive, long-term, and multi-stakeholder collaborative approach can help pave the way for a more digital, sustainable, and liveable future for generations to come.

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CHAPTER 6

Smart Farming Technologies and Sustainability

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Abstract This chapter discusses how smart farming technologies are being used to optimise and transform agricultural practices and food systems to make them more sustainable and resilient to the climate change and food security crises. These include precision farming, water-smart, weather-smart, carbon, and energy-smart, as well as knowledge-smart agricultural practices. Adoption of these technologies comes with various barriers and drivers which hinder or aid farmers in their transition to

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digital agriculture. These are categorised into socio-demographic, psychological, farm characteristics, technology-related, systemic, and policy factors. The chapter also discusses international visions of future food systems based on digital technology promoted by international agencies such as the United Nations (UN) Food and Agriculture Organisation (FAO), the Organisation for Economic Co-operation and Development (OECD), and the World Bank as well as the European policy framework to support and monitor digitisation in agriculture and the food system.

Keyword Smart farming; technology adoption; policy

6.1 Introduction

Modern-day agriculture and the challenges it is currently facing are at the epicentre of international and European policy agendas. Climate change with its extreme and unpredictable weather patterns (e.g., extreme high and low temperatures, floods, and long dry periods) jeopardises food production causing a global food security crisis. Agriculture is expected to feed the rising global population which is estimated to reach 9.7 billion by 2050 increasing food demands by 50% (Kumar et al., 2022). At the same time, agriculture is a major cause of environmental degradation with its negative impacts on soil erosion, water use, water and air pollution, greenhouse gas (GHG) emissions, and biodiversity loss (Begho et al., 2022). Smart farming technologies promise to tackle these challenges by enabling optimisation of resource use, increased performance and productivity while creating sustainable production systems (Pathak et al., 2019). The modernisation and the digitalisation of the agricultural sector are a high priority at international and European levels. At an international level, agencies such as the United Nations (UN) Food and Agriculture Organisation (FAO), the Organisation for Economic Co-operation and Development (OECD), the World Bank as well as the European Union (EU), with its notable Green Deal, Farm-to-Fork strategy and Common Agricultural Policy (CAP), pave the way to the transition of food systems to digital agriculture. Despite the prominent benefits associated with the technologies and the policies that support the transformation of the agricultural sector, adoption of smart farming technologies remains slow and low. Various barriers hinder farmers and food systems from their transition to smart farming technologies. In order to foster transition, we need to understand farmer behaviour and integrate behavioural insights into policy design. This chapter aims to present the current trends, challenges, and policy agendas in the context of smart farming technologies and provide some recommendations for future research and policy.

The remainder of this chapter is structured as follows. Section 6.2 provides an overview of the existing smart farming technologies along with the evaluation of the benefits and costs associated with the environmental, economic, and social dimensions. Sections 6.3 and 6.4 outline the barriers and drivers for adoption of smart farming technologies and the policy framework at both international and European levels, respectively. Key regulations and initiatives are discussed with respect to their impact in the transition to digital agriculture. Section 6.5 concludes the chapter with some final remarks about smart farming and sustainability.

6.2 Smart Farming Technologies: Social, Environmental, and Economic Benefits

Smart farming is seen as a pivotal strategy for breaking away from conventional farming technologies and practices, offering an orchestrated path towards sustainable agriculture by achieving significant savings in crop inputs while maintaining or even increasing crop yield. This can benefit environmental protection resulting in less air, water, and soil pollution. Furthermore, smart farming contributes to food security and health protection while also maintaining the livelihoods of rural communities. As such, the adoption of smart farming technologies, including precision agriculture, water-smart, and carbon and energy-smart practices, coupled with knowledge-enhancement activities, is essential for realising a more sustainable, efficient, and socially responsible agricultural sector (Erickson & Fausti, 2021; Pathak et al., 2019). The rest of this section will explore the various smart farming technologies and methods, along with their associated benefits and costs, highlighting their potential to transform agriculture.

Precision Farming

Precision farming, also known as precision agriculture, encompasses a range of technologies and practices aimed at optimising various aspects of crop production, such as sowing, spraying, fertilisation, irrigation, and harvesting by optimising crop inputs which consequently lead to minimising environmental impact. Precision farming utilises many technologies, such as sensors, global navigation satellite systems (GNSS), robots, smart implements, Artificial Intelligence (AI), and Information and Communication Technologies (ICTs), which can be found in space, air, water, on ground, or below ground (Anastasiou et al., 2023b; Fountas et al., 2020; Liakos et al., 2018). By leveraging precision agriculture, farmers can make informed decisions leading to cost savings in relation to inputs (e.g., fertilisers, seeds, nutrients, power, and fuel), reduced waste, and more efficient workload management based on spatial and temporal variability and consequently needs (Anastasiou et al., 2023b; Fountas et al., 2020). Moreover, the social impact of precision farming is significant, as it plays a crucial role in ensuring a stable food supply and reducing health problems across the value chain (farmers, industry workers, and consumers) (Talebpour et al., 2015).

Water-Smart Agricultural Practices

Water-smart agricultural practices, such as rainwater harvesting and micro-irrigation, play a crucial role in sustainable water management, offering significant social, environmental, and economic benefits. These practices can use advanced technologies (e.g., automated actuators) and/or environmentally friendly approaches (e.g., rainwater harvesting, solar-powered irrigation, and aquifer recharge). These practices are essential for addressing the challenges associated with water availability, access, and use in agriculture, particularly in the context of a changing climate (Frimpong et al., 2023). Moreover, water-smart agricultural practices help reduce pressure on traditional water sources, and minimise soil erosion, enhance water-use efficiency, and reduce water waste from an environmental perspective. Economically, water-smart agricultural practices can lead to cost savings and improved productivity. By maximising crop yields per volume of water applied, these practices contribute to enhanced resource utilisation and overall profitability. In relation to the social aspect, water-smart agriculture plays a significant role in ensuring food security and supporting the livelihoods of farming communities due to increased production which results to higher economic profits and welfare (Patle et al., 2019).

Weather-Smart Practices

Weather-smart practices, such as ICT-based agro-meteorological services and index-based insurance, are essential components of smart farming technologies. These practices leverage weather data and analytics to support informed decision-making and risk management in agriculture. For example, these practices are used to inform farmers of pest infestations or crop phenological stages and therefore to proceed to pest control or other appropriate farming practices (e.g., fertilisation, tillage), respectively (Khatri-Chhetri et al., 2017). Moreover, weather-smart services play a significant role in crop insurance. Weather-based indices are used to determine crop yield loss and consequently loss in farm income due to extreme weather events (e.g., dry weather, heat waves, hail) (Dalhaus et al., 2018). From an environmental perspective, weather-smart activities contribute to sustainable resource management by optimising water use, reducing soil erosion, and minimising the use of chemicals and pesticides. Additionally, weather-smart activities can lead to cost savings and improved productivity by providing real-time weather information and enabling farmers to optimise their operations, reduce risks, and enhance overall profitability. In terms of social aspects, weather-smart activities play a crucial role in ensuring food security and supporting the livelihoods of farming communities due to the better information of farmers which can help them prevent and mitigate production related losses caused by advert weather conditions. Thus, by providing access to weather information and risk management tools, these activities contribute to sustainable food production and the resilience of agricultural systems (Khatri-Chhetri et al., 2017).

Carbon and Energy-Smart Practices

One other aspect to which smart farming technologies can contribute is related to carbon sequestration and energy consumption. Carbon and energy-smart practices in agriculture, such as zero-tillage and residue management, play a crucial role in mitigating climate change and promoting sustainable land use. More specifically, zero-tillage practice, enabled by smart farming technologies such as auto-guidance, minimises soil disturbance by reducing the number of times the soil is tilled, thereby retaining soil carbon, promoting soil health, increasing and decreasing fuel consumption (Javaid et al., 2022). Moreover, by incorporating crop residues into the soil, the soil organic matter is increased, resulting in soil moisture retention, and suppressed weed population. Another relevant practice is cover cropping. Cover cropping is the practice of cultivating crops amidst primary crop production, which serves as a means to maintain soil cover, rather than for yielding produce. This technique is geared towards enhancing soil health and fertility. It effectively helps in minimising soil erosion and preserving soil nutrients (Güven et al., 2023). Finally, crop rotation enhanced by appropriate farm management software can also lead to soil health improvement, reduced need for chemical inputs, and consequently sustainable land use (Lieder & Schröter-Schlaack, 2021). Thus, carbon and energy-smart practices enabled by smart farming technologies can retain soil carbon, reduce GHG emissions, enhance soil health, prevent soil erosion, and promote soil biodiversity. Economically, carbon and energy-smart practices can lead to cost savings by reducing the need for chemical inputs and fossil fuel-based energy sources and increasing efficiency. In relation to the social aspect, carbon and energy-smart practices integrated with smart farming technologies contribute to sustainable food production and the well-being of farming communities (Güven et al., 2023).

Knowledge-Smart Activities

Knowledge-smart activities, such as capacity enhancement, are integral to the adoption of smart farming technologies (Kangogo et al., 2021). These activities can be enhanced using modern technologies such as Augmented Reality/Virtual Reality (AR/VR). AR and VR can help farmers better understand smart farming technologies and practices through immersive digital environments. For example, farmers have the ability to virtually operate smart farming technologies such as robots and Internet of Things (IoT) devices and thus understand their benefits and constraints during an actual farming operation (Anastasiou et al., 2023a). Thus, the farmers are equipped with the necessary knowledge and skills to implement sustainable and climate-resilient agricultural practices without needing to purchase expensive farm equipment before understanding the potential benefits, challenges, and constraints for their farm business. As a result, these activities lead to increased productivity, cost efficiency, and overall economic gains, promote the welfare of farming communities and sustainable rural development, and ultimately, contribute to the food security and resilience of agricultural systems (Makate, 2020; Ogunyiola et al., 2022).

6.3 Barriers and Drivers for the Adoption of Climate-Smart Agriculture Practices and Technologies

Farmer adoption of digital agriculture is key to the transition towards a productive, sustainable, and resilient agriculture. Over the past decades, researchers have increasingly examined farmers' decision-making factors that affect adoption of smart farming technologies (Dessart et al., 2019; Tey & Brindal, 2012; Willy & Holm-Müller, 2013). It is now widely acknowledged that farmer decision-making is a complex and multi-faceted process that is influenced by personal, technological, organisational, institutional, and political factors (Verburg et al., 2022). When examining farmer transition to digital agriculture, it is important to adopt a food system perspective where farmers are not seen in isolation but as embedded actors in the food systems in which they operate which pose power dynamics and trade-offs that affect their behaviour (Hoek et al., 2021). To examine the multiplicity of farmer decision-making factors associated with smart farming technologies adoption and implementation, we adopt a wider perspective and categorise them into socio-demographics, psychological, farm characteristics, technology-related, systemic, and policy factors (Hoek et al., 2021).

Socio-demographic Factors

Socio-demographic factors include farmer demographics (e.g., age, gender, education, farming experience) and household characteristics (e.g., size, income). The global farmer profile is characterised by older age and low education that pose strong barriers to the adoption of smart farming technologies (Bai et al., 2022; Vecchio et al., 2020). Reports indicate that farmer age continues to increase; it is currently 58 years old on average in Europe and USA, 60 in Africa and 77 in Japan (Saiz-Rubio & Rovira-Más, 2020). Farming experience seems to partially reverse the ageing effect since as experience accrues with age, farmers are better equipped to implement digital technologies (Tey & Brindal, 2012). However, the ageing crisis calls for generational renewal and the need to attract younger and more educated farmers who are more open to innovations and less risk averse. Farmers' income (both on-farm and off-farm) plays an important role since it provides farmers with the financial resources to invest in new technological equipment (which is sometimes costly and risky) as well as with better access to credit and information sources (Begho et al., 2022).

Psychological Factors

Psychological factors encompass farmers' cognitive, affective, and dispositional factors (Dessart et al., 2019). Among the plethora of factors that have been investigated in the academic literature, motives exert a strong influence on farmers' behavioural shift to digital agriculture. It has been demonstrated that farming operations that are driven by economic gains, increased productivity, or preservation of family traditions are less likely to result in adoption of smart farming technologies compared with farming motives associated with conservation, modernisation, moral obligation, and social embeddedness (Mazurek-Kusiak et al., 2021; Pinna, 2017). A framework that has been prominently employed to explain farmer intention to adopt sustainable practices is the Theory of Planned Behaviour (TPB) (Ajzen, 1991). According to this theory, intention is shaped by three factors, namely behavioural control, subjective norms, and attitudes. In the context of smart farming technologies, behavioural control refers to the farmers' perceived ease or difficulty to perform smart farming technologies, subjective norms refer to the perceptions about what is socially approved by significant others, and attitudes refer to the evaluative dispositions towards smart farming technologies. Therefore, TPB posits that farmers are more willing to adopt smart farming technologies when they believe they have the ability to implement them, their behaviour is perceived as socially acceptable, and they hold positive attitudes towards these technologies. Similarly, farmers' awareness and knowledge about climate change and the benefits associated with smart farming technologies drive sustainable behaviour (Balogh et al., 2020). With respect to dispositional factors, the most influential are environmental consciousness and risk aversion. Farmers differ in how conscious they are about the impact of their farming activities on the environment and on their propensity to take risks, with farmers who are less environmentally conscious and more risk averse less likely to shift to digital technologies (Karali et al., 2014).

Farm Characteristics

Of the farm characteristics examined in the literature, there is general agreement that farm size is a key driver of smart farming technologies adoption. Larger farms benefit from economies of scale, reduced costs, and higher investment returns compared to small and medium sized farms (Michels et al., 2020). Furthermore, farm ownership has been linked with increased adoption rates of smart farming technologies. This is because compared to owners, farm tenants are faced with more risks, reduced financial capacity while oftentimes their decisions are constrained by the farm owner's will (Karali et al., 2014). Not surprisingly the availability of a successor affects farmers' decisions. Previous studies indicate that farmers are more willing to implement smart farming technologies that will boost profitability and environmental status of the farm when there is a successor because they seek to make their business attractive to the future owner (Barnes et al., 2019).

Technology-related Factors

Technologies are usually costly to acquire but costs can be also associated with time, effort, and training requirements by the new technologies which render the investment risky for the farmers. Hence, costs are posited to be a major barrier to adoption of smart farming technologies (Pinna, 2017). A model that has been consistently used in past research to understand farmer technology adoption is the Technology Acceptance Model (TAM) (Davis et al., 1989). According to TAM, decisions to adopt are based on the perceived usefulness and ease of use of smart farming technologies as well as perceived compatibility (added subsequently). A number of technologies are still considered complex and difficult to use which, in turn, negatively affect technology's usefulness for farming operations (e.g., farm productivity, reduced workload) and compatibility with current farming practices, goals, and values (Michels et al., 2020). Furthermore, the advent of data-driven technologies (e.g., precision agriculture), which require large amounts of data collected from farms, has given rise to data privacy and ownership concerns. Due to lack of control and transparency in the way data is collected and shared, farmers appear unwilling to share their data with technology providers and hence, to adopt these technologies (Kaur et al., 2022).

Systemic Factors

Systemic factors refer to the structures and institutions operating at the food systems level. The literature has only recently acknowledged that for food systems to shift to digital agriculture, changes are required in the decision-making of individuals in the whole value chain (Hoek et al., 2021). The social environment plays a major role in farmer adoption of smart farming technologies. It dictates whether a behaviour is approved or disapproved by a community. Social influence can be manifested through social norms, peer pressure (e.g., family, friends, and other farmers), social networks, and social learning effects. Farming communities that are more innovative and technologically advanced exert a "neighbourhood" social influence making farmers mimic their behaviour (Balogh et al., 2020). Similarly, social learning, through peer-to-peer observation of how other farmers implement smart farming technologies, drive adoption (Blasch et al., 2021). Nowadays, farmers need to possess an array of skills to remain competitive, such as entrepreneurial, marketing, and communication skills. However, there is a lack of skilled farmers and as technologies become more complex, the gap between technology advancement and farmer skills is likely to widen in the future. It is widely agreed that access to extension and advisory services such as training courses, field visits, and demonstrations, as well as technical support is crucial for farmers. Proper training and advice are linked with farmer upskilling and increased adoption of smart farming technologies (Blasch et al., 2021). A novel approach to facilitate transition to smart farming technologies is the use of collective and participatory approaches. In this sense, the collaboration and frequent interaction between farmers and other food actors (e.g., processors, retailers, and consumers) is expected to facilitate farmers' access to resources, knowledge sharing, and co-creation of pathways to change. The building of social capital will foster collective action ultimately resulting in transition of entire food systems to smart farming technologies (Pinna, 2017; Willy & Holm-Müller, 2013).

Policy Factors

Policies set the regulatory framework in which the food actors operate by specifying policy targets towards sustainability. Overall, policies are viewed in a positive light because they provide farmers with the financial means and incentives to support the transition to smart farming technologies. However, not all policy instruments are equally effective. In a European context, a comparative analysis of CAP instruments indicated that measures such as direct payments were less successful in triggering change compared to greening measures, extension and advisory services, and better access to information sources (Linares Quero et al., 2022). Moreover, a number of farmers identify inadequate compensations, bureaucratic procedures, and heavy penalties for mistakes as burdens in policy implementation (Chatzimichael et al., 2014; Pinna, 2017).

6.4 International and European Regulatory Framework

The transition to digital agriculture is considered critical by current international and European policymakers. International agreements and support from agencies such as FAO, OECD, and the World Bank along with European policies, such as the CAP and the European Green Deal, aim to promote the sustainable development of national digital agricultural systems for a sustainable, fair, and competitive future.

International Perspective

At an international level, three key organisations, namely the FAO, OECD and the World Bank, set the international vision for future food systems by influencing the design, implementation, and funding of digital agricultural transformation. Two major international agreements influence agricultural and food policies, strategies, and actions from the global to local level. The first is the 2030 Agenda for Sustainable Development, and its Sustainable Development Goals (SDGs), adopted in September 2015 (United Nations, 2015). Among the 17 goals and 169 targets, SDG 1 (No poverty), SDG 2 (Zero hunger), and SDG 9 (Industry, innovation, and infrastructure) represent the building blocks of agricultural policy and establish digital technologies as enablers of sustainable development. The second is the Paris Agreement reached in December 2015. It set out sustainability challenges, especially about meeting climate and biodiversity targets and raised the importance of fully realising the development and transfer of technology to improve resilience to climate change and to reduce GHG emissions (United Nations, 2015).

In 2016, OECD Agriculture Ministers issued a Declaration on Better Policies to Achieve a Productive, Sustainable, and Resilient global food system, which placed a high priority on digitalisation (OECD, 2016). The document outlined a set of shared goals and policy principles to ensure an integrated approach to agriculture and food policies emphasising international cooperation, particularly in trade, investment, innovation, and climate change (OECD, 2016). In the same year, the FAO and the International Telecommunication Union (ITU), together with support from partners, developed the e-Agriculture Strategy Guide aiming to assist countries in developing their national digital agriculture strategy by identifying services and solutions based on the use of agricultural digital technologies (FAO, 2016). The FAO further piloted a regional eAgri Index to assess the preparedness of European and Central Asian countries in formulating and implementing a digital transformation strategy and to provide guidance for the areas of emphasis for strategising (e.g., infrastructure, business environment, etc.) (FAO, 2018). The digital divide between small and large farms, and between developed and developing countries remains a key concern for international organisations and mainly lies in differences in skills, access to information and market environment. For instance, the OECD notes differences in the capacity of countries to generate digital knowledge by evaluating the share of expenditure for research and development in the total value of agricultural output. The USA, the Netherlands, and South Korea, for example, achieved 2.7% compared to 0.5% for Canada and Switzerland (Revenko & Revenko, 2019). To reduce the digital divide and ensure easy access to market data and information, the FAO embarked on creating open information platforms to disseminate information in the food and agriculture sectors such as the monitoring of prices, supply, and demand for food products (Revenko & Revenko, 2019).

More recently, in 2021, the World Bank developed a Roadmap for Building the Digital Future of Food and Agriculture for countries to scale up their digital agriculture (Schroeder et al., 2021). Here, the importance of innovation ecosystems, value chain actors, competition in markets, and research and development are recognised as critical for the digital transformation of food systems. The report also stresses the key role of governments in enabling access to agricultural data by providing access to open data and data-sharing platforms, setting data interoperability standards, and promoting FAIR (Findable, Accessible, Interoperable, and Reusable) principles for data use (Schroeder et al., 2021).

Finally, the OECD reports the importance of using digital technologies in agricultural policy because they improve the efficiency and accuracy of decision-making and support data-driven strategies and policies. Digital technologies enable better data-driven monitoring and compliance mechanisms, the enablement of targeted policies, and the better evaluation of the environmental impact of agriculture (OECD, 2019).

European Perspective

The EU is committed to become a forerunner in achieving the SDGs. Consequently, in September 2021, the European Commission (EC) proposed a Path to the Digital Decade (European Commission, 2021). The policy programme, guided by the 2030 Digital Compass, sets concrete targets and objectives for 2030 as a roadmap to Europe's digital transformation. The roadmap is focused on four pillars—digital skills, secure and performant digital infrastructure, digital transformation of businesses and the digitalisation of public services and proposes a set of cooperation mechanisms (European Commission, 2021). Before the Digital Decade Policy Programme (DDPP), the Digital Single Market strategy paved the way for bridging the digital divide between urban and rural areas and across EU member states, and for providing high-speed connectivity across the EU. This initiative offered many opportunities for agriculture and the food value chain to become smarter, more efficient, and more connected and was later expanded by the Strategy for Connectivity for a European Gigabit Society (European Commission, 2015). Additionally, the EU Cohesion Policy makes a key contribution to delivering Digital Single Market objectives on the ground, through significant financial allocations from the European Regional Development Fund (ERDF), aiming to overcome the digital divide both socially and geographically. To monitor progress towards the 2030 targets, the Digital Economy and Society Index (DESI) was established to evaluate Europe's digital performance based on a set of indicators capturing the four pillars of the DDPP. The 2022 report showed that, although EU member states are making progress towards digital transformation, insufficient digital skills, lack of connectivity infrastructure and investments along with low adoption of key digital technologies, such as AI and Big Data hamper growth (European Commission, 2022).

The European Green Deal comprises a set of policies that provide a roadmap to the green transition and the realisation of the SDGs following a just and inclusive transition of the food systems. In its Farm-to-Fork strategy, the flagship initiative of the legislative framework for sustainable food systems, it demonstrates the commitment to digital innovation, knowledge, and skills development in the agricultural sector. Moreover, the CAP, the main EU agricultural policy, currently accounting for 40% of the EU budget, operates a complex system of subsidies and support measures for the agricultural sector. A key objective for the period 2023–27 is for member states to form their national CAP strategic plans to modernise agriculture and rural areas through fostering and sharing knowledge, innovation, and digitalisation (European Commission, 2023b). The present CAP tools and interventions to favour the adoption of digitalisation are:

- Direct payments and eco-schemes to provide financial support for the adoption of sustainable practices;
- Sectoral interventions (e.g., fruit and vegetables, etc.) to invest in digital technologies at any stage of the supply chain;
- Investments in rural development, for instance for broadband connectivity or the installation of digital technologies;
- Farm advisory services on digital transformation of agriculture and rural areas;
- Knowledge exchange, dissemination of information, and training to boost digital skills, with strengthening the role of Agricultural Knowledge and Innovation Systems (AKIS).

At the regional level, Smart Specialisation Strategies aim to strengthen digitalisation. They focus on identifying the regions' competitive assets and strategic areas for investment, and foster innovation partnerships through better collaboration between different societal stakeholders. The 2023 European Council's report, *Conclusions on a Long-Term Vision for Rural Areas* (LTVRA), highlights that rural areas are essential contributors to EU prosperity and economic strength and to the green and digital transitions, assuming a pivotal role in matters such as food production (European Council, 2023). Digital technologies can contribute to the development of rural areas by providing better accessibility and connections (European Council, 2023). Additionally, the 2020 Industrial Strategy announced actions to support the green and digital transitions of EU industry. These actions include: (1) provide a coherent regulatory framework to achieve the objectives of Europe's Digital Decade; (2) provide SMEs with Sustainability Advisors and support data-driven business models to make the most out of the green and digital transitions; and (3) invest in the upskilling and reskilling of workforce to support the twin transitions (European Commission, 2020). The EU provides various other sources of funding that can be tapped to promote digitisation of agricultural sector, such as the Horizon Europe research and innovation programme and the agricultural European Innovation Partnership programme (EIP-AGRI).

Issues of data sharing and open access data have raised data privacy and ownership concerns. The lack of agricultural data is viewed as an impediment in the design of informed policies, better decision-making as well as monitoring and control procedures. The Declaration, *A Smart and Sustainable Digital Future for European Agriculture and Rural Areas,* noted the importance of using the European space programmes, EGNOS and Galileo, and the Earth observation programme, Copernicus, for more accurate and efficient agricultural operations (Kondratieva, 2021). Moreover, the Directorate-General for Agriculture and Rural Development (DG AGRI) collaborates with the Directorate-General for Communications Networks, Content, and Technology (DG CONNECT) to develop a common European agricultural data space to provide for the digital transformation of Europe's farming industry. Current actions are co-funded through Horizon Europe. Finally, the European Data Strategy aims to set the framework for data governance by facilitating data access and sharing for farmers and value chain actors, creating data interoperability standards, and setting standards that address any risks associated with data use (European Commission, 2023a).

6.5 Conclusion

In conclusion, agricultural sector and food systems can benefit from digital transformation and the transition to smart farming. The latter includes an array of technologies ranging from precision farming, to water-smart, weather-smart, carbon and energy-smart as well as knowledge-smart practices. These technologies have been associated with positive environmental, social, and economic outcomes. Despite the technologies being there for some time, evidence suggests that adoption remains slow and is hampered by various socio-demographic, psychological, farm and technology-related, systemic and policy factors. The policy landscape at the international and EU level is active in setting the standards, framework and regulations for the transition to digital agriculture. International organisations, such as the FAO, OECD and the World Bank influence policy-making while the EU has set a number of policies and initiatives to enable transformation. However, monitoring, control, and evaluation mechanisms are currently lacking, and hence, it is difficult to measure the effectiveness of these policies.

Future research is needed to explore the benefits and costs associated with various smart farming technologies. In particular, while the environmental and economic benefits and costs have been extensively studied in the past, evidence about the social impacts is stil nascent Understanding all three aspects of impacts will enable us to evaluate the overall sustainability of the various smart farming technologies by accounting for the trade-offs that may exist between environmental, social, and economic impacts. Moreover, more evidence on the role of systemic factors in farmer decision-making is required. A food system approach to the digital transformation of the agricultural sector acknowledges the significance of other actors, systems, and structures on farmers' decisions to adopt smart farming technologies. Gathering more insights on how the factors affect behavioural shifts and how future strategies can capitalise on their effect will be valuable. On the policy side, studies need to investigate the impact of various policies on the transition using quantitative or qualitative methodologies. Currently, several policies are in place but their performance in achieving their targets is unknown. Therefore, evaluation studies will enable measurement of their performance and adjustment or tailoring of policies where needed.

By providing incentives and removing barriers to adoption, governments can create a conducive environment for farmers to adopt smart agricultural technologies. Future policies need to take advantage of the availability of agricultural data to inform better decision-making, policy design, and monitoring. Policymakers need to create environments that enable access to data and data sharing by addressing issues concerning data privacy, ownership, and data interoperability. This will facilitate a performance-based policy design and implementation by allowing measurement of progress towards policy targets, enable the design of targeted policies while reducing the information asymmetries and power imbalances in the food systems. Based on the analysis above it is evident that future policies need to be behaviourally-informed rather than focusing on the rational-agent model. For instance, farmer differences that arise from different ages, incomes, farm sizes, economic *vs* environmental objectives, access to markets and credit, social influences should be taken into account and be differentially addressed by policies in order to remove barriers to adoption. When designing policies to foster the adoption of smart farming technologies, local entities and governments should engage in a proactive dialogue that engages farmers and other value chain actors, such as advisors, technology providers, processors, and retailers. Participatory and collective decision-making has been shown to effectively result in digital transformation of the agricultural sector. Finally, to increase policy coherence, there is a need for a systematic and inclusive assessment of current policies. Hence, policies need to establish certain monitoring and control mechanisms with specific set of indicators that will evaluate performance and enable to measure progress towards the targets and ultimately to the SDGs.

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CHAPTER 7

Digital Technologies for Sustainable Product Management in the Circular Economy

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Abstract This chapter provides comprehensive insights into the potential of digital technologies for sustainable product management (SPM). Four key technologies (Artificial Intelligence, Big Data analytics, the Internet of Things, and blockchain) and their application for SPM are presented and discussed. Their potential is explored with regard to Life Cycle Assessment and Product Service Systems. Furthermore, the concept of the digital product passport is discussed, and their use in an SPM context is illustrated with reference to electric vehicle batteries. This chapter concludes with a critical reflection on the deployment of digital

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technologies for SPM and associated challenges relating to ethical and sustainability concerns.

Keywords Blockchain · Artificial intelligence · Big Data · Circular economy · Electric vehicle batteries · Digital product passport

7.1 Introduction

In an age characterised by rapid technological changes and ecological challenges, the interplay between digital technologies, circularity, and sustainable development gains significant attention. This chapter explores this nexus with a particular focus on sustainable product management (SPM). SPM represents an umbrella term that includes several established concepts and strategies underpinning a comprehensive sustainability-oriented management on the product level (Rusch et al., 2023). Those concepts comprise, among others, sustainable supply chain management, eco-design and design for sustainability, sustainability assessments, and in particular, the circular economy (Rusch et al., 2023). The circular economy is described as an economic system aimed at minimising waste and making the most of resources, representing a shift from the traditional linear model of 'take, make, dispose' to a more sustainable approach of reuse, repair, recycle, and regenerate (Reike et al., 2018).

Digital technologies such as Artificial Intelligence (AI), Big Data, the Internet of Things (IoT), and blockchain are central to the current wave of technological advancements. They offer innovative ways for SPM as they can track, analyse, and optimise material and energy flows and resource use along a product's life cycle, thereby supporting the idea of circularity and sustainability. This chapter delves into the research question: How can digital technologies support sustainable product management, i.e. help to improve sustainability and circularity of products along their life cycle?

The practical application of these technologies is varied and profound. From enhancing efficiency in practice to playing a crucial role in Life Cycle Assessment (LCA), these technologies offer a new lens through which sustainability and circularity can be viewed and managed. An interesting and new application is the development of digital product passports. In this chapter, we illustrate this through a case study on electric vehicle batteries.

The remainder of this chapter, which is based on the research activities and specific publications of the Christian-Doppler-Laboratory for Sustainable Product Management, is structured as follows. Sections 7.2 and 7.3 provide an overview of the application of digital technologies in manufacturing companies and in LCA, respectively. Then, Sect. 7.4 presents the potential of digital product passports and illustrates this through a case study on their use for SPM in the context of electric vehicle batteries. Finally, Sect. 7.5 concludes the chapter with a discussion of some of the ethical and sustainability concerns relating to the use of digital technologies in SPM and some potential avenues for future research.

7.2 Application of Digital Technologies for Sustainable Product Management and Product Service Systems

As outlined above, digital technologies have considerable potential to facilitate the transition to a more sustainable and circular economy. However, to leverage the full potential of these technologies, it is paramount to understand their individual and combined benefits and use cases. Rusch et al. (2023) provide a comprehensive mapping of current and potential examples of AI, Big Data analytics, IoT, and blockchain technology in the context of sustainable and circular product management. The authors focused on these four digital technologies because they are perceived as essential enablers for accelerating the transition to more circular value chains and the dematerialisation of the economy (European Commission, 2020a). In their systematic review of the scientific literature,146 examples were identified in 186 scientific papers where digital technologies are or could be applied to SPM. Of the 146 examples, 66 of them featured a case study or a real-life example (Rusch et al., 2023). The other 80 examples were only conceptual descriptions of potential applications of digital technologies for SPM. The study highlights that the potential of digital technologies covers the entire product life cycle, from the beginning to the end-of-life phase (Rusch et al., 2023). Most of the examples presented in Rusch et al. (2023) relate to IoT, followed by Big Data analytics, blockchain, and AI.

As can be seen in Fig. 7.1, most studies only describe the general potential that digital technologies can offer to SPM (i.e. the first line in the figure). Less often, the examples could be assigned to one of the following four areas of SPM: supply chain management, (sustainability) assessment, product design, and business modelling. The technologies also vary according to the benefits they offer to SPM with IoT, Big Data, and AI mostly focusing on increasing the efficiency of existing processes, while blockchain applications aim to increase transparency and trustworthiness in exchanging information along value chains (Rusch et al., 2023).

Figure 7.2 presents more details on the specific SPM activities that can be supported by one or more of the four digital technologies (Rusch et al., 2023). A total of 23 specific activities were identified in the study (Rusch et al., 2023). AI appears to be related to only four of these activities, namely supplier selection, Life Cycle Inventory (LCI) modelling, condition monitoring, and R-strategies (i.e. Reuse, Repair, Refurbish, Remanufacture, or Recycle). IoT was most often discussed concerning its use for (predictive/preventive) maintenance, followed by its use for condition monitoring of products and processes, the collection of data relevant to R-strategies, or for monitoring energy demands (Rusch et al., 2023). Big Data analytics is often discussed and used in conjunction with data collection from IoT sensors, such as in the case of maintenance (Rusch et al., 2023). However, it is also used on data from other sources, such as in the case of trend mining or risk assessment (Rusch et al., 2023). Finally, while blockchain can add a layer of trust to processes in which other technologies are involved, it also has individual applications, such as in compliance-related data exchange along value chains or incentives (Rusch et al., 2023).

In summary, Rusch et al. (2023) highlight that digital technologies have considerable and wide potential for facilitating SPM practices. To date, most applications have primarily resulted in incremental improvements (e.g., increased efficiency of existing processes), with more radical forms of improvement remaining relatively uncommon. Thus, there is room for a wider and effective utilisation of digital technologies in various areas of SPM to accelerate the transition towards a more sustainable and circular economy.

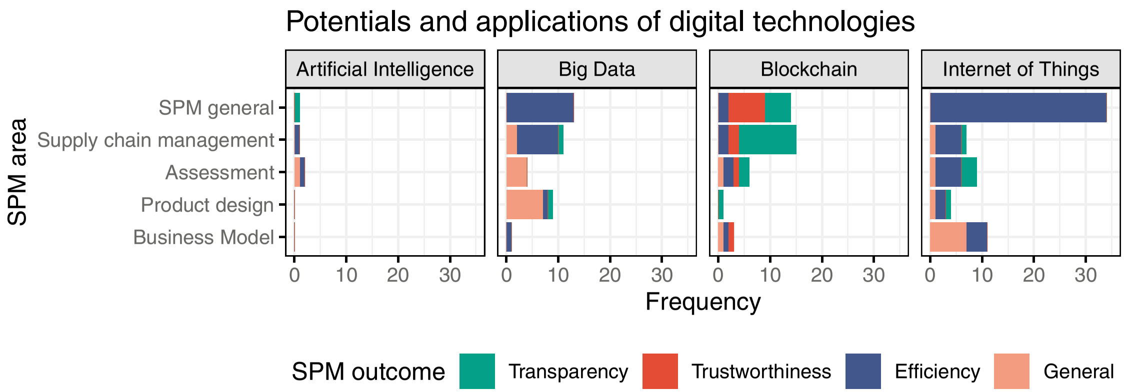

Fig. 7.1 Classification of potential and application examples of digital technologies by area of application and improved SPM outcome (n = 146) (Rusch et al., 2023)

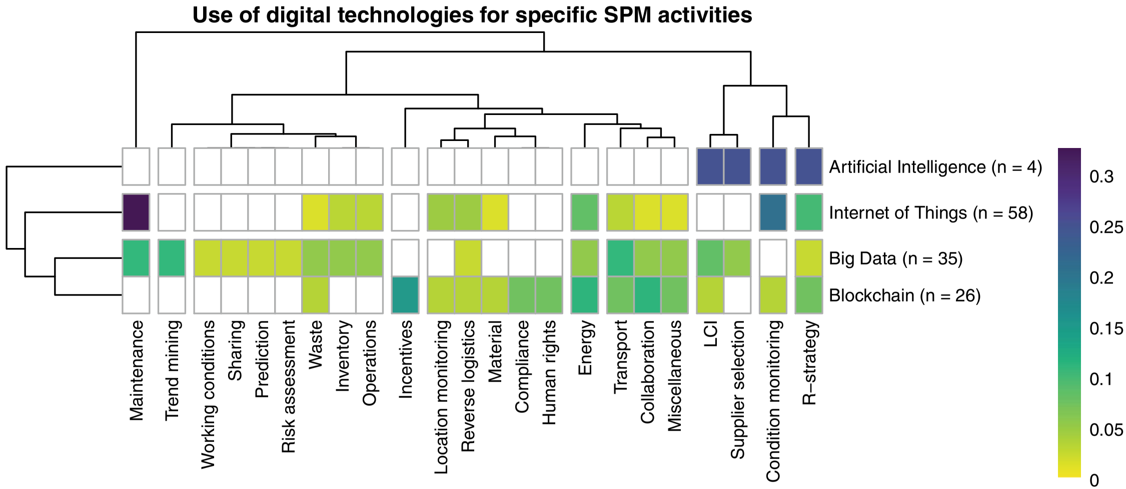

Fig. 7.2 Relative share of specific SPM activities by digital technology (n = 120) (Rusch et al., 2023)

The ways in which digital technologies are leveraged for sustainable business practices is highlighted by another review by Neligan et al. (2023). The authors report the findings of a representative survey of 583 German companies. The study shows that the degree of digitalisation of a company correlates positively with the adoption of Product Service Systems (PSSs) for resource efficiency. PSSs refer to combined product and service offerings (Ingemarsdotter et al., 2020). They can enable reduced resource use as respective business models are based on access rather than ownership (Ingemarsdotter et al., 2020). Thus, one product may satisfy many customers' need for a specific function which is in particular of interest in case of products that are seldomly used (Ingemarsdotter et al., 2020). As can be seen in Fig. 7.3, the use of PSS for resource efficiency increases with the degree of digitalisation in general and of the business model in particular. While only around a third of computerised companies (i.e. that use information and communication technology and/or electronic data processing) use PSS, considerably more (approximately three out of five of fully digitalised firms—i.e. firms with virtualised products) use PSS for resource efficiency. The same can be seen when comparing companies according to their business model, where those with data-driven business models (BMs) considerably more frequently employ PSS than those with computerised or traditional BMs. One reason why PSS for resource-saving become more common with an increasing degree of digitalisation is that additional services to a product often depend on the exchange of data and digital networking (Neligan et al., 2023). In addition, company size also plays an important role as PSS for resource-saving is considerably more often used in large firms than small to medium enterprises (SMEs).

One common takeaway from the two empirical studies by Schöggl et al. (2023) and Neligan et al. (2023) is that companies must prevent potential lock-ins and economic and environmental rebound effects in their digitalisation efforts. This entails more explicit recognition of the specific purposes for which digital technologies may be applied. In relation to this, Sect. 7.3 will provide deeper insights into the potential of digital technologies in the context of LCA and Sect. 7.4 regarding digital product passports.

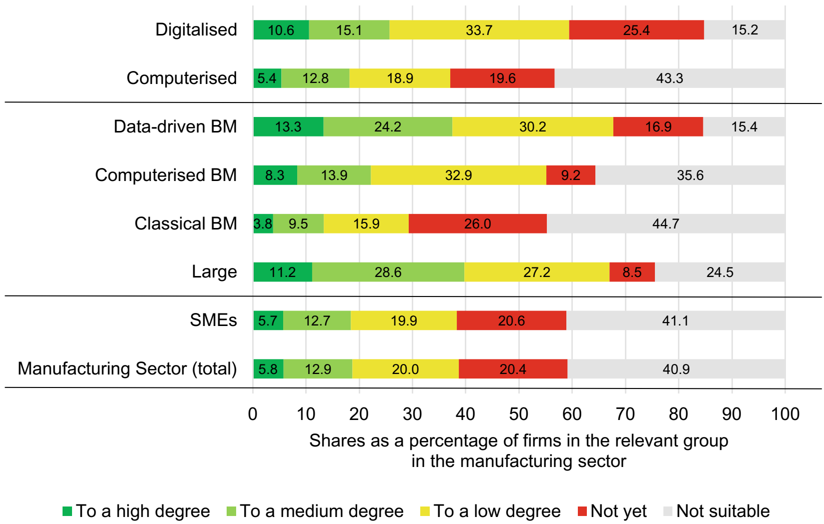

Fig. 7.3 Degree of use of product service systems for resource efficiency. Question: To what extent does your company use the following ways/options to use resources efficiently? (N = 583) (Neligan et al., 2023)

7.3 Application of Digital Technologies for Life Cycle Assessment

LCA is a methodological framework that allows one to estimate and assess environmental impacts linked to the life cycle of a product (Finnveden et al., 2009). The distinct feature of LCA is the applied life cycle perspective (i.e. from cradle-to-grave) to assess the impacts of a product, thus avoiding burden shifting (Finnveden et al., 2009). LCA studies comprise in general four phases. First, the goal and scope of the LCA study need to be defined (Finnveden et al., 2009). This phase comprises a description of the product system under study in terms of system boundaries and a functional unit (Rebitzer et al., 2004). The functional unit enables the comparison between alternative goods and services (Rebitzer et al., 2004). This phase is of importance as it influences methodological and data choices for subsequent LCA study phases (Rebitzer et al., 2004). The second phase is the Life Cycle Inventory (LCI) analysis (Finnveden et al., 2009). The LCI comprises a compilation of the inputs (i.e. resources) and outputs (i.e. emissions) of the product system of interest; those inputs and outputs are in relation to the previously defined functional unit (ibid.). The third phase is the Life Cycle Impact Assessment (LCIA) and is designated to interpret the inventory results of the LCI analysis phase (Finnveden et al., 2009). This phase involves the selection of impact categories and classification, the selection of characterisation methods and characterisation, normalisation and weighting (ibid.). The fourth phase is entitled interpretation (Finnveden et al., 2009). This phase is designated to evaluate the results from the previous study phases in relation to the goal and scope, enabling to reach conclusions and recommendations (Finnveden et al., 2009).

As briefly mentioned earlier, digital technologies can enhance the accuracy and efficiency of conducting LCA. This specific potential is analysed by Popowicz et al. (2024) in a recently published systematic literature review of 104 peer-reviewed papers at the intersection of IoT, blockchain, AI, Big Data, and LCA research. These were categorised across the four phases of LCA according to the ISO 14040/44 standard (ISO, 2006): (1) Goal and Scope, (2) LCI, (3) LCIA, and (4) Interpretation.

With regard to IoT devices, Popowicz et al. (2024) find that their use occurs predominantly in the collection of (real-time) data in the LCI phase. For example, IoT sensors can be used to collect manufacturing process data (Garcia-Muiña et al., 2018), such as machine's electricity consumption easing the collection of accurate primary data (Tao et al., 2014). LCA-related data can also be stored directly on components and combined with data from decentralised IoT sensors and data from centralised repositories (Van Capelleveen et al., 2018).

While blockchain is less often discussed than IoT, it has the potential to increase the transparency and reliability of the primary data collected in value chains (Popowicz et al., 2024), benefitting all four phases of an LCA. Specific applications identified in the literature encompass, among others, data reliability, data traceability, data collection, data exchange, and data validation in LCA (Popowicz et al., 2024). One example from the literature refers to the use of a blockchain for carbon footprint tracking in food supply chains based on IoT data collected from trucks (Shakhbulatov et al., 2019). Another example comes from Rolinck et al. (2021), who propose a blockchain-based data management approach for LCA in aircraft maintenance and overhaul.

Of the four technologies studied by Popowicz et al. (2024), AI was discussed most often in the sample, and a wide range of potential applications in all four phases of LCA were identified (Popowicz et al., 2024). With regard to the goal and scope phase, one of the reviewed studies demonstrated how relevant aspects, such as the lifespan of buildings, can be predicted using machine learning (Ji et al., 2021). In the LCI phase, AI can, for instance, help estimate missing unit process data, as shown by Zhao et al. (2021), who use a decision tree-based approach, or Khadem et al. (2022), who predict impact data using neural networks. In the LCIA phase, characterisation factors can be estimated, uncertainties quantified, or results predicted (Popowicz et al., 2023). For instance, Hou et al. (2020) illustrate how machine learning can be used for estimating ecotoxicity characterisation factors and specifically hazardous concentration levels. Dai et al. (2022) developed a framework for obtaining best-fit secondary data, employing Gaussian process regression (GPR) models to predict secondary data based on covariance functions. Concerning the interpretation phase, Romeiko et al. (2020) demonstrate how machine learning can be used to identify key contributors among various factors to the life cycle impacts.

Lastly, Popowicz et al. (2024) find that Big Data analytics can facilitate the second, third, and fourth phases in an LCA: in the LCI phase, Big Data analysis helps in extracting and managing large datasets. An example is a data-mining-based approach for obtaining data for the foreground system from scientific articles (Belaud et al., 2022). During the impact assessment, it can be used for uncertainty reduction and enhanced analysis, for instance of highly granular data from a product's use phase (Ross & Cheah, 2019).

7.4 Digital Product Passport for Electric Vehicle Batteries

A digital product passport (DPP) is described as an electronic record that resumes the function of a unique product identifier and product life cycle data carrier (European Parliament, 2023). Consequently, a DPP can be envisioned as a digital technology-based tool that can support the establishment of circular information flows along value chains (Berger et al., 2023a; Jensen et al., 2023). This instrument holds promise to enhance the sustainability and circularity of various industries. For example, in the building industry DPPs are perceived to contribute to greater circularity as those tools could support the end-of-life management (e.g. reuse, recycling) of buildings via recording, storing, and sharing information about incorporated materials and components (Cetin et al. 2023). Considering the electronics and information and communication industry, DPPs enhance transparency along the value chain by enabling the support of audits and verification of sustainability claims, contributing to greater trust among stakeholders (Navarro et al., 2022). Similar potential benefits (i.e. increased transparency, verification of sustainability claims) are also anticipated for the textile industry (Jaeger and Myrold 2023). Furthermore, by including detailed material compositions, a DPP could support sorting and selecting textile waste more accurately, as well as support the identification of appropriate recycling pathways (Niinimäki et al., 2023).

Due to the previously described potential to bridge data gaps, the idea of DPPs has recently received increased attention. This is mirrored in policy papers (European Commission, 2020a, 2020b), upcoming regulation (European Commission, 2022; European Parliament, 2023), industry initiatives (Battery Pass Consortium, 2023; Global Battery Alliance, 2020), and sustainability research (Adisorn et al., 2021; Berger et al., 2022; Jensen et al., 2023). In particular, batteries have received increased attention as regulatory bodies are demanding the deployment of DPPs for this particular product group (European Parliament, 2023). This increased interest is founded in the perception that DPPs can support the establishment of a sustainable European battery ecosystem (European Commission, 2022; European Parliament, 2023). This is of interest because an increase in demand of electric vehicle batteries (EVBs) is projected due to the electrification of powertrains (Neumann et al., 2022). When pursuing SPM for EVBs, actors along the product life cycle have different established strategies and concepts at their disposal (Berger et al., 2022). As discussed earlier, these include sustainable product development, life cycle management, sustainable supply chain management, or the circular economy (Berger et al., 2022; Rusch et al., 2023). The concept of the circular economy has received particular attention as it comprises value-retention strategies such as repurposing and recycling (Kiemel et al., 2020). As the listed concepts and strategies affect different levels of the EVB production system (Huamao & Fengqi, 2007), it can be argued that respective decision situations are characterised by high complexity (Rusch et al., 2023). Thus, decision-makers require high-quality product life cycle data for respective decision support (Rusch et al., 2023). As previously discussed, persistent data gaps along the product life cycle pose a challenge when pursuing SPM. This has also been found for the EVB life cycle (Berger et al., 2023a). Such data gaps could be bridged by a DPP if it were to provide seamless product life cycle data allowing relevant actors to derive information needed to support SPM (Berger et al., 2023a).

Conceptualisation of a Digital Product Passport for Sustainable Battery Management

The conceptualisation and development of a DPP for sustainability-oriented EVB management requires consideration of a holistic life cycle perspective (Berger et al., 2022; Rusch et al., 2023). Thus, the entire life cycle of an EVB needs to be considered when pursuing strategies and concepts for improving its sustainability and circularity (Berger et al., 2023a). Furthermore, a comprehensive life cycle perspective is required to identify decision-makers and their respective SPM-related decision situations along the EVB life cycle (Berger et al., 2023a. This allows one to derive corresponding data needs and requirements that a DPP needs to fulfil to support SPM (Berger et al., 2023a). The EVB life cycle can be partitioned into four phases: the beginning-of-life (BoL), middle-of-life (MoL), end-of-life (EoL), and battery second use (B2U). For illustration purposes, four corresponding value chain actors have been selected to highlight their specific SPM use cases and current data management challenges.

Battery Designer and Developer

The product design is critical for incorporating sustainability and circularity aspects in an EVB (Diaz et al., 2021). To address sustainability issues, product design-affiliated actors require information about the sustainability performance of an EVB. This is currently challenging due to the lack of primary data that is needed for the assessment (Buchert et al., 2015; Diaz et al., 2021). Thus, DPPs of in-use and retired EVBs could serve to establish information feedback to the early design stage, providing designers with information about (dynamic) sustainability performances based on primary product life cycle data. Furthermore, information feedback of B2U and EoL process efficiencies (e.g. encountered challenges during EVB disassembly) could support the consideration of circularity aspects in future EVB designs.

Original Equipment Manufacturer
To identify and support suitable SPM strategies and concepts, an original equipment manufacturer (OEM) requires information about the EVB's sustainability performance from cradle-to-grave (Berger et al., 2022). This would allow the OEM to identify life cycle hotspots and thus, to define appropriate strategies for improvement (Berger et al., 2022). The current challenge lies in the lack of high-quality product life cycle data to support sustainability assessments. In this case, a DPP of in-use, as well as retired EVBs, would be beneficial as it could provide either product life cycle data needed for sustainability assessments or could even directly provide information about an EVB's sustainability performance. In addition, if a DPP were to provide value chain actor information an increase in value chain transparency could support the identification of those value chain actors that require support to improve upon the sustainability of their value-adding activities.

Third-party Actor Focusing on Repurpose
To identify suitable EVBs, or rather EVB modules for B2U applications information about their state is vital (Berger et al., 2023b). For this purpose, at a minimum, information about an EVB's state-of-health is required (Nigl et al., 2021). However, additional in-use battery data is also beneficial to make more accurate statements about battery health. The current challenge lies in the inaccessibility of battery in-use data by third-party actors that want to establish B2U business models (Berger et al., 2023b). Furthermore, disassembly instructions are required to produce B2U applications and support an efficient production process (Berger et al., 2023b). Consequently, a DPP could prove valuable if containing battery in-use data, as well as information about EVB disassembly.

Recycler
To ensure safe EVB handling and storage recyclers need information about the EVB status in terms of safety (i.e. how dangerous is the EVB at hand) (Berger et al., 2023b). This requires information about the EVB's state-of-health or even control over battery in-use data (Nigl et al., 2021). However, such information is not transferred from the MoL to the EoL phase (Berger et al., 2023b). Furthermore, information about the material composition is of interest to support the design of efficient recycling processes (Berger et al., 2023b). This concerns the composition of the

battery chemistry, as this allows to design recycling processes that can recover battery-grade secondary material (Berger et al., 2023b). In addition, disassembly instructions are considered highly valuable for recyclers, as they facilitate the design of the recycling process (Berger et al., 2023b). Consequently, a DPP that could transfer such product and product status data from the MoL to the EoL phase would prove useful.

Digital Product Passport Concept for Sustainable Product Management

In light of the SPM use cases presented above and the consideration of a holistic life cycle perspective, the sustainability-oriented management of an EVB requires control over four major information categories (see Fig. 7.4):

- Product information—this category contains information that allows the decision-maker to clearly identify the product of interest. Thus, it ranges from general information (e.g. battery chemistry, battery type, manufacturer) to more specific information (e.g. performance-related information, electrical engineering-related properties, material-related properties).
- Value chain actor information—this category contains information that enables clear value chain actor identification and, thus greater value chain transparency. As well as general information, such as value chain actor name or type, it includes information about the chain of custody (e.g. for materials and components).
- Sustainability and circularity information—this category includes information about the sustainability and circularity properties of an EVB. Regarding sustainability properties, information includes both social and environmental sustainability performance data. Furthermore, inventory data, applied assessment, and calculation methods are considered enabling greater understanding of respective key performance indicators. Regarding circularity properties, as well as information about the circularity performance, information about the product design is included in terms of disassembly and repair options.
- Diagnostics, maintenance, and performance information—this category comprises data points such as state-of-health and state-of-charge. In addition, information about the maintenance history (including triggers for needed maintenance actions) are included in

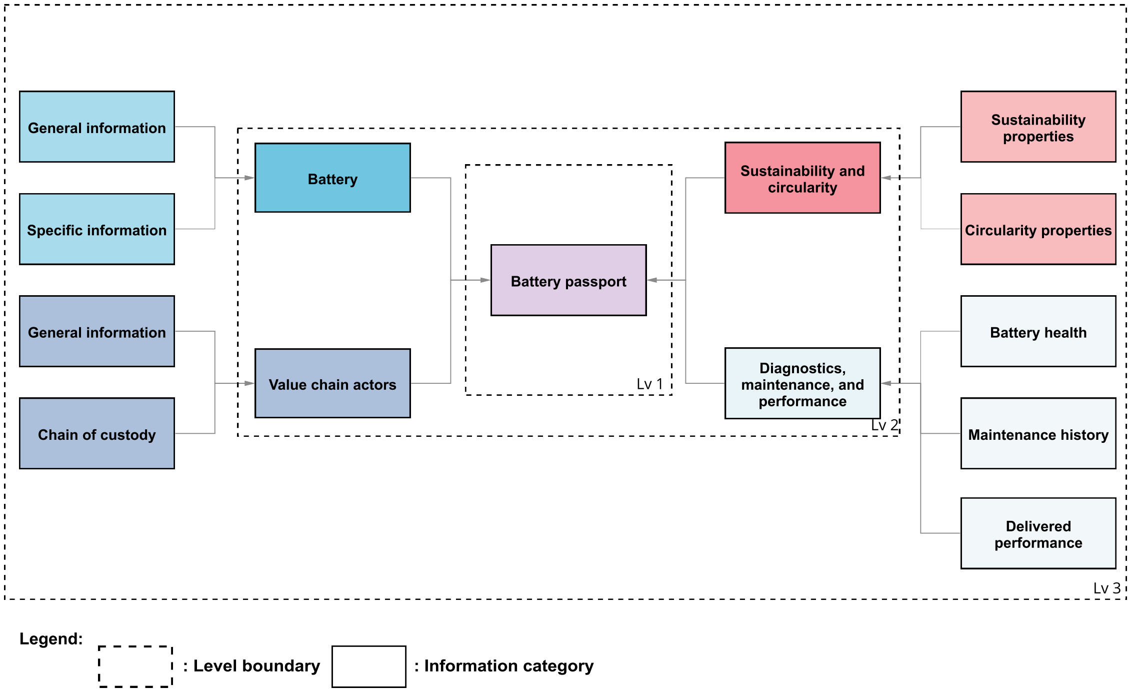

Fig. 7.4 Overview of a Digital Product Passport concept for sustainability-oriented Electric Vehicle Battery management (Berger et al., 2022)

this category whice can support value-retaining strategies enabling a B2U.

While the vision of DPP functioning as product life cycle data carrier has great potential for SPM support, possible challenges regarding DPP deployment need to be acknowledged. One of the most prominent challenges concerns insufficient willingness to share product life cycle data by value chain actors' (Bergeret al., 2023a, 2023c). This may be explained by perceived intellectual property rights concerns, loss of business integrity and reputation, competitive disadvantages, or lack of data sharing incentives (Berger et al., 2023c). Some of those barriers could be overcome by selecting suitable digital technologies or machine learning approaches that enable confidentiality-preserving data exchange (Berger et al., 2023a). Furthermore, upcoming data spaces and ecosystems (e.g., Catena-X (2023) and Gaia-X (2023)) offer potential infrastructure to share data in a "trustworthy" environment.

7.5 Conclusion

The nexus between digital technologies, circularity, and sustainability is a fertile ground for innovation, offering both transformative opportunities and significant challenges. As one delves into this complex relationship, it is essential to recognise the multifaceted roles that technologies like AI, Big Data analytics, IoT, and blockchain can play in this arena.

AI and Big Data analytics have emerged as critical drivers in the realm of sustainable development. These technologies facilitate the analysis of large datasets to uncover patterns and insights that can lead to more efficient resource use. For example, in the realm of waste management, AI algorithms can predict resource and energy consumption as well as waste generation of production processes, enabling companies to increase their environmental performance significantly. Big Data analytics aid in designing products for longevity and recyclability, consistent with the principles of sustainability and circularity. IoT has revolutionised the way resources, processes, and machines are monitored and managed. By equipping objects with sensors and connecting them through networks, resource flows can be tracked in real-time. This visibility is crucial in identifying inefficiencies and leaks in systems. The data generated by IoT devices support decision-making processes that prioritise sustainability and circularity, enabling a more responsive and responsible approach to

SPM. Blockchain's contribution to the circular economy and sustainability is predominantly in enhancing transparency and traceability. This ability to create secure and immutable records makes it ideal for tracking the life cycle of products. In the context of recycling, blockchain can trace the journey of materials from production to end-of-life, ensuring that materials are responsibly sourced and recycled. This level of traceability is vital in building trust in circular economy practices and promoting more sustainable consumption patterns.

While the potential for sustainability and circularity of these digital technologies is immense, it is important to acknowledge and address the challenges they pose. Concerns around data privacy, cybersecurity, and ethical implications of AI decision-making are paramount (Ashok et al., 2022). Furthermore, the environmental impact of the technologies themselves (Schöggl et al., 2023; Bohnsack et al. 2021), such as the energy demands of data centres and the generation of e-waste, must be considered. Addressing these challenges will require a coordinated effort from different actors including corporate actors, innovators, policymakers, and civil society to ensure that the digital transformation aligns with sustainable and ethical principles.

The future of digital technologies in sustainability seems promising, with advancements enabling more efficient and autonomous systems for SPM. Innovations in blockchain could provide even greater transparency in supply chains (Kouhizadeh et al., 2021), facilitating the circular movement of materials. Advancements in IoT technology could lead to smarter production and consumption networks where resource flows are optimised for minimal environmental impact (Ren et al., 2019). Future research could address empirically whether the potential benefits of digital technologies for sustainability and circularity, which are often derived from case studies, really materialise in business practice. Additionally, it could be analysed how these digital technologies can enable radical sustainability strategies aiming for net zero environmental impacts in practice. Finally, future research could address the implementation of digital technologies and their potential for enabling radical sustainability solutions.

In summary, this chapter underscores the transformative potential of digital technologies in advancing the circular economy and sustainability. The future of sustainability in the digital age is not just about the technologies employed but how they are used responsibly and inclusively. Embracing these technologies while addressing their inherent challenges is pivotal in our common journey towards a more sustainable and circular world.

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