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**DAIRY 4.0 MATURITY AND ESG ENABLEMENT IN
VISEGRAD GROUP DAIRY PROCESSORS (2019-2024)**

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PROCESSORS (2019-2024)**

The aim of this dissertation is to obtain a doctoral (PhD) degree in the scientific field of
„Management and Business”

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I undersigned (name: **Anastasiia Burdiuzha**, date of birth: November 11th 1992) declare under penalty of perjury and certify with my signature that the dissertation I submitted in order to obtain doctoral (PhD) degree is entirely my own work.

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- I examined the Code of the Károly Ihrig Doctoral School of Management and Business Administration and I acknowledge the points laid down in the code as mandatory;
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- No dissertation which is fully or partly identical to the present dissertation was submitted to any other university or doctoral school for the purpose of obtaining a PhD degree.

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LIST OF ABBREVIATIONS

3DFP = Three-Dimensional Food Printing
AEI = Agri-Environmental Indicators
AI = Artificial Intelligence
AMS = Automated Milking Systems
CAP = Common Agricultural Policy
CAPEX = Capital Expenditure
CMS = Conventional Milking Systems
CSRD = Corporate Sustainability Reporting Directive
ERP = Enterprise Resource Planning
ESG = Environmental, Social, and Governance
ESRS = European Sustainability Reporting Standards
EU = European Union
GHG = Greenhouse Gas
GVC = Global Value Chain
HACCP = Hazard Analysis and Critical Control Points
I4.0 = Industry 4.0
IED = Industrial Emissions Directive
IoT = Internet of Things
IPPC = Integrated Pollution Prevention and Control
IT = Information Technology
MES = Manufacturing Execution System
PLC = Programmable Logic Controllers
PLF = Precision Livestock Farming
PDF = Precision Dairy Farming
ROI = Return on Investment
R&D = Research & Development
SCADA = Supervisory Control and Data Acquisition
SDF = Smart Dairy Farming
V4 = Visegrad Four

INTRODUCTION

Sustainability has emerged as one of the defining organising challenges of the twenty-first century – a concept encompassing the full spectrum of human and economic activity across three interconnected pillars: environmental, social, and economic. The environmental dimension concerns the responsible use of natural resources, the reduction of emissions, and the preservation of ecosystems underpinning agricultural and industrial production. The social pillar addresses access to health, education, fair labour practices, and the equitable distribution of economic opportunity. The economic dimension reflects the imperative that productive systems generate sufficient value to sustain themselves, their workforces, and the societies they serve. Critically, these pillars do not function in isolation: environmental degradation erodes the natural capital on which economic activity depends; social instability undermines the conditions necessary for sustained growth; and economic underdevelopment constrains both environmental protection and social progress. The Brundtland Commission's foundational definition – development that meets the needs of the present without compromising the ability of future generations to meet their own needs (WCED, 1987) – captures precisely this systemic interdependence. Translating such principles into measurable, sector-specific practice, however, remains a substantial challenge for industries across the globe.

A key component of the way in which contemporary societies address many of today's most pressing social problems (whether globally or locally) is innovation. Innovation can have a significant impact on our ability to mitigate climate change, and it can be a major factor in increasing productivity and improving business' resiliency to changing market conditions (OECD, 2013). This is a widely held view, with the OECD Innovation Strategy (2010) stating that future growth must increasingly come from innovation-induced productivity growth. Similarly, the European Commission emphasizes that as the economic environment continues to change, industry actors must respond by implementing technological innovations (EUROPEAN COMMISSION, 2015).

Building on this global perspective, national strategies are also prioritizing innovation in specific sectors, for instance, the U.S. Department of Agriculture (USDA) has set ambitious goals through its Agriculture Innovation Agenda (AIA) – to significantly boost agricultural output – by 40% – while at the same time dramatically reduce the environmental impact of farming in the United States by 50% by the year 2050 (USDA, 2021).

Across Europe, sustainability expectations toward food industries are also tightening. Regulators, investors, and customers increasingly demand consistent information on

environmental impacts, risk management, and governance practices. In the EU, sustainability disclosure is moving from largely voluntary CSR communication toward a more standardised and regulated reporting regime through the Corporate Sustainability Reporting Directive (CSRD) and the European Sustainability Reporting Standards (ESRS) (EUROPEAN COMMISSION, 2025; EUROPEAN UNION, 2022; EUROPEAN COMMISSION, 2023a). As these requirements expand, firms are expected to provide comparable, decision-useful information and to apply a double-materiality perspective (impacts on the firm and impacts of the firm) (EUROPEAN COMMISSION, 2023b). While implementation timetables and scope have been subject to recent EU simplification debates and adjustments, the direction is clear: the demand for auditable sustainability data is increasing and becoming more structured over time (EUROPEAN PARLIAMENT, 2025).

Achieving such a major transformation will require a completely new way of thinking, which prioritizes innovation as the key part of agricultural strategies and operations. Dairy industry players are already applying technological advancements and adjusting to the needs of the changing environment. An increasing number of studies also suggest that the adoption of technologies of the Fourth Industrial Revolution (named Industry 4.0) has significant potential for contributing to the innovation, creation of new insights and enablement of progress in different aspects of food production.

Blockchain, Artificial Intelligence (AI), the Internet of Things (IoT), Big Data, 3D Printing, Robotics are Industry 4.0 technologies, that are also considered as the main enablers of Dairy 4.0 (HASSOUN et al., 2023a). The Dairy 4.0 concept represents a move from basic mechanization towards a data-driven ecosystem, where digital tools are incorporated across dairy value chains, including milk production, processing plants, and distribution. It presents a promising way to confront significant global issues like growing populations, constrained resources, and ecological consequences. It focuses on the use of technology to improve efficiency, quality assurance, traceability, and sustainability measurement across the sector.

In this dissertation, Dairy 4.0 is operationalised as a processor/plant-relevant capability stack measured through eight subdimensions: strategy and governance; IoT/sensing; automation and robotics; MES/SCADA/ERP; quality and traceability; analytics/AI; digital supply-chain integration; and ESG measurement enablement.

Although the adoption and immediate benefits of Dairy 4.0 are well-covered, a deeper look into the problem, points out that systematic assessment of agricultural innovation is still at an early stage (LAPPLE et al., 2015). In comparison with other industries, the assessment of innovation in agriculture has not been properly measured (BURDIUZHA, 2021). Most of the research

papers in the agricultural sector are narrow in scope and are based on case studies, focusing on a single invention or a small group of innovative practices (D'EMDEN et al., 2008; JHA et al., 2020; MARSH et al., 2000; PANNELL et al., 2006; WU, 2022). Studies do not provide comparative, multi-country evidence on how digital capability is developing in dairy processing and how it relates to sustainability measurement. In addition, digital transformation is not directly observable for external researchers: many implementation details are internal, and disclosure incentives vary by firm size, ownership, and institutional context.

This dissertation addresses these gaps by focusing on major dairy processing companies in the Visegrad Group. The V4 provides a meaningful comparative setting: the countries share EU membership since 2004 and certain historical and structural similarities, but they differ in market structure, investment trajectories, and regulatory-document visibility. These differences help illuminate how digitalisation becomes visible in corporate and regulatory disclosures and how this visibility evolves over time.

Methodologically, the dissertation adopts a disclosure-based approach. Rather than claiming to measure the full internal deployment of technologies, it measures disclosure-visible evidence of Dairy 4.0 maturity and sustainability-related measurement capability using publicly available documents (statutory filings, plant permits and monitoring obligations, sustainability and corporate disclosures). This design supports cross-country comparison and transparency by linking coded indicators to traceable documentary evidence.

The dissertation's core empirical contribution is a company-year panel for 2019–2024 that maps Dairy 4.0 maturity across the V4, tests whether disclosure intensity increases over time, and examines how digital transformation is framed in sustainability-related disclosure. A central finding motivating the analytical strategy is that ESG-related enablement and measurement evidence is often more visible in public documents than advanced technology narratives such as AI. This supports a broader interpretation: in the V4 dairy processing sector, sustainability reporting and compliance documentation can function as a primary channel through which digital transformation becomes publicly legible.

By providing a structured and replicable dataset and a comparative analysis of Dairy 4.0 maturity and ESG enablement, the dissertation contributes to scholarship on digital transformation in agri-food systems and to policy and managerial discussions about how the EU's evolving sustainability reporting landscape interacts with operational digitalisation. The results are intended to support policymakers and industry stakeholders seeking to accelerate resilient and sustainable transformation in the regional dairy sector.

1. TOPICS AND OBJECTIVES

This chapter sets out the analytical foundations of the dissertation. It identifies the research problem, states the aims and objectives, formulates the research questions, and presents the hypotheses tested in the empirical chapters that follow. The chapter also explains the relationship between the core concepts – Dairy 4.0 maturity, ESG enablement, and the V4 dairy processing sector – and situates the study within the broader literature on digital transformation and sustainability disclosure in agri-food systems.

1.1 Research aims

This dissertation investigates the character and extent of Dairy 4.0 digital maturity among the leading dairy processing companies in the Visegrad Four (Czech Republic, Hungary, Poland, and Slovakia) over the period 2019-2024. The central aim is to characterise what these companies disclose about their digital transformation, to understand the role that ESG-related reporting plays as a primary channel through which that transformation becomes publicly observable, and to examine the temporal dynamics and financial correlates of disclosure-visible Dairy 4.0 adoption. Rather than assuming that higher disclosure scores translate directly into superior financial performance, the study treats the disclosure itself – what is reported, through which documents, and in which institutional contexts – as the primary object of empirical inquiry.

1.2 Research objectives

Six objectives organise the empirical work:

1. Map the current state of Dairy 4.0 adoption among leading dairy processors in the V4, using a structured disclosure-based coding instrument applied to publicly available corporate, regulatory, and sustainability documents (2019-2024).
2. Examine cross-national heterogeneity in D4 maturity across the Czech Republic, Hungary, Poland, and Slovakia, identifying differences in the level, composition, and institutional drivers of digital technology disclosure.
3. Analyse the temporal dynamics of D4 disclosure over the 2019-2024 period, testing whether aggregate disclosure intensity increases within firms over time and characterising the drivers of any observed improvement.
4. Investigate the relationship between D4 maturity scores and financial performance indicators (turnover and profit margin) among V4 dairy processors, distinguishing

cross-sectional associations from within-firm dynamics using fixed-effects panel models.

5. Examine the ESG-Dairy 4.0 nexus: establish whether ESG Enablement is the dominant D4 sub-dimension, characterise the institutional mechanisms driving that dominance (regulatory compulsion through IPPC permitting, global value chain diffusion through multinational subsidiaries, and the narrative accessibility of environmental disclosure), and explore whether ESG disclosure shows evidence of leading broader technology adoption.
6. Draw out the implications of the empirical findings for how digital transformation should be measured, supported, and governed in the V4 dairy sector – and, more broadly, in Central-Eastern European agri-food industries operating under increasingly demanding EU sustainability reporting obligations.

1.3 Research questions

The overarching research question is: *How extensive is Dairy 4.0 digital maturity among leading dairy processors in the Visegrad Four, and what role does ESG enablement play as the primary channel through which digital transformation is disclosed?* Four sub-questions structure the empirical analysis:

1. What is the current level and composition of Dairy 4.0 adoption among major dairy processors in the Czech Republic, Hungary, Poland, and Slovakia? How does this vary across countries and firm types?
2. Has disclosure-visible Dairy 4.0 maturity increased over the 2019-2024 period? If so, is this increase driven by genuine deepening of digital capability within firms, or by compositional and documentary coverage effects?
3. To what extent does Dairy 4.0 disclosure intensity correlate with financial performance (revenue and profit margin) among V4 dairy processors? Does this association reflect genuine adoption-performance dynamics or firm-size effects?
4. Why does ESG Enablement dominate Dairy 4.0 disclosure in the V4 context? What institutional mechanisms explain its systematic advantage over operational technology dimensions, and is there exploratory evidence that ESG disclosure precedes and is positively associated with subsequent technology disclosure in temporal sequence?

1.4 Research hypotheses

Four hypotheses are tested across four analytical domains: H1 addresses cross-national heterogeneity, H2 temporal dynamics, H3 financial performance, and H4 the ESG-Dairy 4.0

nexus. H4 is addressed through two related propositions: H4a tests the dominance claim confirmatorily; H4b examines temporal disclosure sequencing as an exploratory supplement.

1. Dairy 4.0 adoption level and cross-national heterogeneity

H1: The distribution of Dairy 4.0 maturity scores differs significantly across the four V4 countries, reflecting structural differences in firm ownership, market concentration, regulatory exposure, and document availability.

2. Temporal dynamics of D4 disclosure

H2: Aggregate Dairy 4.0 disclosure intensity in the V4 increases significantly between 2019 and 2024; however, this increase is driven primarily by growth in document volume and between-firm compositional change rather than by within-firm content deepening.

3. Financial performance and D4 maturity

H3: The positive cross-sectional association between Dairy 4.0 maturity score and firm revenue is primarily attributable to firm-size heterogeneity rather than to an independent adoption-performance dynamic; within-firm panel models controlling for firm-level fixed effects are hypothesised to show no significant association between D4 disclosure intensity and contemporaneous turnover or profit margin, while the supplementary lagged growth specification is likewise hypothesised to show no significant relationship.

4. ESG dominance (H4a) and exploratory disclosure sequencing (H4b)

H4a (ESG dominance – confirmatory): The ESG enablement sub-dimension is the highest-scoring and most widely adopted Dairy 4.0 dimension across the full panel, significantly and stochastically dominating all operational technology dimensions (IoT & Sensing, Automation & Robotics, Analytics & AI, MES/SCADA/ERP) in mean score, adoption rate, and verified-evidence achievement rate.

H4b (disclosure sequencing – exploratory): As a supplementary temporal proposition, lagged ESG disclosure (ESG_{t-1}) is expected to show a positive association with subsequent technology sub-dimension scores ($tech_sum_t$), a pattern consistent with ESG functioning as a disclosure precursor rather than a lagging consequence of technology adoption. This proposition is treated as exploratory: the design is observational, the sample is bounded, and the result does not support causal inference.

2. LITERATURE REVIEW

The literature review is broken down into several sections. In the first section is presented an overview of dairy sector in the V4 region. The following sections develop the conceptual and empirical foundations needed to interpret Dairy 4.0 adoption and ESG enablement in this regional context. Section 2.2 traces the historical development of Dairy 4.0 and its conceptual boundaries. Sections 2.3 and 2.4 review the core enabling technologies and their documented advantages. Section 2.5 addresses the principal challenges and barriers to adoption. Section 2.6 synthesises the prior quantitative research on economic and environmental sustainability outcomes. Section 2.7 reviews the ESG disclosure landscape and the theoretical link between digital maturity and sustainability reporting. Section 2.8 consolidates the review into a set of research hypotheses, including the dissertation's primary research hypothesis regarding the ESG-Dairy 4.0 nexus.

2.1 Dairy sector overview in Visegrad Four region

The European Union is the world's largest producer of cow's milk, accounting for approximately 23% of global output (EUROSTAT, 2025). In 2024, EU milk collection reached around 153 million tonnes, with the sector generating a farm-gate value of EUR 77.73 billion – equivalent to 14.6% of the total value of EU agricultural production (EUROSTAT, 2025). The industry spans primary farming through processing and retail, with dairy processing constituting a significant share of EU food manufacturing turnover. Structurally, however, the sector is highly heterogeneous: while the Netherlands, Germany, France, Ireland, and Denmark host large-scale, highly capitalised processors, Central and Eastern European dairy industries – including the Visegrad Four – are characterised by a mix of large multinational-affiliated processors, national cooperatives, and a fragmented tail of small independent producers (ÉLTETŐ, 2021; RADLIŃSKA, 2024).

The Visegrad Four – comprising the Czech Republic, Hungary, Poland, and Slovakia – collectively represent a significant and structurally coherent dairy sub-region within the EU. Together, the V4 countries hold approximately 13-15% of EU total milk production (EUROSTAT, 2025). Poland is the largest V4 producer by a wide margin, ranking fourth in the EU, with an annual milk collection of approximately 16 million tonnes and a processing sector that has undergone substantial consolidation and capital investment since EU accession in 2004. The Czech Republic and Slovakia have smaller but mature dairy sectors dominated by a limited number of large processors and cooperative structures. Hungary occupies an intermediate

position, with a processing sector characterised by multinational subsidiaries of Western European groups alongside domestic cooperatives.

The V4 dairy processing sector shares a number of structural characteristics that make it a coherent analytical unit. First, all four countries are subject to the same EU regulatory framework, including food safety standards (EU 852/2004, EU 853/2004), integrated pollution prevention and control (IPPC) requirements for large industrial installations, and the evolving EU sustainability reporting regime under the Non-Financial Reporting Directive (NFRD) and its successor, the Corporate Sustainability Reporting Directive (CSRD). Second, V4 dairy companies have broadly followed a similar investment trajectory since EU accession – a period of structural modernisation, consolidation, and gradual technology upgrading – while remaining, on average, at a lower level of capital intensity and digitalisation than leading Western European processors (WÓJCICKI et al., 2025). Third, all four countries participate in the EU Farm Accountancy Data Network (FADN)¹ and Common Agricultural Policy (CAP) frameworks that provide a degree of policy comparability.

Despite these structural similarities, significant heterogeneity exists within the V4. Market concentration is higher in Poland, where a small number of large cooperative processing groups dominate by volume, compared with a more fragmented structure in Slovakia and the Czech Republic. Foreign ownership shapes disclosure practices and technology investment patterns differently across countries: the high proportion of multinational subsidiaries in Hungary, for instance, creates distinct reporting incentive structures compared with domestically owned cooperatives in Poland or the Czech Republic. These structural differences are directly relevant to the measurement approach used in this dissertation, since both the availability of public documents and the intensity of digital transformation evidence vary systematically with ownership structure, firm size, and institutional affiliation.

From a sustainability and regulatory standpoint, V4 dairy processors operate within an increasingly demanding and evolving environment. Large industrial dairy installations are subject to IPPC permitting requirements under Directive 2010/75/EU on industrial emissions, which mandate the installation of environmental monitoring systems, documentation of energy consumption and emissions data, and regular reporting to environmental authorities. This

¹ The Farm Accountancy Data Network is a representative information system, which supports the Common Agricultural Policy, it was created by the European Commission to analyse the income and management of farms. The system provides the mandatory data reporting required by the EU through the voluntary data provision of farms engaged in agricultural activities, while also contributing to the preparation of national policy decisions. Farms can voluntarily join the system, committing to provide their management and accounting data twice a year.

regulatory layer is particularly important for the analytical purposes of this dissertation, as IPPC permit documentation constitutes one of the most operationally granular and independently produced sources of evidence for digital environmental measurement capabilities in the sector. Beyond IPPC, the entry into force of the Corporate Sustainability Reporting Directive (CSRD) and the associated European Sustainability Reporting Standards (ESRS) is progressively extending structured ESG disclosure obligations to a broader set of V4 dairy processors, with the first CSRD-compliant reports due from large public-interest entities in 2025 and from large private companies from 2026 (EUROPEAN COMMISSION, 2023a). This evolving disclosure landscape directly shapes both what companies report and the analytical strategy of this dissertation.

In Poland, three cooperative groups – SM Mlepol, Grupa Mlekovita, and Grupa Polmlek – account for a disproportionate share of national milk intake, a legacy of the post-1989 consolidation of the country's dairy cooperative movement rather than a foreign-investment story. Hungary's processing landscape looks almost inverted: FrieslandCampina Hungária, Danone Hungary, and Savencia Fromage & Dairy sit alongside the domestically owned cooperative Sole-Mizo, producing a sector where multinational subsidiaries and a strong domestic player compete for the same milk supply. The Czech Republic and Slovakia sit somewhere in between, with firms such as BEL Sýry Česko operating alongside smaller national processors in markets too small to support the scale that Poland's cooperatives or Hungary's multinationals enjoy. These are not interchangeable firms coded identically in a cross-national panel – they arrived at their current scale through different histories, and, as Chapter 4 shows, that history shows up directly in what each company discloses.

The period under study was not a quiet one for the sector. The 2022-2023 energy price shock hit dairy processing particularly hard. Several of the companies in this dataset show visible cost pressure in their financial statements from this period. At the same time, the sector faces a second, slower-moving pressure: the phased rollout of the CSRD is turning what used to be a voluntary sustainability narrative into a mandatory reporting obligation, arriving just as many V4 processors are still working out their green and digital transitions. It is this collision – rising cost pressure and rising disclosure obligation, hitting a sector with uneven digital maturity – that motivates the empirical question this dissertation asks.

2.2 Definition of Dairy 4.0 and its historical development

The global dairy industry is currently facing a challenging situation, with changing consumer preferences, a global shortage of labour along with market and societal pressures pertaining to the environment, food safety, and animal welfare. To address these issues, the industry is

undertaking a radical shift, away from the traditional methods and adopting digital technologies that facilitate transformation, also known as the fourth industrial revolution (Industry 4.0). This change is primarily driven by the following key technological elements: Artificial Intelligence (AI), Augmented Reality (AR), Big Data (BD), blockchain, cloud, cybersecurity, cyber physical systems and digital twins (TRIVELLI et al., 2019; BAI et al., 2020; HASSOUN et al., 2023b) (some of the elements are presented in *Figure 1*). The application of these technologies in agriculture is more broadly referred as precision agriculture, smart farming, or Agriculture 4.0 (JAVAID et al., 2022; SINHA-DHANALAKSHMI, 2022), while application of these digital technologies in dairy industry is termed as “Dairy 4.0” (HASSOUN et al., 2023a).



Figure 1. Dairy 4.0 enabling technologies

Source: HASSOUN et al. (2023a)

Although the term is often used in an innovation-optimistic manner, the literature does not treat Dairy 4.0 as a single, standardised “technology”. Instead, it is more accurately described as a socio-technical bundle: outcomes depend not only on the presence of devices and software, but also on complementary assets such as infrastructure (connectivity, reliable electricity supply), interoperability standards, data governance, advisory services, and the farm’s managerial capability to translate data into timely interventions. This heterogeneity is essential for interpreting later empirical findings, because it implies that economic and environmental outcomes are unlikely to be uniform across farms, regions, and production systems, even when similar tools are deployed.

The concept of Dairy 4.0 is described as the integration of advanced digital technologies. The synergy between IoT and AI, and Big Data Analytics (BDA), is the defining characteristic of Dairy 4.0. IoT devices are useless without data cloud platforms which are necessary for storing the information, as well as without AI and machine learning algorithms there are no means to process obtained raw data into usable information (CABRERA et al., 2025).

This interdependence also explains why some studies report strong performance gains while others emphasise implementation barriers: benefits materialise when multiple components function together and when the farm can act on alerts and recommendations within appropriate time windows.

Dairy 4.0 framework allows the dairy sector to develop solutions and meet the challenges specific to the dairy industry, it helps to build efficient and sustainable dairy farms, making every process in the dairy value chain (from farm to table) as optimized as possible. Solutions assist in optimizing and managing the herd, milk quality, breeding practices, and enabling the sector to become sustainable. The purpose is to integrate all necessary technology solutions to meet business and industrial product needs while enhancing the value chain intelligence across the entire lifecycle “cradle to cradle” (SANGODE, 2025).

Dairy 4.0 has not emerge in a vacuum but instead it is the most recent stage in a long history of agricultural innovation. The evolution of dairy farming can be divided into four distinct eras, based on the core technologies and value propositions that drove the industry forward:

- **Dairy 1.0** (1784): A traditional, labour-intensive approach, powered by minimal machinery. Common activities include animals grazing and feeding, as well as using rudimentary genetic selection and methods like hand-churning to produce dairy products (HASSOUN et al., 2023a).
- **Dairy 2.0** (1870): Includes introduction of mechanical innovation (separator, homogenizer) in combination with preservation science (pasteurization, refrigeration) and logistics (tank cars on railroads, motor truck transport) to develop an efficient dairy processing industry that could process large quantities of milk (FRISVOLD, 2020).
- **Dairy 3.0** (1990): this period is also known as Precision Agriculture Era. Information Technology (IT), Computer Systems were utilized for improving agricultural techniques and processes for farmers. During this era discrete agricultural processes were automated using logic processors and Programmable Logic Controllers (PLC) (HASSOUN et al., 2023a).
- **Dairy 4.0** (2011): also called as Smart Dairy Farming (SDF). This period represents a significant integration of digital technology into physical processes. It goes beyond the automated management of individual tasks (Dairy 3.0) and enables the decentralized, flexible, and real-time management of all its activities using Cyber-Physical Systems (integration of computing and physical processes) (SANGODE, 2025).

As the dairy industry progressed through the development stages, the main priority of operation itself has transitioned from milk output maximization during Dairy 2.0 era into resource

efficiency in Dairy 3.0 period, and now eventually into the currently considered focus of interoperable, real-time data aggregation for efficiency and sustainability improvements within Dairy 4.0 (HASSOUN et al., 2023a). *Table 1* provides a summary of key technologies and primary value drivers related to dairy farms evolution during Dairy 1.0-4.0 eras.

Table 1. Dairy 1.0-4.0 characteristics and key technologies applied

Era	Defining Characteristic	Key Technologies	Primary Value Driver	Primary Business Focus
Dairy 1.0	Traditional, manual labour-intensive	Basic hand tools	Human and animal labour	Survival, local use
Dairy 2.0	Introduction of basic machinery	Mechanization, pasteurization, formulated feeds	Labor supplementation, controlled processes	Volume, yield maximization
Dairy 3.0	Heavy mechanization and industrialization	Milking machines, artificial insemination, electronic records	Mechanical efficiency, scale, and labour reduction	Optimization of resource use (inputs)
Dairy 4.0	Digital integration and data-driven systems	IoT, AI, Robotics, Big Data, Blockchain	Information, optimization, and real-time decision-making	Efficiency, sustainability, traceability

Source: Constructed by author (2025)

The pre-4.0 developments and technologies (such as automated milking systems (AMS)) provided a foundation upon which the digitalization could take place to generate new value. In Dairy 1.0-3.0, the primary sources of value were derived from substituting labour with machines and improving mechanical efficiency; consequently, farmers could milk cows at higher rates, with less physical effort per hour (SANGODE, 2025). The digital transition to Dairy 4.0 creates an additional layer of value generation, as it is based on the capture, analysis and use of data to improve each and every process and animal (TIMMONS, 2022). The ability of systems to collect and analyse thousands of data points daily per cow shifts animal husbandry management from a herd level to a cow-by-cow basis (TANGORRA et al., 2024).

Dairy 4.0 rests on five interdependent enabling technologies – each contributing a distinct layer to the digital capability stack reviewed in the sections below. Understanding the functional role and maturity of these technologies is essential for interpreting later empirical findings, as the sustainability outcomes attributed to Dairy 4.0 depend not only on adoption per se, but also on the specific technological configurations implemented at farm level.

2.3 Core enabling technologies of Dairy 4.0

Dairy 4.0 is characterized by an interdependent set of digital tools working together rather than a single technology. Each tool works synergistically with the others, where the output of one serves as the input for another, thereby establishing a self-reinforcing process of collecting data, analysing data, and taking action based on the data collected. The practical implication is that individual components frequently deliver limited benefits in isolation, while integrated solutions can generate larger gains – yet also face higher implementation complexity, higher capital requirements, and a greater need for skilled users and support services (CABRERA et al., 2025; HASSOUN et al., 2023a).

The literature reviewed in Sections 2.3 to 2.5 is drawn predominantly from dairy farming contexts – farm-level deployments of IoT sensors, automated milking systems, precision livestock farming, and robotics. These studies are used here not as direct evidence on processor outcomes, but to map the digital capability families – sensing, automation, analytics, traceability, and governance – that form the conceptual basis of the D4 scoring instrument applied in this dissertation. Where evidence from processing contexts exists, it is noted explicitly; where it does not, the farm-level literature provides the closest available conceptual analogue.

2.3.1 Internet of Things and real-time data collection

The Internet of Things in dairy are extensively documented at the farm level – wearable sensors, smart collars, and barn-embedded infrastructure – with comparatively limited published evidence on IoT deployment within processing facilities. The review that follows draws on this farm-level literature to characterise the IoT capability family, recognising that the underlying sensing and data-collection logic translates across the farm-to-factory boundary even where direct processor evidence is sparse.

IoT forms the base layer of Dairy 4.0 and acts as the core foundation for the smart dairy farming. The IoT allows to collect real-time data through a comprehensive network of connected sensors, cameras, and Radio Frequency Identification (RFID) tags. These sensors can be worn directly by cows through smart collars and ear tags, can be attached to barn infrastructure, or embedded into milking systems (VILLA-HENRIKSEN et al., 2020). Compared with periodic manual observation, IoT systems can increase measurement frequency and reduce informational blind spots, enabling earlier detection of deviations from expected behavioural or physiological patterns.

- **Applications in Animal Health and Welfare:** used to collect continuous physical and behavioural data at the individual-animal level. Commonly measured parameters include body temperature, rumination patterns, activity levels, and heart rate, which serve as proxies for physiological status and behavioural changes (RUTTEN et al., 2013; KHATUN et al., 2018). These data streams form the basis for automated health monitoring and alerting systems and enable the identification of deviations from normal patterns that may be associated with health disorders such as mastitis or lameness (LAMANNA et al., 2025).
- **Applications for Reproduction Management:** wearable sensors and activity trackers applied in three critical areas of dairy cow reproduction management: oestrus detection, calving detection, and body condition scoring. Technologies for calving and oestrus detection monitor secondary indications in behavioural changes such as increased physical activity, altered lying/standing, or reduced rumination time (RUTTEN et al., 2013; DAS et al., 2023). These systems generate time-series data that allow deviations from normal reproductive patterns to be identified and recorded, forming the informational basis for automated alerts and decision-support tools in herd reproduction management (SILVA et al., 2021).
- **Environmental Management Applications:** Environmental Monitoring Systems monitor barn and farm conditions that influence animal comfort and production processes. Sensors are commonly used to measure ambient temperature, relative humidity, air velocity, gas concentrations, and other microclimatic parameters, often in combination with behavioural indicators such as lying time or activity levels (LELIVELD et al., 2024; MYLOSTYVYI et al., 2024). These data streams enable continuous assessment of environmental conditions and provide inputs for automated or semi-automated control systems related to ventilation, cooling, and housing management.

Several studies report that applications in animal health and welfare management and IoT-enabled Precision Livestock Farming systems can detect changes related to mastitis or lameness at earlier stages than traditional visual inspection methods (RUTTEN et al., 2013; KHATUN et al., 2018; LAMANNA et al., 2025). However, the literature also consistently emphasises that detection performance depends on calibration quality, herd-specific baselines, data reliability, and the ability of farm staff to interpret and respond to alerts in a timely manner (RUTTEN et al., 2013; STEENEVELD et al., 2015). Consequently, IoT technologies should be understood as information-generating tools whose effectiveness depends on subsequent management actions rather than as autonomous solutions.

The IoT literature presents an instructive contrast between technological potential and documented outcomes. While sensing systems are well-validated at the device level, the evidence base for system-level value creation – particularly at the processing plant rather than the farm – remains notably sparse. For the V4 context, this gap carries a specific implication: if processor-level IoT deployment is genuinely less visible in public documentation than farm-level adoption, then any cross-company comparison of digital maturity will likely undercount actual deployment for this sub-dimension. I find this asymmetry between real-world adoption and public legibility to be one of the most important boundary conditions for interpreting the kind of multi-country comparison this study undertakes – and one that the literature, by concentrating almost exclusively on farm-level outcomes, has not yet adequately acknowledged.

2.3.2 Big Data analytics and Artificial Intelligence

Without management of the IoT network's obtained results, the raw data remains largely uninformative. The function of aggregating, processing and interpreting of these large and heterogeneous datasets fall within the domain of Big Data Analytics (BDA) and Artificial Intelligence (AI), which have been described as the “Dairy Brain” of digital dairy farming systems (CABRERA et al., 2020).

- **Big Data and BDA:** data analytics represents a paradigm shift in the way that dairy farms have traditionally been operated, as it enables the integration and analysis of large volumes of data derived from diverse sources. In the literature, BDA is often associated with the potential to support more data-driven management approaches compared with conventional, experience-based decision-making (LOKHORST et al., 2019). At the same time, the strategic value of BDA depends fundamentally on the ability to integrate and harmonise data originating from multiple applications and sensors.

Data integration is widely identified as one of the most critical challenges for unlocking the full potential of precision dairy farming, which is characterised by real-time monitoring, predictive health management, and accelerated genetic improvement. Fragmented datasets derived from heterogeneous sources – such as genomics, environmental sensors, milking equipment, and farm management software – are often stored in incompatible formats and lack common standards for interoperability. The absence of standardised data architectures significantly constrains the effective processing of these rich but disparate datasets (CABRERA et al., 2025).

Several studies demonstrate that, when data integration challenges are addressed, BDA can support the transformation of raw data into structured, action-oriented information for

agricultural decision support, including in dairy farming systems (CABRERA & FADUL-PACHECO, 2021; CABRERA et al., 2020). At the same time, authors caution that such outcomes depend on data quality, system interoperability, and user engagement, rather than on analytical capability alone. Consequently, moving from siloed digital applications toward integrated data environments is frequently described as a strategic objective for the dairy sector, requiring coordinated technological and organisational development (LOKHORST et al., 2019).

- **Artificial Intelligence:** Artificial Intelligence (AI) builds on integrated data infrastructures by applying advanced algorithms to identify patterns, generate predictions, and support decision-making processes. In dairy farming, AI applications are increasingly used to shift management perspectives from herd-level averages toward individual-animal analysis, with implications for health monitoring, reproduction management, and feeding strategies (SERRANO-TORRES et al., 2025). Integration of AI with dairy farm data systems allows farm managers to apply sophisticated prediction models using algorithms to better predict and optimize the outcome of milk production by analysing animal genetics, feed intakes and environmental factors (CABRERA et al., 2020; WANGEN et al., 2021).

The lameness detection applications of AI are an example where AI algorithms were able to achieve 99.05% accuracy with no false negative results (100% sensitive) when tested in laboratory validated environments (KANG et al., 2025). However, the literature also highlights that such performance metrics are typically obtained in validated or experimental environments and may not fully reflect on-farm conditions, where data quality, sensor placement, and management responses vary considerably.

Economic indicators show that AI-based health monitoring for dairy farms provide positive return on investment (ROI): Industry reports suggest productivity gains of this order (THE BULLVINE, 2025), though peer-reviewed evidence on ROI varies considerably by farm type and management context (RUTTEN et al., 2013).

Application of AI also improves efficiency and reduces environmental footprint of dairy supply chain in a sustainable way: it has positive impact on the production and distribution of milk from a waste reduction standpoint due to optimization of resource consumption and supply/demand alignment, prediction of product expiration and other factors related to food waste through data and logistics (NATH et al., 2024; SMITH, 2019). From an environmental perspective AI optimizes agricultural practices by helping to minimize the use of chemical products, thereby improving the use of these products in the production process (MARVIN & BOUZEMBRAK, 2020).

Taken together, Big Data Analytics and Artificial Intelligence provide the computational and analytical foundation of Dairy 4.0 by enabling the integration, interpretation, and utilisation of complex data streams. At the technological level, these systems primarily function as tools for information generation and decision support. The extent to which AI- and BDA-based applications translate into measurable economic, environmental, or welfare outcomes depends on factors that extend beyond analytical capability alone, including data integration, farm-specific contexts, and organisational adaptation.

I consider the gap between industry-reported productivity gains and peer-reviewed ROI evidence to be one of the most significant unresolved tensions in the Dairy 4.0 literature. The disconnect is not merely methodological – it reflects a deeper problem of how benefits are framed and for whom: industry sources tend to report headline productivity improvements under favourable conditions, while academic studies using matched comparison or fixed-effects designs consistently find smaller, more conditional, and often statistically non-significant effects once firm size and prior investment capacity are controlled for. Any empirical study operating in this space should apply that scepticism consistently; where a short observation window coincides with documented capital expenditure suppression of current-period margins, null financial results ought to be treated as theoretically expected rather than as evidence of poor data quality.

2.3.3 Blockchain Technology

Food safety concerns, fraud prevention, and traceability requirements represent some of the growing challenges for the global dairy industry. Based on research findings, Distributed Ledger Technology (DLT) (commonly referred to as Blockchain Technology) represents a paradigmatic shift from traditionally isolated, and often manually managed systems, toward an immutable, transparent, digital ecosystem (FENG et al., 2020). Blockchain is a technology which provides peer-to-peer networks to store and share data in a secure way with a “chain of blocks” structure, creating an environment where traditional supply chain trust deficits and integrity failures are minimized (VU et al., 2023).

According to HUA et al. (2018) blockchain systems are able to trace food data including farm operations. TIAN (2017) states that a Hazard Analysis and Critical Control Points (HACCP)-based platform utilizing IoT and blockchain technology can be employed to monitor the physical condition of food as well as the food tracking. Research studies also show brand loyalty increases among consumers when dairy brands utilize blockchain technologies to track their products (ALESSA et al., 2025).

Blockchain assures that information is immutable and is largely dependent upon the accuracy of the data received into it. Therefore, a viable DLT system requires strong integration with devices that can physically monitor items for quality and/or other characteristics (IoT) (PAKSERESHT et al., 2024). Platforms, such as “Milk Chain”, use machine learning with blockchain and IoT sensors to create a trustworthy, unalterable and sustainable food supply chain. The system tracks important quality factors (such as pH, temperature, smell, taste, fat content, clarity/opacity, colour, etc.) through sophisticated algorithms to identify factors affecting quality and, in real time, alert users to possible adulteration (NUKAPEYI et al., 2024). Each batch of milk receives its own unique digital identity allowing all parties to track the origin of any adulterated product and, thus, greatly reduce product waste and streamline product recalls (PADMA et al., 2023).

Investment in blockchain within dairy supply chains requires much more than a technology rollout – it must address the systemic issues that create financial barriers for smaller farms and the persistent lack of interoperability between existing systems (VARGAS-BELLO-PEREZ et al., 2025).

Taken together, blockchain represents the most conceptually overpromised technology in the current Dairy 4.0 discourse. Its theoretical traceability properties are genuinely compelling, but the practical constraints – cost, governance, interoperability – are sufficiently severe that widespread processor-level adoption visible in public disclosures is unlikely to materialise within a short observation window. The majority of published work remains at the level of conceptual architectures and stated intent rather than documented deployment, which means disclosure-based measurement of this sub-dimension will capture expressed ambition more reliably than confirmed operational use.

2.3.4 Robotics

Adoption of robotics (also called Automatic Milking System) in the dairy industry has evolved from an experimental novelty in the early 1990s to an operational need in the mid-2020s. It shifts the farm from a “milking schedule” (humans decide when cows are milked) to a “voluntary system” (cows choose when to be milked) (BHOJ et al., 2022).

The necessity of the milking systems transformation is primarily driven by socio-economic factors affecting the dairy sector. Several studies identify physically demanding labour, increasing regulatory requirements, heightened monitoring obligations, and persistent labour shortages (particularly among younger generations), as structural challenges that influence technology adoption decisions (PEÑA-LÉVANO et al., 2025; RANA et al., 2024). In this

context, AMS are often discussed as part of a broader transition in farm organisation rather than as stand-alone technological innovations.

Besides labour substitution, robotics represent a transformation in animal welfare and farm productivity. Conventional milking parlours operate on a batch basis and require animals to follow a human dictated timetable, regardless of lactation stage or udder pressure. The AMS allows the cow to take control of her own biology, aligning production with the circadian rhythm, being in control of her physiological needs, and potentially reducing stress and prolonging life (LAGE et al., 2024; COGATO et al., 2021).

Automated Milking System generates a vast amount of detailed, real-time data about the overall udder health, milk quality, reproductive performance and body weight changes on each cow through the collection of information during every milking process (COGATO et al., 2021). Some AMS utilize the electrical conductivity of milk and milk colour to provide alerts regarding mastitis (KHATUN et al., 2018; INZAGHI et al., 2021), while other systems measure milk somatic cell counts by using optical methods. Data generated by additional sensors in milking robots, such as 3D camera-based body condition scoring systems, as well as automated weighing systems and lameness assessment systems, can be used for monitoring herd welfare and health (SILVA et al., 2021).

The literature frequently categorises the potential contributions of AMS across several functional dimensions:

1. **Economic Resilience:** lower labour costs are the major reason for generating a faster return on investment (ROI) on AMS. Academic estimates of payback periods range from 3 to 6 years depending on herd size and labour costs (BENTLEY et al., 2018; SALFER et al., 2017), with industry sources reporting similar ranges (CCFBANK, 2025).
2. **Productivity Maximization:** with AMS, the dairy cow's natural milking cycle dictates how frequently she will be milked, and as a result milk yield increases by as much as 2-12% compared to cows that are milked at fixed times (COGATO et al., 2021).
3. **Risk Mitigation and Health:** use of advanced sensors and machine learning assist dairy farmers in predicting illnesses before they occur. Early illness detection is made possible by real-time diagnostic technology (i.e., mastitis detection has been shown to be as accurate as 98.1%), which improves mastitis management (GHAFOOR & SITKOWSKA, 2021).
4. **Sustainability and Efficiency:** although overall farm operation utilities may increase by using AMS, the system achieves higher levels of resource efficiency than conventional

milking systems. VANDERZAAG et al. (2025) note that dairy farms with AMS use more water, produce more milk, and achieve better water use efficiency per liter of milk.

However, literature also reports that AMS's long-term success is heavily dependent on management approaches and decision making, as operational metrics (e.g., energy use and milk quality) depend on effective cow traffic management (free flow vs. guided flow) and feeding strategies (TREMBLAY et al., 2016). Farmers must obtain a certain level of technical proficiency in using the software and electronics. KLIMPEL (2016) states that although an AMS may require less labour, the workers needed for an AMS will need to be far more educated and trained than the average traditional dairy operator.

Future development should focus on maximising the value from large volumes of obtained data that AMS collects. The accuracy and resilience of Decision Support Systems will be improved by ongoing integration of high-precision sensors and advanced artificial intelligence, allowing farmers to convert predictive diagnostics into efficient management plans in real time (COGATO et al., 2021).

2.3.5 3D Printing

Historically the dairy industry has used manufacturing processes which are either subtractive/formative in nature, such as moulding cheese curd into a block, churning cream into butter or fermenting milk into yogurt using standard cups. These processes are efficient in terms of mass production, but do not offer much flexibility. Additive manufacturing (AM), however, offers a new paradigm referred to as “mass customization,” where food can be produced layer-by-layer based on a digital model (TOFAIL et al., 2018). The primary value proposition of Three-Dimensional Food Printing (3DFP) within the dairy industry lies in its ability to create complex geometrical shapes that cannot be produced through the use of traditional moulding. Therefore, the texture of the product can be modified and new flavour components can be released while consuming products (PRITHVIRAJ et al., 2025). Dairy Products present a substantial opportunity for 3D printing since they have diverse compositions and strong structure-forming properties, which may be controlled through gelling mechanisms and melting behaviours (GODOI et al., 2018).

In addition to its geometric possibilities, 3D printing also offers opportunities for the “digitalization” of nutrient content. Through the integration of 3D printers with personal health data, dairy products can be customized with exact amounts of vitamins, minerals or probiotics that are directly related to the specific dietary deficiencies of an individual. Academic work on 3DFP confirms its potential for nutrient customisation (GODOI et al., 2018), enabling what

industry practitioners describe as a transition from commodity to personalised functional food (STABLE MICRO SYSTEMS, 2024).

Several technological adoption drivers are commonly cited in the literature to explain growing research and experimental interest in 3DFP within the dairy sector:

- **Sustainability:** 3DFP can use dairy by-products (such as whey proteins) in its inks reducing food waste (DOU & REN, 2024). Application of technologies with 3D sensors (such as Laser triangulation or X-ray) also reduces food waste during the cheese cutting process thanks to the ability of mapping the density and volume of each specific block (SISWANTORO et al., 2013; BOSAKOVA-ARDENSKA, 2024).
- **Technological Convergence:** as the cost and accessibility of 3D Printing are decreasing, more applications in manufacturing and prototyping are emerging (ARSHAD et al., 2025). 3DFP is now being utilized by R&D labs and high-end food service establishments. The dairy industry is utilizing this technology to produce customized shapes, textures, and nutritional characteristics for products such as cheese, yogurt gel, and milk-based snack foods (e.g., printers such as Foodini, Focus, Print Cheese NL) (FOOD STANDARDS AGENCY, 2024).
- **Alternative Proteins:** plant proteins often lack the natural folding and melting properties of dairy casein. In this application, 3D printing is used as a texture generating technology - forming the plant paste into fibrous or gel-like structures that approximate the texture of cheese. AINIS et al. (2023) found that Soy Protein Isolate exhibits better elasticity and stability than Pea Protein Isolate, and is currently superior for creating self-supporting "cheese" blocks. The research conducted by TOHIC et al., (2018), demonstrated that additive manufacturing (3D printing) produces physical structural alterations both before and after processing of the final product and offers a potential solution by depositing layers in specific patterns that can mechanically mimic the cheese structure.

Overall, three-dimensional food printing represents an emerging and experimental component of Dairy 4.0 that is currently situated closer to product development, processing, and niche applications than to routine farm-level production. From a technological standpoint, 3DFP contributes to the broader digitalisation of the dairy value chain by enabling digitally controlled fabrication, material customisation, and integration with sensing and data systems.

Having outlined the principal technological components underpinning Dairy 4.0, the literature next addresses the benefits these technologies are expected to deliver in practice. The reported

advantages of Dairy 4.0 technologies span four domains – animal welfare, productivity, labour efficiency, and quality management – though the empirical evidence varies considerably in rigour, and benefits are consistently shown to be contingent on firm size, implementation quality, and institutional context.

2.4 Advantages of Dairy 4.0 technologies

Dairy 4.0 represents an opportunity for a holistic transformation of the whole industry as it enables optimization of all activities in the supply chain. The research studies prove the positive impact of these technologies on the dairy sector presenting measurable outcomes in areas such as productivity, animal welfare, food safety and environmental sustainability. At the same time, a growing body of research emphasises that these advantages are neither automatic nor uniform, but instead depend on farm-specific conditions, complementary investments, and the capacity to integrate digital tools into everyday decision-making. Consequently, advantages should be interpreted as potential outcomes rather than guaranteed results.

2.4.1 Operational monitoring and process reliability

The use of Precision Livestock Farming technologies in Dairy 4.0 greatly improves animal care and monitoring, which leads to better health results:

- **Precision Disease Detection:** application of wearable sensors and accelerometers, which are often integrated with machine learning algorithms, provide farmers with continuous, real-time information regarding each cow's behavioural patterns (e.g., rumination, eating activity, lying time), as well as physiological metrics (e.g., temperature). The scientific evidence indicates that the use of these devices can identify serious disease conditions such as lameness or mastitis several days prior to clinical symptoms being observable by the farmer (ARCIDIACONO et al., 2017; NEETHIRAJAN et al., 2017).
- **Mitigation of Environmental Stress:** heat stress can be effectively reduced by using digital tools, such as automatic cooling and fan systems that are triggered by real-time data from environmental monitoring sensors (such as the Temperature-Humidity Index). Studies have indicated that use of automatic cooling devices can enhance cow comfort and sustain milk output during warmer climates (CHEN et al., 2024; MYLOSTYVYI et al., 2024).

- **Enhanced Herd Management:** PLF enables individualised care, guaranteeing optimal health management techniques, which as a result reduces emissions and ensures long-term profitability and sustainability in the dairy industry (MARCHEGIANI et al., 2025).

However, the welfare literature also highlights important caveats. First, welfare improvements depend on the use of information rather than its mere availability; alerts that are ignored or poorly interpreted do not translate into better outcomes. Second, critics argue that the reduction of animal well-being to measurable indicators risks overlooking qualitative aspects of animal–human interaction and tacit knowledge acquired through daily physical presence (BOS et al., 2018). As a result, while Dairy 4.0 technologies can support welfare-enhancing management, their net effect is conditional on management quality, farmer engagement, and ethical framing. Taken together, the evidence on operational monitoring and process reliability points to a consistent pattern: Dairy 4.0 sensing technologies deliver measurable health and welfare improvements under controlled or well-managed conditions, but their real-world performance is heavily contingent on how farms and processing plants act on the data generated. The distinction between data availability and data use is particularly relevant for the V4 dairy sector, where management capacity and digital literacy vary considerably across firm sizes and ownership types (see Section 2.1). This gap between documented investment and verifiable use creates a systematic challenge for disclosure-based measurement: corporate filings may signal the presence of monitoring infrastructure without providing evidence of how that infrastructure is acted upon. Addressing this distinction requires a coding approach that differentiates between the existence of systems and evidence of their operational application.

2.4.2 Process efficiency, productivity and resilience

Through optimised production processes, digital transformation in the dairy industry offers a definite and quantifiable positive impact on costs and profits:

- **Productivity:** academic studies document that use of modern agricultural technology can be a tool for improving production and productively, as well as increasing food and nutrition security in varied agricultural sectors (SHARMA et al., 2021). Research of LEE et al. (2024) on robotic milking systems indicated that adopters increased daily milk production by 2.44 kg to 2.88 kg/cow and had approximately 0.10 more calves each year than a non-adoption group, largely because the system allows cows to be milked as often as they want at their own lactation frequency. Industry analyses similarly characterise this as a “Digitalization Productivity Bonus” (SIEMENS FINANCIAL SERVICE, 2020; MCKINSEY & COMPANY, 2025).

- **Labour Management:** use of Dairy 4.0 technologies, especially Automatic Milking Systems and monitoring sensors, reduces physical labour and allows farmers to deal with management tasks. Research studies have shown that the implementation of these systems reduces repetitive manual work. For instance, a study by TSE et al. (2018) on the introduction of AMS systems, found that the time spent on milking related activities was reduced by 62% (from 5.2 hours to 2.0 hours per day) and required about 20% fewer employees to run the operation. Similarly, SHORTALL et al. (2016), stated that the total amount of used labour can be reduced by as much as 36% through automation which would allow farmers to focus on more high value functions (strategic decision making and monitoring animal welfare) rather than manual tasks. This technological change also helps to mitigate labour shortages by maximizing the productivity of available workers (BHOJ et al., 2022).
- **Environmental Resource Optimization:** precision farming techniques and automated systems contribute to optimization of resources use and environmental sustainability of milk production, which maximizes output while minimizing both input of resources and emissions. According to the research conducted by LOVARELLI et al. (2024) mechanical ventilation with sprinklers installed at the dairy farm reduced climate change by 16% compared to the baseline scenario; while the subsequent automatic milking system upgrade provided an additional 3% reduction in environmental impacts. Research study of PARDO et al. (2022) indicates that PLF platforms can result in a notable 11% decrease in greenhouse gas emissions per kilogramme of milk by offering assistance in various decision-making procedures, which also enhances herd health and shortens periods of inactivity. Furthermore, it has been demonstrated that technology-driven water conservation techniques, like automatic plate-cooler water recycling and precision cleaning procedures, have the potential to lower overall farm water consumption by 19% per year (LE RICHE et al., 2017). On the feed management matter (responsible for the majority of a farm's carbon footprint) use of precision feeding systems, which continuously update rations based on real-time milk spectral data, can increase nitrogen efficiency, and, therefore, reduce ammonia emissions and nutrients runoff in local waters (CHASE & FORTINA, 2023).

Nevertheless, the productivity literature also reveals conflicting findings. While physical labour inputs decline, total labour requirements do not always fall proportionally due to increased needs for system supervision, data interpretation, and maintenance. Moreover, productivity gains do not necessarily translate into higher profitability if capital and operating costs rise

simultaneously. This tension between technical and economic efficiency is particularly acute in heterogeneous regional settings such as the Visegrad Four, where firm size, ownership structure, and access to capital vary substantially across and within countries. The implication for this study is twofold. First, if adoption-performance dynamics differ by country and firm type, cross-national variation in D4 disclosure intensity is expected to be statistically significant rather than attributable to random variation alone – consistent with hypothesis of this dissertation – H1. Second, any cross-sectional positive association between D4 score and revenue is more likely to reflect a firm-size confound than an independent adoption-performance effect, since larger and better-resourced firms both adopt more readily and earn more revenue, supporting the null prediction in H3.

2.4.3 Product quality, safety and traceability

Beyond on-farm biological and operational performance, Dairy 4.0 technologies also extend their influence across processing and supply-chain interfaces, particularly in relation to product quality assurance, food safety, and traceability. It brings a new level of monitoring as well as transparency to the dairy supply chain to meet the rising demands of consumers and regulation authorities to produce safe and better-quality milk.

- **Real-Time Quality Control** in Dairy 4.0 changes food safety control from periodic, time-consuming laboratory tests to continuous inline monitoring through IoT-enabled smart sensors and spectroscopy. The study by JAYAMURUGAN et al. (2025) indicates that integrating multiple sensors can improve the speed and continuity of milk quality monitoring. In processing contexts, such systems support earlier anomaly detection, faster batch segregation, and more traceable quality assurance routines.
- **Traceability** in the dairy industry is unavoidable, given the short shelf life of dairy and the growing international concern about food fraud. Literature confirms that utilizing blockchain-based platforms combined with IoT and QR codes can transform current dairy supply chains to decentralized, robust, and transparent systems. A case study conducted by VARAVALLO et al. (2022), on the Fontina PDO cheese supply chain, demonstrated that “Green Blockchain” platforms create a tamper proof digital history for each item produced – from the time it was collected as milk to when it was packaged for sale - which does not only assure authenticity but also increases consumers' confidence in their purchases by providing them assurance that the claim made about the origin and the treatment of animals has been validated. Furthermore, the use of Smart Contracts improves this process by making compliance audits automatic, ensuring that if any temperature abuse occurs during transportation and it is detected by IoT, the

information is automatically documented to prevent those items from ever being sold at a retail location (RAO et al., 2025).

Despite these advantages, the literature cautions that advanced traceability systems primarily generate value at the supply-chain and consumer interface, while farm-level economic benefits are less consistently documented. High implementation costs, governance complexity, and uncertain price premiums limit direct incentives for farmers, particularly small and medium-sized producers. Consequently, while Dairy 4.0 technologies clearly enhance quality assurance and traceability, their contribution to farm-level sustainability remains contingent on institutional arrangements and market structures.

While the literature highlights numerous potential advantages of Dairy 4.0 technologies, it simultaneously documents a range of economic, technical, social, and ethical challenges that complicate their adoption and performance. The following section therefore balances the preceding discussion by examining the principal disadvantages and constraints identified in empirical and conceptual research.

2.5 Disadvantages and challenges of using Dairy 4.0 technologies

Although Dairy 4.0 has the potential to implement positive changes in the industry, there are a complex set of economic, technical, social, and ethical challenges associated with these technologies. The literature increasingly recognises that digital transformation can generate new forms of vulnerability and inequality if implementation constraints are not adequately addressed. These challenges are not uniform across farms, but instead interact with scale, capital access, infrastructure, and skills, reinforcing the need for context-specific analysis. The adoption barriers documented in the literature fall into four categories: economic, technical, data governance, and socio-ethical – each creating distinct friction points for V4 dairy processors operating under tight capital constraints and fragmented institutional support.

2.5.1 Economic barriers and high investment costs

The financial aspect of Dairy 4.0 may be the biggest obstacle for its adoption, leading to the creation of a digital divide that could possibly threaten the existence of small and medium-sized farms:

- **High Capital Expenditure (CAPEX):** the biggest obstacle is the high upfront cost of robotic infrastructure, sensors, and automated milking systems, which are required for transitioning to process automation. The scientific literature has shown that Dairy 4.0 technologies are capital intensive. BENTLEY et al. (2018) indicate that installing one

automatic milking system unit usually costs between \$220 000 and \$280 000, while equipping a traditional milking parlour to milk the same number of cows would cost roughly half of what was spent on the AMS. According to the study, these expenses can be excessive, especially for family farms and small-to-medium-sized businesses (SMEs), resulting in a gap where only large-scale companies can afford adopting Dairy 4.0 technologies (WÓJCICKI et al., 2025).

- **Uncertain Return on Investment:** efficiency benefits from automation technologies do not always result instant or predictable profit. Farmers frequently encounter difficulties in measuring the actual costs of software subscriptions and maintenance against the immediate economic benefits of data-gathering technologies (VILLA-HENRIKSEN et al., 2020).

A “profitability paradox” has been identified by research studies with the potential for savings in labour costs through automation or robotics to be completely offset by an increase in other types of fixed cost (i.e., depreciation, interest, and energy costs). A study of BIJL et al. (2007) on the adoption of Automatic Milking Systems in Dutch dairy farms reported that AMS resulted in approximately a 30% decrease in labour hours, but the net farm income of those farms in the first few years was lower than those with traditional milking systems due to the large increases in capital expenditures.

STEENEVELD et al. (2012) found no statistical differences in farm efficiency when comparing robotic farming and conventional farming during initial years of adoption of these systems. In fact, the “break even” point for many dairy farmers who adopt Dairy 4.0 technologies typically occur within 5-7 years. Dairy market volatility also has a negative impact on adoption of Dairy 4.0 systems: when milk prices decline, it becomes difficult to maintain a positive cash flow due to the fixed costs associated with Dairy 4.0 systems, which could result in an unsustainable financial burden on less resilient dairy farm operations (FRICK & SAUER, 2021).

These findings directly challenge overly optimistic narratives about the financial returns to digitalisation. For this study, they establish a key prior: that within a six-year panel observation window covering the volatile 2019-2024 period – including the COVID-19 disruption and the 2022-2023 energy price shock – D4 maturity scores are unlikely to predict within-firm profit margin improvement, even if larger firms systematically score higher in cross-sectional comparison. This asymmetry between cross-sectional and within-firm results is precisely what H3 predicts: a size-driven cross-sectional correlation that does not survive fixed-effects identification.

2.5.2 Technical and infrastructure limitations

There are a number of major technical obstacles to the adoption of Dairy 4.0, especially for small and medium-sized businesses (SMEs) and in areas with developing infrastructure:

- **Connectivity and reliability:** potential for effective Dairy 4.0 is reliant upon consistent and fast internet connectivity that allows for the transmission of sensor data to the cloud. Specifically, the lack of rural infrastructure along with issues related to interoperability, create significant risks to the functionality and reliability of Dairy 4.0 systems. ROTZ et al. (2019) indicate that advanced sensors become useless in areas without high-speed internet (4G/5G), as real time data transmission to the cloud systems cannot be achieved. RAO & NEETHIRAJAN (2025) also confirm that a number of dairy applications require millisecond-level feedback, and cannot rely on unstable internet connection in rural regions, and propose a shift to Edge Computing, where data is processed locally, rather than in the cloud.
- **Data silos and interoperability:** one of the biggest technical frustrations is the lack of interoperability between the various types of equipment used by farmers and the lack of standardization for the manufacturers. Devices from different producers often cannot “communicate” with one another, which creates an environment of “data silos” (BALDIN et al., 2025). As a result, farmers are required to manually stitch together data from varied dashboards and data sources. According to a GAO report from 2024, the lack of consistent API standards makes it extremely difficult to create a “Holistic Digital Twin” of the farm, which reduces the management system's overall effectiveness.

These issues help explaining why reported benefits vary widely across empirical studies, even when similar technologies are deployed.

2.5.3 Data privacy and security risks

The introduction of Dairy 4.0 includes new vulnerabilities related to data governance and cybersecurity (VATN et al., 2023). The shift from analogue to “Cyber-Physical Systems” (CPS) means that dairy farms are now data-driven businesses rather than just food producers, which makes them appealing targets for threat actors and creates new and complex legal issues associated with data ownership (NEETHIRAJAN, 2025).

- **Operational disruption:** critical equipment can be stopped by a malware infection or denial-of-service (DoS) attack. Even a 24-hour system lockout can lead to serious animal welfare problems and substantial financial loss, since cows need to be milked regularly to prevent mastitis and maintain lactation (COE SECURITY, 2025).

Ransomware can paralyze supply chains, prevent milk pickup and interfere with payment systems, as seen by recent events like the attack on the Dairy Farmers of America (DAIRY HERD, 2025).

- **Data ownership:** structural constraint arises from the lack of clarity regarding who has ownership rights to the substantial volumes of data created through the use of smart devices: the producer (farmer), the vendor (equipment manufacturer) or the software supplier. Farmers have legitimate concerns about the potential for their production data to be sold to third parties for manipulating commodity prices, or distributing it to regulatory bodies without their explicit agreement (CUE et al., 2021).
- **Privacy risks:** at the grain level of Dairy 4.0 – tracking the health, location, and movements of each cow – the ripple effects of the privacy issues spread to the employees and farmers. The research of ROTZ et al. (2019) warn about the increasing presence of “Digital Taylorism” in the agricultural sector. This is due to the fact that the combination of RFID tags, smart cameras and automatic loggings enable managers to monitor the minute details of all the actions of their staff – from how long it takes for a worker to clean a cow's teats to the time taken for feeding cows – down to the second. Often justified as a means to improve safety, a review of the use of wearable technology in Agriculture 4.0 has shown that continuous monitoring through technology can result in increased levels of psychological distress for employees, a breakdown in trust between employers and employees, and a reduction in employee autonomy, as instead of using their own professional judgement, employees feel under pressure to match the algorithms' unrelenting speed (APICELLA & TARABELLA, 2025; BALL, 2021). Additionally, workers become “data subjects” whose job security is determined by metrics they cannot control or dispute, creating a power imbalance that raises serious ethical concerns about privacy and the “right to disconnect” in an all-online farm environment (KLERKX et al., 2019).

These concerns can reduce willingness to adopt digital technologies, particularly where legal frameworks remain underdeveloped.

2.5.4 Social and ethical challenges

While Dairy 4.0 is commonly viewed as an answer to labour shortfalls, literature review has shown both social and ethical downsides, namely the loss of human-animal connection, a potential for “deskilling” of the workforce, and increasing inequality in rural areas:

- **Re-skilling:** BOS et al. (2018) and WERKHEISER (2018) state that Precision Livestock Farming changes the role of the farmer from being directly involved in the animal care to “screen-based management”. This shift to being away from livestock may result in a lack of an emotional bond with herd and the loss of “tacit knowledge”, which allows to identify an animal's health through day-to-day visual contact and touch.
- **De-skilling:** a study of GOLLER et al. (2021) on the digitalization of German dairy farms shows that as the farmers’ reliance on algorithms for detection of oestrus and/or illness increases, it is possible that the farmer will lose the hands-on skill for manual diagnosis. This leads to a dangerous vulnerability because if the digital system fails (due to a cyber-attack a loss of electrical power), farmers may be without the necessary hands-on skills to maintain the overall health of the herd during the failure of the digital systems.
- **Objectification of animals:** critics in animal ethics have argued that by reducing animal well-being to measurable numbers (for example, rumination time or number of steps taken), there are risks that complex emotions which is not possible to measure with sensors will be ignored ultimately resulting in a “de-animalization” of the livestock in pursuit of increased efficiency (BOS et al., 2018; DOIDGE et al., 2023).
- **Cognitive overload:** according to HOSTIOU et al. (2017) the flood of data might cause “informational terror”, as farm workers are overtaken by thousands of notifications, rather than making their jobs easier. This cognitive burden can result in anxiety and decision paralysis in the absence of data literacy training, which could drive employees to complete disregard of warnings.

Taken together, the disadvantages discussed in the literature do not negate the potential benefits of Dairy 4.0 technologies, but they strongly suggest that outcomes are context-dependent and mediated by economic, institutional, and human factors. This reinforces the need for empirical analysis rather than normative assumptions. In the V4 processing context, it also suggests that the structural and institutional factors mediating adoption outcomes – firm size, ownership type, regulatory exposure, multinational affiliation – are likely to produce measurably different D4 disclosure patterns across countries, underpinning H1. At the same time, the stickiness of disclosure behaviour documented in the institutional literature suggests that within-firm improvement over a six-year panel will be more limited than aggregate cross-sectional comparisons imply, a dynamic central to H2.

Taken together, the barriers documented in this section are not evenly distributed across the industry. They are disproportionately concentrated among smaller, domestically-owned processors operating in institutional environments with weaker investment support and lower

disclosure expectations – largely the profile that characterises a substantial portion of the V4 dairy processing sector. This structural asymmetry has a direct implication for the empirical analysis: if adoption barriers translate into lower disclosure visibility for smaller firms, then panel datasets built from public documents will overrepresent large, internationally affiliated processors. The analytical strategy in this dissertation accounts for this through a firm-size control and sensitivity tests reported in Chapter 4, but the underlying selection effect remains a boundary condition on the generalisability of the findings.

Taken together, the advantages and challenges discussed above suggest that the impacts of Dairy 4.0 technologies cannot be assessed in isolation from broader economic and environmental objectives. Consequently, the next section shifts the unit of analysis from technology characteristics to firm-level outcomes, reviewing empirical studies that evaluate how Dairy 4.0 adoption relates to economic performance and environmental monitoring capability specifically among dairy processing companies – the population that forms the empirical base of this dissertation.

2.6 Previous research on Dairy 4.0 and its impact on sustainability of dairy processors

Empirical evidence on Dairy 4.0 adoption among processing companies is less extensive than the farm-level literature, but converges on two dimensions directly relevant to this study: disclosure-visible economic performance and environmental monitoring capability. It should be noted that even within this processor-focused review, a portion of the cited studies conflate farm and processing stages of the dairy value chain, or draw on farm-level investment data to proxy processor behaviour. Where this occurs, it is flagged. The empirical analysis in Chapter 4 is based exclusively on documentary evidence from 80 V4 dairy processing companies and does not rely on farm-level outcome data.

This chapter reviews empirical research on the factors driving and constraining D4 adoption at the firm level, and on the sustainability outcomes that processing firms associate with digital investment in public documents. The review is conducted using the PRISMA approach (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) (PAGE et al., 2021) and applies VOSviewer mapping to visualise keyword co-occurrence structures and temporal trends (VAN ECK & WALTMAN, 2010). While much of the available evidence base concerns primary dairy farming rather than processing, the institutional, financial, and regulatory dynamics discussed are directly relevant to the V4 processing sector and inform the hypotheses tested in Chapter 4.

A systematic literature search was conducted using Scopus database by combining different keywords to identify literature related to “Dairy 4.0”, “smart dairy farming”, “precision livestock farming”, “digital dairy technologies”, “Automated Milking Systems”, “robotic milking”, “sensor-based dairy monitoring”, “IoT dairy”, “economic sustainability”, “environmental efficiency”, “resource efficiency”, “adoption”, “technology diffusion”.

The PRISMA flow diagram and the VOSviewer visualisations presented below summarise the Dairy 4.0 + sustainability literature corpus retrieved from Scopus for the defined search period and screening criteria.

The inclusion criteria for this study were: journal articles that were peer reviewed between 2012 and 2025; studies focused on digitalization within the dairy sector; studies measuring either economic or environmental impact of digitalization; empirical, review, conceptual and modelling-based studies.

The exclusion criteria for this study were: livestock that are not dairy unless explicit transferability of results from non-dairy livestock studies was provided; all papers lacking sufficient methodological detail; sources that are not academic.

Every article that was included into the literature review was coded for: type of technology (PLF, AMS, IoT, AI, blockchain, etc.); methodology approach (qualitative surveys, econometrics, ML validation, LCA); farm typology; geographical area; economic results (labour savings, revenue changes, and expenses); environmental outcomes (water/energy use, nutrient loading, greenhouse gas emissions); welfare results.

A total of 1 393 records were identified in the database for the 2012-2025 period, which were screened by titles, abstracts, and keywords. The next step involved a dairy relevance screening process, after which 1 222 records that did not reference dairy systems were excluded, leaving 171 dairy relevant studies. Thematic eligibility screening was used to determine which of these records had the inclusion criteria of both Dairy 4.0 technology concepts (e.g. PLF/Sensor systems; Internet of Things; Robotics/Animal Management Systems; Artificial Intelligence/Decision Support Systems; Traceability) and sustainability results (economic performance or environmental efficiency metrics). This step resulted in 95 records being excluded from the study (sustainability without Dairy 4.0 technology, $n = 74$; technology without sustainability outcomes, $n = 12$; neither criterion, $n = 9$) resulting in 76 studies included in the final bibliometric and thematic synthesis. Screening process results are presented in PRISMA flow summary in *Figure 2*.

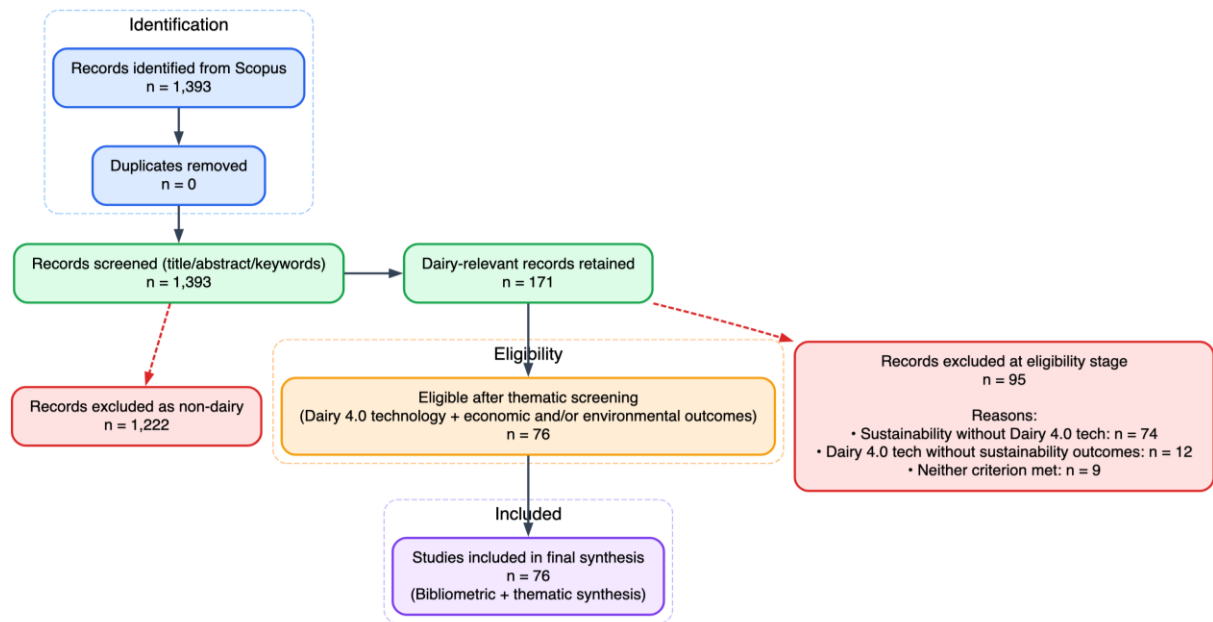


Figure 2. PRISMA 2020 flow diagram documenting identification, screening, eligibility, and inclusion counts for the Scopus dataset

Source: Constructed by author (2025)

In addition to PRISMA selection, a bibliometric mapping was carried out with VOSviewer, a software that uses co-occurrence and distance-based visualizations to show clusters of related terms and their structural relationships (VAN ECK & WALTMAN, 2010).

As shown in *Figure 3*, the keyword co-occurrence map illustrates a dense conceptual space centred around “sustainability” and linked to “artificial intelligence”, “sustainable development”, and “environmental sustainability”. The retrieved corpus is organised around inter-related research areas such as digital/AI-enabled decision support, sustainable development and governance framing (e.g., SDGs), supply chain transparency, and operations/optimisation techniques. The centrality of sustainability indicates that it functions as a conceptual bridge linking managerial techniques, policy-oriented sustainability agendas and technical innovations.

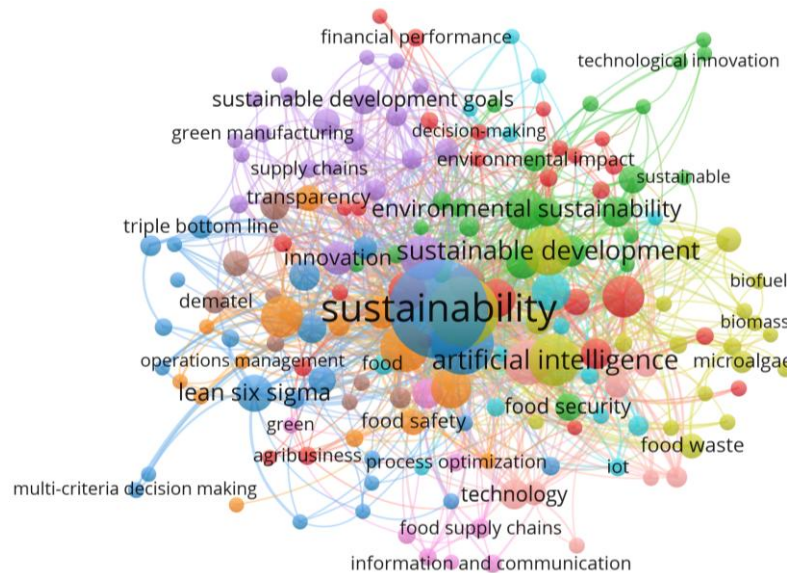


Figure 3. VOSviewer network visualization of keyword co-occurrence in the research studies on Dairy 4.0 and sustainability

Source: Constructed by author (2025)

As shown in *Figure 4*, the overlay visualisation colours the keyword network by average publication year (blue = earlier; yellow = later). The pattern suggests an acceleration of digital transformation narratives after 2020, while established operations management and decision-method clusters remain prominent. In the Dairy 4.0 context, this supports the interpretation that newer digital topics build on established optimisation and multi-criteria decision-making approach.

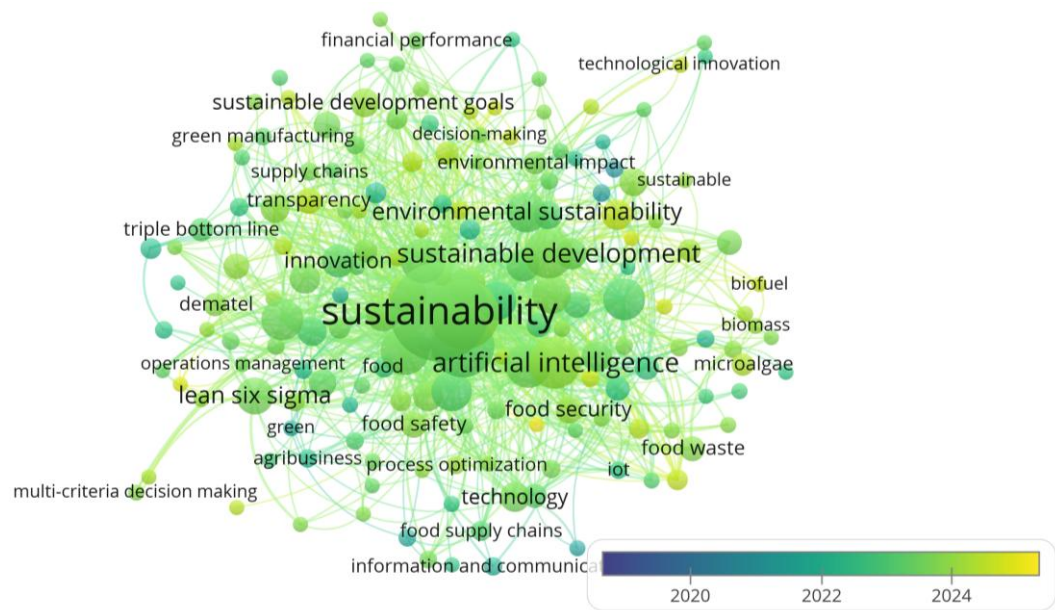


Figure 4. VOSviewer overlay visualization of research studies on Dairy 4.0 and sustainability coloured by average publication year

Source: Constructed by author (2025)

Within the sustainability literature, economic performance is most frequently identified as the primary driver of adoption decisions. Accordingly, the following subsection focuses on the economic sustainability implications of Dairy 4.0 technologies, with particular attention to productivity, labour efficiency, and profitability.

2.6.1 Economic sustainability

2.6.1.1 Methodological approaches used to assess economic outcomes

In the Dairy 4.0 and precision farming literature, economic sustainability is one of the most frequently cited motivations for the adoption. It is usually defined as the farm's capacity to maintain long-term viability by improving (a) profitability and cash flow, (b) productivity and efficiency (milk output per cow, per labour hour, per unit of feed), (c) cost control (capital and operating costs), (d) resilience to shocks (milk price volatility, labour constraints, disease and climate risks). Empirical studies look at Dairy 4.0 as an integrated technology system that influences inputs use on farms (labour, feed, energy), biological performance (animal health, fertility, yield), and managerial decision-making quality, which affects economic outcomes.

The synthesis set from a Scopus database includes 66 articles that contain at least one of an economics term in the title/abstract/keywords (e.g. cost, labour, productivity, profitability, investment). Productivity/economic efficiency and behavioural intention/adoption are the two most common ways to measure “economic sustainability”, while comprehensive investment appraisal (ROI/payback) and long-term resiliency are much less used.

Several research designs are used in Dairy 4.0 to demonstrate evidence about economic sustainability. First, farm accounting and benchmarking studies compare financial performance between adopters and non-adopters of new technology, often with a primarily focus on AMS (e.g., BIJL et al., 2007; STEENEVELD et al., 2012; SALFER et al., 2017; HANSEN et al., 2019). Second, after adoption of PLF technologies, partial budgeting and cost–benefit approaches measure changes in labour demand, veterinary/health-related expenses, milk output and revenues, and annual capital costs (such as interest and depreciation), and in some cases payback periods are reported under scenario assumptions (SALFER et al., 2017; ADENUGA et al., 2020; KIEFER et al., 2025). Third, econometric and efficiency studies use matched comparisons, regression, or DEA/SFA to estimate relationships between technology adoption and productivity outcomes (e.g., FRICK & SAUER, 2021; PALMA-MOLINA et al., 2025). Fourth, survey and behavioural studies apply adoption theories (e.g., Diffusion of Innovations, Technology Acceptance Model, Theory of Planned Behaviour) to explain the reasons for adopting, perceived value, and barriers to adoption (SHORTALL et al., 2016; SCHEWE &

STUART, 2015; LAGE et al., 2024). Finally, a smaller set of studies uses modelling (scenario-based simulation/optimisation) and whole-farm or systems approaches to analyse the long-term impacts, often highlighting uncertainty and context sensitivity (KIEFER et al., 2025; FERGUSON et al., 2024; LOVARELLI et al., 2023; BANG et al., 2025).

As shown in *Table 2*, the methods used in the research studies exported from the Scopus database were classified using keyword screening. The summary is based on 59 articles.

Table 2. Summary of methods used in the economic sustainability literature on Dairy 4.0 technologies and obtained research outputs

Method type	Share of studies (%)	Research outputs
Review/synthesis	35.6	Consolidating fragmented evidence; identifying gaps/standardisation needs
Mixed methods	18.6	Capturing cross-pillar trade-offs; multi-technology bundles
Econometric/ efficiency (DEA/SFA, regression, matching, panel)	13.6	Multi-farm inference and association estimation
Survey/adoption models	13.6	Explaining drivers/barriers and decision logic
Bioeconomic/ simulation modelling	8.5	Scenario outcomes (milk price, labour, interest); long-term viability/resilience under uncertainty
Partial budgeting/cost-benefit	5.1	Investment appraisal and “what-if” decisions
Qualitative case/work studies	3.4	Capturing organisational change and non-monetised costs/benefits
Farm benchmarking/ accounting comparisons	1.7	Observed economic performance comparisons

Source: Constructed by author (2025)

2.6.1.2 Literature findings on economic impacts by Dairy 4.0 technologies

The economic impact of AMS has been most studied since it involves significant capital investment and obvious labour implications. The overall cost benefit of adopting Robotic Milking varies greatly depending on initial capital costs for equipment, financing methods, herd size, and management adjustment. Early studies reported that hours spent doing routine milking labour can be dramatically reduced at first, however, net income could potentially decrease due to increased depreciation and/or financing costs associated with the larger capital investment (BIJL et al., 2007). Further studies have shown mixed efficiency impacts during the early years of adoption (STEENEVELD et al., 2012) and greater variation in financial results of dairy farms (SALFER et al., 2017). More recently, researchers have found that AMS is financially

profitable as long as it is used as part of an overall herd management system, cow traffic design, and feeding program, and when labour deficit or labour costs can be used as a flexible resource (HANSEN et al., 2019; LAGE et al., 2024).

Labour efficiency constitutes a second major channel through which Dairy 4.0 technologies are expected to influence economic sustainability. Labour scarcity and rising labour costs are repeatedly identified as structural constraints in modern dairy farming, particularly in developed economies. Empirical studies indicate that AMS adoption can substantially reduce time spent on routine milking tasks, with reported reductions in milking-related labour of up to 60% and overall labour use reductions of 20-36% (TSE et al., 2018; SHORTALL et al., 2016). By reallocating labour from repetitive manual tasks toward supervision, data interpretation, and strategic management, Dairy 4.0 technologies may increase milk output per labour hour and improve operational flexibility.

PLF and real-time monitoring sensors contribute to the economic sustainability of farms by avoiding losses due to earlier disease detection (mastitis/lameness), as well as through the improvement of reproductive performance and reduction in waste of inputs. The literature shows that the potential economic benefits from these systems depend upon the farm's ability to implement effective and timely responses to the alerts and integrate data streams across devices (CABRERA et al., 2020; CABRERA & FADUL-PACHECO, 2021; CABRERA et al., 2025). In practice, sensor systems usually result incremental gains as opposed to “step” increases, however, when they prevent costly events or significantly decrease treatment and culling costs, the value added is highly significant (BRITO et al., 2025).

IoT platforms, big data analytics and AI are positioned as productivity and management enhancers (“Dairy Brain”), yet few return on investment studies at the farm level exist in comparison to many technical validation research works. The literature is also clear that the value of analytics depends on interoperability, data quality, and decision support integration into workflows (CABRERA et al., 2020; CABRERA et al., 2025; BALDIN et al., 2025). As a result, most of the economics claims are often prospective and therefore require greater causal evidence.

Blockchain and traceability studies discuss possible value creation through reduced fraud, better compliance and potential higher prices or market access. However, the majority of publications discuss conceptual architectures and barriers to adoption and do not measure quantifiable farm gate benefits. Among key constraints are high set up costs, lack of standardization, and governance challenges (VILLA-HENRIKSEN et al., 2020; FENG et al., 2020; VARGAS-BELLO-PEREZ et al., 2025).

The overall finding of previous research studies is that Dairy 4.0 does not deliver uniform economic results and its benefits vary based on farm and system characteristics. Two main factors that influence the adoption and profit potential of systems are farm size and capital availability. Larger farms have greater ability to spread out their fixed assets and retain specialized labour and therefore tend to be more likely to adopt technologies and gain a greater profit through its use. The fit of AMS and monitoring technologies is influenced by production system (confinement vs. pasture-based), as well as regional labour availability and level of wages paid. In addition, digital literacy of farmers, availability of advisory services and organisational readiness greatly impact farmer's ability to turn obtained data into better decision-making, and prevent occurrence of additional costs associated with data overload. Lastly, vendor lock-in and interoperability can result in hidden transaction costs (training, software subscriptions, integration work) that are rarely fully accounted for in farm budgets (VILLA-HENRIKSEN et al., 2020; BALDIN et al., 2025).

Conflicting views and reported results are therefore not a contradiction but a recurring theme in the literature. Some authors stress that labour substitution and higher productivity can improve farm margins, especially when labour is scarce or expensive (TSE et al., 2018; COGATO et al., 2021). By contrast, other studies report that net income can fall in the early years after adopting capital-intensive systems such as AMS, because depreciation, interest payments and maintenance costs can offset labour savings (BIJL et al., 2007; STEENEVELD et al., 2012).

Another conclusion which could be made is that profitability effects are conditional: positive outcomes tend to materialise when farms redesign herd management (cow traffic, feeding, health protocols) and operate at a scale that spreads fixed costs, while poor integration and “data silos” can create additional transaction costs and limit realised benefits (HANSEN et al., 2019; LAGE et al., 2024; VILLA-HENRIKSEN et al., 2020; BALDIN et al., 2025).

Taken together, the literature suggests that Dairy 4.0 technologies have a strong potential to enhance productivity and labour efficiency, while their effects on profitability are conditional, heterogeneous, and sensitive to structural and managerial factors. This combination of supportive evidence and unresolved contradictions is directly informative for this study's approach to H3. The consistent finding that larger, better-capitalised, and more institutionally connected firms adopt earlier and realise returns sooner implies that any cross-sectional correlation between D4 disclosure intensity and firm revenue is contaminated by firm-size confounds. A within-firm fixed-effects identification strategy – which strips out all time-invariant firm characteristics – is therefore needed to separate genuine adoption-performance

dynamics from firm heterogeneity. The literature's silence on consistent within-firm profitability gains over short horizons, combined with the documented capital expenditure suppression of current-period margins, supports the expectation that the Fixed Effects coefficient will be non-significant across the 2019-2024 window, as H3 predicts.

Across these methodological approaches, the literature splits into two clear positions rather than a single consensus. Farm-accounting and partial-budgeting studies (e.g., BIJL et al., 2007; SALTER et al., 2017) tend toward caution, emphasising that capital costs and adjustment periods can offset labour savings, particularly for early adopters. Behavioural and diffusion-theory studies (e.g., SHORTALL et al., 2016; LAGE et al., 2024), by contrast, tend toward optimism, framing non-adoption primarily as a barrier-and-awareness problem rather than as evidence that the underlying economics are unfavourable. Econometric and efficiency studies (FRICK & SAUER, 2021; PALMA-MOLINA et al., 2025) sit between these positions methodologically but functionally support the cautious reading, since they are the only design capable of separating genuine productivity effects from the size and management-quality confounds that adoption-intention studies cannot address.

This dissertation's document-based approach is methodologically closer to the third camp in spirit – prioritising verifiable, traceable evidence over self-reported intention or attitude.

2.6.1.3 Research gaps and implications for the Visegrad Group context

Although the economic performance literature on Dairy 4.0 is extensive, it is dominated by Western European and North American farm-level contexts. For the Visegrad Group, this creates a transferability problem: processor-level capital structures, market concentration, ownership types, and regulatory environments in Central and Eastern Europe differ materially from the settings analysed in most studies (BURDIUZH, 2021). Industry-facing sources further emphasise that cost pressure and financing conditions can substantially alter technology payback in the V4 context (DAIRY INDUSTRIES INTERNATIONAL, 2023; IFCN, 2024). Critically, no existing study examines financial performance correlates of Dairy 4.0 disclosure intensity among processing companies using a longitudinal panel design that can separate firm-size effects from genuine adoption dynamics.

First, the existing literature relies almost exclusively on farm-level accountancy data, farm surveys, or agronomic trials to measure economic outcomes. There are no studies that use documentary evidence coding of corporate disclosures to assess the relationship between D4 maturity and financial performance at the processor level, leaving a gap in understanding how digital transformation intensity is reflected – or obscured – in what processing companies publicly report (FRICK & SAUER, 2021). A second gap is that most studies employ cross-

sectional designs that cannot separate genuine adoption-performance dynamics from firm-size effects or pre-existing management quality advantages, a problem that is particularly acute when larger processors both invest more in digital systems and generate more revenue (FRICK & SAUER, 2021; VILLA-HENRIKSEN et al., 2020).

Third, the existing literature has not examined how D4 maturity at the processing level is reflected in corporate disclosure documents – annual reports, sustainability statements, and regulatory filings. Whether firms that invest in digital systems report more extensively on this investment, and whether the composition of that reporting (ESG-led versus technology-led) varies systematically by country and ownership type, remain open questions not addressed by farm-level investment studies (VILLA-HENRIKSEN et al., 2020; BALDIN et al., 2025). Fourth, the total cost of ownership for digital systems in food processing is typically underestimated in the general Industry 4.0 literature, and firms may have incentives to selectively report positive outcomes while omitting cost and downtime information, creating a potential disclosure bias that a documentary evidence methodology must account for (SCHEWE & STUART, 2015; LAGE et al., 2024).

Finally, there is no existing longitudinal study covering V4 dairy processors that jointly examines D4 disclosure intensity, company financial performance, and the institutional context – ownership structure, multinational affiliation, and regulatory exposure – that shapes both adoption and disclosure behaviour. Building on these gaps, this dissertation uses a documentary evidence panel of 80 V4 dairy processing companies across 471 company-year observations (2019-2024) to test whether D4 disclosure scores are associated with financial performance. Because the evidence base flags firm size, ownership structure, and institutional embeddedness as persistent confounders, the empirical analysis employs two-way fixed-effects panel regression to isolate within-firm variation from between-firm heterogeneity – a design directly motivated by the gap in long-run, within-firm panel evidence identified above. *Table 3* summarises the key research gaps and their implications for a Visegrad-relevant research design.

Table 3. Key research gaps in Dairy 4.0 economic sustainability studies

Literature gap	Why it matters for this study?
No disclosure-based panel study of D4 maturity among dairy processors	Existing studies measure adoption via surveys or trials; no study codes corporate documents to construct a multi-year D4 maturity panel for processing companies.
Weak causal identification and scarce longitudinal evidence	Cross-sectional designs conflate firm-size effects with adoption effects; a within-firm fixed-effects estimator is needed to test H3 credibly.

Selective disclosure bias: firms may report digital investment benefits while omitting costs, integration failures, and downtime	Documentary evidence captures what companies choose to disclose; a coding protocol must distinguish verified evidence from narrative claims to limit upward bias in D4 scores.
No evidence on D4 disclosure intensity and financial performance for V4 processors using longitudinal panel data	Without a V4-specific panel, it is impossible to test whether D4 disclosure scores correlate with revenue or margin within firms over time, or whether any cross-sectional association merely reflects company size.
Limited evidence on cross-national heterogeneity in D4 adoption among V4 dairy processors	Structural differences in firm ownership, market concentration, and regulatory exposure across Czech Republic, Hungary, Poland, and Slovakia predict heterogeneous D4 maturity; no existing study tests this empirically, motivating H1.
No longitudinal analysis of temporal dynamics of D4 disclosure in V4 processing sector	Without a six-year panel, it is impossible to distinguish genuine within-firm deepening of D4 capability from between-firm compositional effects and document volume growth – the distinction that H2 is designed to test.
ESG-D4 nexus not investigated: no study tests whether ESG disclosure leads or follows operational technology adoption in dairy processing	The theoretical mechanisms in Section 2.6 predict ESG Enablement is structurally dominant and temporally prior to other D4 dimensions; this prediction (H4) has not been empirically tested in any dairy processing context.

Source: Constructed by author (2025)

Although economic considerations often dominate adoption decisions, environmental efficiency has become an increasingly central concern in both policy and academic debates. The subsequent subsection therefore examines how Dairy 4.0 technologies are argued to influence environmental performance, focusing on emissions intensity and resource-use efficiency.

2.6.2 Environmental efficiency

2.6.2.1 Methodological approaches used to assess environmental outcomes

Environmental efficiency in Dairy 4.0 research is generally defined as the ability to produce milk using fewer resources while generating lower environmental impacts per unit of output. Therefore, the most common metrics in the literature are related to climate (GHG total emissions and GHG emissions per kilogram of fat- and protein-corrected milk, occasionally complemented by other metrics such as energy and water use, nutrient loss and multi-dimensional composite indicators which include environmental with social and economic sustainability components.

To mirror the mapping of economic sustainability, the Scopus-exported corpus was filtered to identify those studies that (a) were focused on dairy cow systems, (b) used Dairy 4.0

technologies, and (c) included environmental efficiency outcomes (e.g., carbon footprint, greenhouse gas emissions, energy or water efficiency) in their titles, abstracts or keywords. Using this keyword-tagging approach, 24 publications met both the technology-environment criteria as well as having an explicitly dairy focus in the title. As recorded in *Table 4*, methodology approach is dominated by modelling and reviews, with comparatively fewer farm-based empirical studies and foot printing/LCA researches.

Evidence on environmental efficiency are based upon a limited range of research methods compared with economics literature. Most environmental efficiency research has used systems modelling and scenario analysis, which translate assumed improvements in performance due to PLF tool usage (i.e., improved calving intervals, reduced replacement rates, increased yields, early disease detection) into reductions in farm level emission intensities. A smaller number of studies use carbon foot printing and life cycle assessments for evaluating differences in emission levels of baseline vs. technology enabled management practices, while econometric studies apply farm-survey datasets to estimate associations between digital technology use and carbon-emission efficiency. *Table 4* identifies the most commonly used research design methods and their typical output.

Table 4. Summary of methods used in the environmental efficiency literature on Dairy 4.0 technologies and obtained research outputs

Method type	Share of studies (%)	Research outputs
Systems modelling/simulation	37.5	Scenario outcomes for emissions intensity and resource use under alternative management enabled by PLF/AI (fertility, health, yield); sensitivity analysis (prices, performance, adoption)
Review/synthesis	33.3	Narrative synthesis of mitigation pathways; proposed metrics; typologies of technologies; evidence gaps and standardisation needs
Life cycle assessment/footprint	16.7	GHG emissions (kg CO _{2e}), emissions intensity (kg CO _{2e} /kg FPCM), carbon footprint % change; selected midpoint impacts
Survey/behavioural	4.2	Perceived environmental benefits, perceived barriers to “green” technologies, and implementation constraints
On-farm measurement/case study	4.2	Empirical measurements of animal behaviour/resource use and before–after comparisons of management scenarios; farm-level indicator dashboards
Other/mixed	4.2	Framework papers, conceptual net-zero roadmaps, and hybrid multi-criteria sustainability indicators

Source: Constructed by author (2025)

2.6.2.2 Literature findings on environmental impacts by Dairy 4.0 technologies

Literature review shows that the strongest data-based evidence for reduced emissions intensity is associated with animal mounted sensors and PLF Decision Support Systems, which can be also attributed to increased efficiency, better reproductive performance, improved health management and overall production. A modelling study utilizing commercially available fertility and health sensors in representative Scottish dairy systems estimated that implementing both technology and management changes would lead to small reductions in total greenhouse gas emissions as well as greater reductions in emissions intensity (FERGUSON et al., 2024). Likewise, an indicator-based analysis of Italian dairy case studies found that adoption of PLF technologies combined with improved management practices resulted in carbon footprint reductions, however the magnitude of these reductions depends upon the specific technology applied and farm environment (LOVARELLI et al., 2023).

Another conceptual framework views environmental efficiency as being measured by “digitalization” at a farm or sector level. Research from China has shown that there is a positive correlation between the application of digital technology on dairy farms with their carbon emission efficiency. Training, incentives have also been found to influence this relationship (LIU et al., 2023). However, the majority of the studies in this field provide very little information on the specific technology bundle applied (e.g., whether benefits arise from sensors, AMS, software platforms, or energy technologies) and thus limit the ability to directly apply research findings to an investment decision for Dairy 4.0 systems.

Lastly, studies focused on net-zero and digital twins indicate that Big Data, AI, and digital twins could help mitigation through targeted interventions, early detection of inefficiencies, and optimised feeding; however, the evidence base is still primarily conceptual or simulation-based rather than validated in long-term farm trials (NEETHIRAJAN, 2024; RAO & NEETHIRAJAN, 2025). According to Lamanna et al. (2025), systematic reviews of wearable technologies emphasise the potential for better management and efficiency, but also highlight validation, data quality, and implementation constraints that affect whether environmental benefits are actually realised.

Impacts on the environment are frequently described as context-dependent. Baseline herd productivity (fertility, replacement rate, health status), type of production system (grazing vs. fully housed) and level of behavioural and management responses to alerts (e.g. changed reproductive strategies, timely treatments) are important moderators. Furthermore, net climate outcomes may be significantly impacted by the electricity mix and energy requirements of related infrastructure (sensors, gateways, data services, cooling, and ventilation control), which

could lead to “burden shifting”, where gains in biological efficiency are partially offset by higher energy consumption.

Conflicting perspectives are also visible in the environmental literature. On the one hand, modelling and case-based studies link Dairy 4.0-enabled improvements in health, fertility and yields to lower emissions intensity (FERGUSON et al., 2024; LOVARELLI et al., 2023). On the other hand, several authors caution that the environmental footprint of digital infrastructure and automation can increase electricity demand and create burden shifting, where biological efficiency gains are partially offset by energy consumption and upstream impacts (NEETHIRAJAN, 2024; RAO & NEETHIRAJAN, 2025). When it comes to empirical evidence using aggregated “digitalisation” indicators, positive associations with carbon-emission efficiency are being observed, but often studies lack detail on the underlying technology bundles and on whether the benefits come from sensors, management practices, or complementary investments (LIU et al., 2023).

Taken together, the literature indicates that Dairy 4.0 technologies have substantial potential to improve environmental efficiency through productivity gains, precision feeding, and targeted environmental control. At the same time, empirical evidence remains fragmented, and net environmental outcomes are contingent on energy use, system boundaries, and management responses. Critically for this study, the primary mechanism through which environmental performance becomes publicly visible in a processing company context is not voluntary disclosure of life-cycle analysis results, but mandatory and quasi-mandatory regulatory documentation – specifically, IPPC environmental permit filings and, increasingly, CSRD-aligned sustainability reports. This institutional channel generates a distinctive prediction: environmental monitoring capability, as evidenced in regulatory permits and ESG disclosures, will be more systematically present in V4 dairy processor documentation than operational technology evidence, because it is legally compelled rather than strategically chosen. This reasoning directly underpins H4, which predicts that ESG Enablement – the D4 sub-dimension capturing digital environmental monitoring, energy management systems, and sustainability data governance – will stochastically dominate all operational technology dimensions across the panel. In particular, evaluating the sources and institutional mechanisms behind ESG-visible digital capability in the V4 processing context contributes to addressing a gap that the farm-level literature, focused on voluntary technology adoption, has not yet engaged with.

2.6.2.3 Research gaps and implications for the Visegrad Group context

While environmental claims about Dairy 4.0 are increasingly prominent in both academic and corporate discourse, the evidence base for environmental performance in the dairy processing

sector – as distinct from primary farming – remains underdeveloped. Most of the studies reviewed in Section 2.6.2 concern farm-level emissions intensity, energy use, and nutrient cycling, with very limited coverage of how processing companies measure, document, and disclose their environmental digital capabilities (LOVARELLI et al., 2023; NEETHIRAJAN, 2024). This gap is particularly significant for the V4 context, where IPPC permitting and the accelerating CSRD reporting regime are creating compulsory environmental data governance requirements that directly interface with the ESG Enablement sub-dimension of the Dairy 4.0 framework

First, the environmental sustainability literature overwhelmingly focuses on farm-level outcomes – GHG emissions per kg of milk, nutrient cycling, energy use in housing systems – and almost entirely neglects the processing stage of the dairy value chain, where energy-intensive pasteurisation, chilling, drying, and packaging operations represent a substantial share of the sector’s environmental footprint. This creates a direct gap for this study: the literature cannot tell us what environmental monitoring capabilities V4 processors have actually deployed, or how they document those capabilities in publicly available documents. Second, no existing study has examined whether ESG-type environmental reporting among dairy processors is driven by regulatory compulsion (IPPC permitting, CSRD obligations) rather than voluntary corporate strategy – a distinction that is central to understanding why ESG Enablement may structurally dominate other D4 sub-dimensions as H4 suggests.

Third, the temporal relationship between ESG disclosure and broader digital technology adoption has not been investigated in the processing sector. The farm-level literature implicitly treats environmental capability as a consequence of operational technology investment – sensors improve herd health, which reduces replacement rates, which lowers emissions intensity (VILLA-HENRIKSEN et al., 2020; BALDIN et al., 2025) – but in a processing company context, the causal arrow may run in the opposite direction: environmental monitoring infrastructure, installed and documented for IPPC compliance, may create the organisational and data-systems foundation from which broader digital transformation becomes visible and measurable.

These gaps collectively point toward a research design that approaches environmental capability not through measured emissions outcomes but through disclosure ecology: examining which companies produce environmental monitoring evidence, through which document types, in response to which institutional pressures, and whether this pattern of disclosure co-evolves with broader D4 maturity over time. *Table 5* summarises the key environmental gaps and their implications for this study’s research design.

The gaps identified in both Sections 2.6.1 and 2.6.2 point consistently toward a single analytical space that the existing literature has not occupied: the disclosure ecology of Dairy 4.0 digital transformation among processing companies in a Central European institutional context. The economic performance literature establishes that firm size, ownership, and institutional embeddedness are persistent confounders that require within-firm panel identification to control.

Table 5. Key research gaps in Dairy 4.0 environmental efficiency studies

Literature gap	Why it matters for this study?
No study examines environmental monitoring disclosure among dairy processors using documentary evidence	This study's ESG Enablement sub-dimension directly addresses this gap by coding environmental monitoring evidence from IPPC permits, sustainability reports, and annual reports across 80 V4 processors.
Environmental disclosure driven by regulatory compulsion vs. voluntary strategy not investigated in processing sector	IPPC permit requirements legally mandate environmental monitoring and documentation, generating ESG-type digital evidence regardless of voluntary strategy – a key mechanism behind H4 that the farm-level literature does not address.
GVC diffusion of environmental digital capability through multinational parent companies not examined in V4 dairy context	Multinational subsidiaries are subject to parent-company ESG governance mandates; whether this transmission mechanism elevates ESG Enablement scores relative to domestic firms has not been tested.
No comparative analysis of ESG Enablement dominance across V4 countries using stochastic dominance or fixed-effects methods	H4 requires both a cross-country comparison of ESG Enablement against other D4 sub-dimensions and a formal test of stochastic dominance; neither has been attempted in prior dairy processing research.

Source: Constructed by author (2025)

The environmental literature establishes that regulatory compulsion – rather than voluntary strategy – is the primary driver of environmental digital capability in large food processing operations. Together, these two streams of evidence set up the core theoretical contribution reviewed in Section 2.7: the ESG-D4 nexus, and the hypotheses that flow from it.

2.7 ESG reporting, digital maturity frameworks, and the ESG-Dairy 4.0 nexus

The prior sections have reviewed the technology-specific and performance dimensions of Dairy 4.0 adoption. A key dimension that has not yet been addressed is the institutional and regulatory context through which digital transformation becomes publicly observable – namely, the corporate sustainability reporting landscape and the role that Environmental, Social and Governance (ESG) disclosure frameworks play in documenting digital capabilities. This section

reviews the relevant regulatory frameworks, explains how they interact with Dairy 4.0 adoption, and establishes the theoretical basis for the dissertation's core empirical hypothesis regarding the ESG-D4 nexus.

2.7.1 The EU sustainability reporting landscape

Corporate sustainability reporting in the EU has evolved from voluntary, largely narrative Corporate Social Responsibility (CSR) communication toward a structured, mandatory, and auditable reporting regime. The principal regulatory milestones are the Non-Financial Reporting Directive (NFRD, Directive 2014/95/EU), which established disclosure requirements for large public-interest entities from 2018; and its successor, the Corporate Sustainability Reporting Directive (CSRD, Directive 2022/2464/EU), which substantially broadens both the scope of covered entities and the content requirements (EUROPEAN UNION, 2022; EUROPEAN COMMISSION, 2023a). CSRD is accompanied by the European Sustainability Reporting Standards (ESRS), which specify the topical areas and indicators that covered companies must disclose, including climate, pollution, water, biodiversity, and workforce dimensions (EUROPEAN COMMISSION, 2023b).

For the V4 dairy processing sector, the phased CSRD implementation schedule is particularly relevant. Large public-interest entities (listed companies, banks, and insurers with more than 500 employees) were subject to NFRD requirements from 2018 and will produce their first CSRD-compliant reports in 2025 (covering financial year 2024). Large private companies – including many of the dominant dairy processors in Poland, Czech Republic, and Hungary – are subject to CSRD reporting from 2026 (financial year 2025). Smaller listed companies follow in 2027, and a further wave of SME-relevant standards is under development. Within the V4, this creates a graduated disclosure pressure that is affecting the larger, more institutionally embedded processors first, with consequences for the trajectory of ESG disclosure evidence observable in the 2019-2024 panel that this dissertation analyses (EUROPEAN COMMISSION, 2025; EUROPEAN PARLIAMENT, 2025).

2.7.2 IPPC regulation and environmental monitoring obligations

A second and often underappreciated regulatory driver of digital environmental capability in the dairy processing sector is the Integrated Pollution Prevention and Control (IPPC) framework, now embedded in the Industrial Emissions Directive (IED, Directive 2010/75/EU). Dairy processing installations above defined throughput thresholds (for slaughterhouses and food processing, typically installations treating more than 75 tonnes per day of animal raw materials) require an IPPC permit as a precondition for operation. These permits specify Best

Available Techniques (BAT) requirements for energy use, water consumption, wastewater treatment, and air emissions management, and require permit-holders to install and maintain environmental monitoring systems, document performance data, and report to competent environmental authorities on a defined schedule (EUROPEAN COMMISSION, 2006).

The significance of IPPC regulation for the measurement approach adopted in this dissertation is twofold. First, IPPC permits are publicly accessible documents available through national environmental permitting authorities in all four V4 countries, providing an independently produced and legally grounded source of evidence for digital environmental monitoring capabilities at the plant level. Second, the legal obligation to install, operate, and document environmental monitoring systems means that IPPC-covered dairy processors are effectively required to deploy a minimum level of digital environmental measurement infrastructure, regardless of their voluntary ESG disclosure preferences. This creates a regulatory floor for the ESG Enablement dimension of the Dairy 4.0 framework used in this dissertation, and means that ESG Enablement evidence is partially generated by regulatory compliance activity rather than solely by voluntary strategic communication. This distinction between compliance-driven and strategy-driven ESG capability is theoretically important and is explored empirically in Chapter 4.

2.7.3 Digital maturity frameworks and Industry 4.0 assessment

A growing body of research has sought to operationalise and measure Industry 4.0 adoption using maturity models and index-based frameworks. The conceptual groundwork was laid by SCHWAB's (2016) four-revolution framing of industrial development and RÜßMANN et al.'s (2015) nine-pillar technology architecture – a model that identified IoT, autonomous robots, simulation, horizontal and vertical integration, the industrial internet, cloud computing, additive manufacturing, augmented reality, and big data as the defining technological pillars of I4.0. Together, these models shaped the conceptual basis for subsequent empirical measurement approaches in both manufacturing and agri-food sectors.

Most existing maturity assessments in dairy and agri-food contexts have relied on primary survey data or case study approaches (TRIVELLI et al., 2019; WÓJCICKI et al., 2025), which create well-documented limitations for large-scale comparative analysis: survey responses are costly to obtain, subject to social desirability bias, and difficult to validate against objective evidence. A disclosure-based measurement approach – the method adopted in this dissertation – represents a complementary strategy that exploits the growing volume of publicly available corporate documents to construct a consistent, cross-country panel of digital maturity evidence. This approach has precedent in the broader corporate governance and sustainability accounting

literature (GRAY, 2006; DEEGAN, 2014) but has not previously been applied systematically to Dairy 4.0 adoption in the V4 context.

These maturity-model contributions are not read uniformly across the literature. Optimistic accounts (e.g., SCHWAB, 2016) treat index-based maturity scores as reasonably close proxies for underlying technological capability – an assumption that much of the subsequent Industry 4.0 measurement literature has adopted implicitly. A more sceptical strand, closer to the disclosure and voluntary-disclosure literature (VERRECCHIA, 1983; GRAY, 2006), treats any externally-observed maturity indicator – whether survey-based or document-based – as a communication artefact that is systematically shaped by firm size, reporting capacity, and strategic disclosure incentives rather than as a neutral technological ruler.

This dissertation sides explicitly with the sceptical approach: the D4 framework is presented throughout as a measure of documented visibility, and the comparison with survey-based maturity assessments in this section is intended to make the resulting trade-off – transparency and cross-country comparability at the cost of a direct capability read-out – explicit rather than implicit.

2.7.4 The ESG-Dairy 4.0 Nexus: theoretical foundations

ESG Enablement – the digital environmental monitoring and data governance systems required for credible sustainability reporting – is included in the D4 framework as its external-facing disclosure dimension, distinct from the operational technology subdimensions (IoT, automation, analytics, MES/SCADA/ERP) in one fundamental respect: its adoption is driven primarily by regulatory compulsion and GVC pressure rather than voluntary investment choice. This structural difference is what makes it the primary channel through which digital transformation becomes publicly observable in the V4 dairy processing sector, and the mechanism behind the prediction that it will systematically dominate the operational dimensions. Three theoretical mechanisms, drawn from institutional theory, global value chain governance, and disclosure theory, support this claim.

First, coercive isomorphism (DIMAGGIO & POWELL, 1983): regulatory mandates, principally IPPC permitting and the emerging CSRD/ESRS framework, create legal compulsion to install, operate, and document environmental monitoring systems. Firms subject to these mandates are institutionally required to acquire digital environmental measurement capability regardless of their voluntary investment preferences. In institutional theory terms, this coercive pressure produces organisational conformity in ESG-digital capability not because regulated entities necessarily view it as optimal, but because non-compliance carries legal,

reputational, and operational consequences. The dairy sector's regulatory exposure to IPPC and CSRD is thus expected to create a structural floor of ESG Enablement adoption that exceeds comparable floors for voluntary digital technologies.

Second, through global value chain (GVC) governance and subsidiary practice transfer (GEREFFI et al., 2018; KOSTOVA & ROTH, 2002): lead firms shape the standards and governance frameworks adopted by suppliers and subsidiaries further down the chain. In the dairy sector, this means multinational companies headquartered in Western Europe can impose sustainability reporting standards and ESG governance frameworks on their V4 subsidiaries as part of group-level corporate sustainability obligations, through which ESG-related digital capability – energy management information systems, sustainability data platforms, and emissions monitoring infrastructure – diffuses from multinational headquarters to Central European operations independently of local competitive dynamics or stand-alone technology investment decisions. This pathway is particularly relevant for the Hungarian dairy sector, where multinational subsidiaries form a substantial share of the leading processors.

Third, narrative accessibility: producing disclosure-visible ESG evidence requires less capital-intensive implementation than most operational digital technology dimensions. As VERRECCHIA (1983) established in voluntary disclosure theory, firms exercise discretion over what they disclose based on the cost of producing that disclosure – and generating a qualitative score on ESG Enablement (e.g., a reference to energy monitoring, waste reduction initiatives, or emissions management in an annual report) can be achieved with relatively modest digital infrastructure. By contrast, generating equivalent evidence for IoT & Sensing or Analytics & AI dimensions requires capital investment in specific equipment and systems that must be identifiably described. This differential accessibility creates an incentive structure where firms with limited resources or early-stage digital transformation preferentially generate ESG-type evidence in their corporate documents. The result, consistent with MEYER & ROWAN's (1977) concept of decoupling – where formal organisational structures reflect institutional expectations rather than underlying technical capabilities – is that ESG Enablement may become the dominant D4 disclosure channel not because firms are genuinely more advanced in environmental digitalisation, but because ESG-related digital evidence is structurally easier to produce and disclose.

Taken together, these three mechanisms generate a clear and testable theoretical prediction: among V4 dairy processors in the 2019-2024 period, the ESG Enablement dimension of Dairy 4.0 maturity should be systematically and substantially higher than operational technology dimensions (IoT, Analytics/AI, MES/SCADA/ERP), and this ESG advantage should be

observable across all four countries and throughout the study period. The prediction also implies that ESG disclosure precedes or accompanies broader technology disclosure, functioning as a gateway or co-predictor of overall D4 maturity rather than as a dependent outcome of advanced technology adoption.

What lends this prediction particular robustness is that the three mechanisms do not operate in isolation: regulatory compulsion establishes a mandatory disclosure floor; GVC governance transmits best-practice standards from parent to subsidiary; and narrative accessibility reduces the marginal cost of adding verifiable ESG evidence relative to capital-intensive operational technology evidence. A firm subject to IPPC permitting is, simultaneously, a likely subsidiary of a multinational dairy group and subject to the cost-asymmetry pressures that VERRECCHIA's (1983) model predicts. The confluence of these mutually reinforcing mechanisms at firm level is what makes ESG Enablement the predicted dominant sub-dimension rather than merely a well-scoring one – and it is this compound logic that motivates the ESG-specific hypotheses formulated in Section 2.8.

Two alternative interpretations of this theoretical account merit consideration. A more parsimonious reading would attribute ESG dominance entirely to the narrative-accessibility mechanism, treating the regulatory and GVC channels as reinforcing rather than essential. A strict institutional-compulsion reading, conversely, would treat narrative accessibility as epiphenomenal, since firms could not sustain unsubstantiated ESG narratives without at least a minimal compliance or governance basis. The dissertation does not attempt to adjudicate between these readings on theoretical grounds alone; instead, Section 4.4 examines which pattern of evidence (regulatory, group-level, or narrative) the data best supports.

2.7.5 Literature gaps on empirical ESG reporting

The preceding sub-sections established the regulatory architecture and theoretical mechanisms that position ESG Enablement as the dominant channel of Dairy 4.0 disclosure in the V4 processing sector. What they did not do is anchor those mechanisms in the empirical ESG reporting literature – the body of research that has examined why firms disclose what they do, under what institutional conditions disclosure quality improves, and what organisational and ownership factors systematically shape the content and completeness of sustainability reports. This sub-section reviews that literature across five streams relevant to this dissertation's hypotheses, before identifying the specific gaps that the empirical chapters address.

The first and most foundational stream is legitimacy theory as applied to sustainability disclosure. PATTEN (1992) established that firms facing greater public pressure – measured

through political exposure and environmental visibility – disclose more on environmental performance, interpreting this as an attempt to manage legitimacy with key stakeholders rather than as a straightforward reflection of underlying environmental capability. DEEGAN (2002) extended this framework, arguing that sustainability reports are fundamentally instruments of legitimization: firms respond to perceived legitimacy threats by expanding disclosure scope and investing in narrative credibility. GRAY et al. (1995) reached a similar conclusion through a longitudinal content-analysis of UK corporate reports, finding that environmental and social disclosure volumes increased in response to regulatory pressure and adverse media attention rather than to internal improvements in environmental performance. The consistent implication across this literature is that what firms disclose about digital and environmental capabilities may be systematically decoupled from their actual operational state – a finding directly relevant to interpreting D4 maturity scores derived from documentary evidence. Legitimacy-driven disclosure behaviour would produce ESG-type content even in firms with limited genuine environmental digitalisation, inflating ESG Enablement scores relative to operational technology dimensions where documentary evidence is harder to generate without underlying investment. This mechanism reinforces the narrative accessibility argument developed in Section 2.7.4 with an independently grounded theoretical basis.

The second stream concerns the determinants of voluntary ESG disclosure quality and scope. CLARKSON et al. (2008) demonstrated, in a study of US environmental disclosers, that genuinely superior environmental performance predicts harder, more verifiable disclosure – emissions data, audit certifications, quantified targets – while weaker performers preferentially produce soft, narrative disclosure. This distinction between hard and soft evidence maps directly onto the scoring architecture of the D4 framework used in this dissertation, which awards zero, one, or two points based on whether evidence is narrative, reported, or independently verified. DHALIWAL et al. (2011) showed that firms with better environmental and social performance are more likely to initiate standalone sustainability reporting and that early disclosure is associated with lower cost of equity capital – implying that disclosure quality signals genuine capability rather than merely managing perceptions. HAHN & KÜHNEN (2013), in a systematic review of sustainability disclosure determinants, found firm size, industry membership, public ownership, and regulatory pressure to be the most consistently significant predictors across studies. All four factors are heterogeneous across the V4 dairy processing sector in ways that H1 captures: large Polish cooperatives, publicly listed Czech processors, Hungarian multinational subsidiaries, and smaller Slovak private firms are expected to display systematically different D4 disclosure intensities partly because these determinants differ across them.

The third stream examines the effects of mandatory versus voluntary ESG reporting regimes. IOANNOU & SERAFEIM (2019) review evidence on the effects of mandatory corporate sustainability reporting: at the country level, drawing on data from 58 countries, they found that mandatory reporting laws were associated with improvements in socially responsible management practices – including corporate governance, ethical conduct, and sustainable development priorities – with effects strongest where enforcement was robust and sustainability reports were independently assured. At the firm level, examining four countries with distinct mandatory disclosure regimes (China, Denmark, Malaysia, and South Africa), they found that treated firms significantly increased disclosure volume and were more likely to seek independent assurance and adopt standardised reporting guidelines relative to matched control firms. CHRISTENSEN et al. (2021), in a comprehensive economic analysis of CSR reporting mandates, found that mandatory regimes generate beneficial effects for capital markets and stakeholders, though implementation and enforcement quality significantly condition outcomes – a finding particularly relevant to the V4 context given heterogeneity in regulatory enforcement capacity across Poland, Czech Republic, Hungary, and Slovakia. If CSRD-related pressure generates meaningful increases in ESG Enablement evidence – as anticipated by H2 – this would be consistent with IOANNOU & SERAFEIM's (2019) finding that mandatory regimes drive disclosure improvements. CHRISTENSEN et al. (2021) emphasis on enforcement conditionality also provides a mechanism through which firms not yet formally covered by NFRD or CSRD during the observation window may nonetheless increase ESG disclosure in anticipation of forthcoming obligations – observable as between-firm compositional change in the panel rather than within-firm deepening, consistent with H2 prediction.

The fourth stream addresses the transmission of ESG practices through global value chains and multinational ownership structures. KOSTOVA & ROTH (2002), in a foundational study of how subsidiaries adopt organisational practices from multinational headquarters, found that institutional pressures – both from the parent's home-country environment and from the relational ties between headquarters and subsidiary – are significant determinants of the depth and internalisation of practice adoption at the subsidiary level. SURROCA et al. (2013) extended this logic by showing that home-country stakeholder pressure on multinational enterprises shapes what practices flow to subsidiaries, and that the degree of headquarters control over subsidiary governance is a critical moderating condition – with subsidiaries under tighter board-level control showing stronger convergence with parent-company behaviour. In the V4 dairy context, these findings directly support the GVC diffusion mechanism articulated in Section 2.7.4: multinational processors such as FrieslandCampina, Danone, Lactalis, and

Savencia operating in the Czech Republic, Hungary, Poland, and Slovakia, are subject to their parent companies' group-level ESG governance frameworks, CDP reporting commitments, and consolidated CSRD obligations. This creates a structural asymmetry in ESG Enablement scores between multinational subsidiaries and domestically owned processors that should be detectable in the cross-national variation tested by H1, and may explain a portion of the cross-sectional association between D4 scores and firm revenue identified in H3 if multinational subsidiaries are both larger and better ESG disclosers.

The fifth stream turns to ESG and sustainability reporting in the agri-food sector specifically. MALONI & BROWN (2006) were among the first to treat corporate social responsibility in food supply chains in a systematic way, mapping the dimensions that attract the most stakeholder scrutiny – animal welfare, biotechnology, environment, fair trade, health and safety, and labour and human rights. HARTMANN (2011), reviewing CSR practice across the European food sector, found that large food manufacturers adopted standalone sustainability reports earlier than most industries, driven more by retailer requirements and consumer pressure than by any regulatory push – a pattern that sits comfortably alongside the GVC and mimetic isomorphism mechanisms discussed above. AURELI et al. (2020) brought a cross-sectoral lens to the question, examining the value relevance of ESG disclosure among large listed European companies and finding considerable variation by firm size and ownership structure. Environmental disclosure emerged as the most consistent and investor-relevant pillar, with social and governance dimensions lagging behind – a disparity that mirrors the preliminary evidence from V4 dairy processors that prompted this study. Taken together, these contributions suggest that the disclosure determinants established in the broader literature – size, ownership, regulatory pressure, GVC integration – operate with particular force in food processing contexts, and that environmental disclosure is the dimension most consistently shaped by both regulatory compulsion and stakeholder scrutiny.

I find this regulatory asymmetry to be the most theoretically significant finding to emerge from the literature review. The fact that environmental compliance documentation – rather than voluntary sustainability strategy or technology investment narrative – constitutes the primary channel through which digital transformation becomes publicly legible in the V4 dairy sector reframes what ESG disclosure actually measures in this context. It is, at its core, a record of regulatory exposure rather than a signal of strategic intent, and I believe this distinction has received insufficient attention in the existing literature on agri-food digital transformation.

The specific gaps relevant to this dissertation are therefore clear. First, no study has applied a disclosure-based measurement approach to examine the relationship between ESG reporting

behaviour and Dairy 4.0 digital maturity in a dairy processing context, particularly in Central Europe. Second, the temporal dynamics of ESG disclosure improvement have rarely been examined at the firm-panel level in Central and Eastern Europe, where the CSRD implementation timeline creates new disclosure pressure. Third, no study has tested whether ESG disclosure – shaped by regulatory compulsion, GVC diffusion, and narrative accessibility – structurally dominates other digital capability dimensions in an Industry 4.0 maturity framework, or whether it functions as an early disclosure-visible marker of broader technology adoption. *Table 6* summarises these gaps and their connections to the dissertation's hypotheses.

Table 6. Key research gaps in the ESG reporting literature and their implications for this study

Literature gap	Hypothesis connection and implication for this study
ESG disclosure determinants (size, ownership, regulatory pressure) not examined in relation to D4 maturity framework scores	H1: Cross-national heterogeneity in D4 scores is linked to structural differences in size, ownership, and regulatory exposure, consistent with ESG disclosure determinant studies such as CLARKSON et al. (2008) and HAHN & KÜHNEN (2013). This relationship has not been tested within a Dairy 4.0 maturity framework.
Temporal effects of CSRD on disclosure quality not analysed at firm-panel level in Central and Eastern Europe	H2: Aggregate D4 disclosure growth over 2019-2024 may reflect regulatory and documentary expansion rather than within-firm deepening. Building on CHRISTENSEN et al. (2021), this study tests that distinction at firm-panel level in the V4 dairy sector for the first time.
Legitimacy-driven ESG disclosure decoupled from actual operational performance not tested at processing company level using hard versus soft evidence scoring	H3: The study tests whether the association between D4 scores and revenue reflects disclosure visibility and firm size rather than an independent adoption-performance dynamic, drawing on legitimacy and decoupling arguments (MEYER & ROWAN, 1977; PATTEN, 1992; DEEGAN, 2002).
ESG disclosure dominance over other capability dimensions within the Dairy 4.0 maturity framework never tested; regulatory compulsion versus voluntary strategy as its driver unexamined	H4: ESG Enablement is expected to dominate operational D4 dimensions because regulatory compulsion, GVC diffusion, and lower disclosure-verification costs favour ESG visibility (KOSTOVA & ROTH, 2002; SURROCA et al., 2013; VERRECCHIA, 1983). This combined mechanism has not previously been tested in dairy processing.
Heterogeneity in ESG disclosure across Central and Eastern European food processors by ownership type and multinational affiliation not studied	H1/H4 context: Multinational affiliation may strengthen ESG Enablement through subsidiary practice transfer and parent-company governance channels (KOSTOVA & ROTH, 2002). Whether this structural advantage is visible in V4 dairy processors is examined here.

Source: Constructed by author (2025)

Legitimacy theory thus provides the overarching explanatory frame within which each hypothesis operates: H1 tests whether structural heterogeneity in legitimacy pressure produces observable variation in D4 disclosure; H2 tests whether regulatory expansion translates into disclosure growth or merely document accumulation; H3 tests whether reported digitalisation reflects genuine operational capability or legitimacy-driven narrative signalling; and H4 tests whether the environmental-disclosure domain is structurally dominant because legitimacy pressure, regulatory compulsion, and GVC governance converge on it simultaneously.

2.8 Hypothesis development and conceptual synthesis

Sections 2.1 through 2.7 show that public evidence of Dairy 4.0 is shaped not only by technology adoption itself, but also by ownership structure, regulatory exposure, and disclosure incentives. This concluding section converts that literature into a set of testable hypotheses (summarised in *Table 6*) organised around four analytical domains: the cross-national distribution of disclosure-visible D4 maturity, its temporal dynamics over the 2019-2024 observation window, its relationship with firm financial performance, and the ESG-D4 nexus.

The V4 dairy processing sector is structurally heterogeneous in ways that the literature on digital adoption in agri-food systems would lead us to expect to translate into measurable differences in D4 maturity. Section 2.6.1 established that Industry 4.0 adoption is path-dependent, shaped by firm size, ownership type, and institutional embeddedness. Section 2.2 reviewed the core technological pillars of the Dairy 4.0 framework and showed that their deployment requires different thresholds of capital intensity, technical capability, and regulatory exposure. Section 2.7 documented the uneven distribution of sustainability reporting across firm types and countries, with larger firms, listed entities, and multinational subsidiaries consistently demonstrating more extensive disclosure behaviour. Taken together, these strands predict that D4 maturity – measured through publicly accessible documentary evidence – should not be uniformly distributed across the Czech Republic, Hungary, Poland, and Slovakia. Poland's large cooperative processors and Hungary's multinational-affiliated firms would be expected to perform differently from Slovakia's fragmented sector, and cross-country variation should be statistically detectable. This reasoning grounds the first hypothesis:

H1 (Cross-national heterogeneity): The distribution of Dairy 4.0 maturity scores differs significantly across the four V4 countries, reflecting structural differences in firm ownership, market concentration, regulatory exposure, and document availability.

On temporal dynamics, the literature presents a mixed picture. At the macro level, aggregate adoption of Industry 4.0 technologies in European food processing has increased steadily since 2015, accelerated by the post-COVID push toward supply chain resilience and by growing sustainability reporting obligations (Section 2.7). At the firm level, however, the adoption process is characterised in the management accounting and institutional theory literature as predominantly sticky: once a firm's disclosure behaviour is established, it tends to persist until a discrete shock – a regulatory threshold crossed, a new ownership relationship, or a group-level reporting mandate – forces a transition. Sections 2.6 and 2.7 showed that the key shocks operating in the V4 dairy context over 2019-2024 include the post-2022 acceleration of CSRD implementation, Poland's consolidation of large cooperative processors, and the expansion of IPPC permit documentation requirements. These dynamics suggest that any observable increase in aggregate D4 disclosure may be driven by between-firm compositional change and document volume growth rather than by systematic within-firm improvement. The fixed-effects estimator – which identifies purely within-firm variation – is therefore expected to yield a weaker or non-significant result even when aggregate trends appear positive. This motivates the second hypothesis, which is formulated as a two-part prediction:

H2 (Temporal disclosure dynamics): Aggregate Dairy 4.0 disclosure intensity in the V4 increases significantly between 2019 and 2024; however, this increase is driven primarily by growth in document volume and between-firm compositional change rather than by within-firm content deepening.

The relationship between digital transformation and financial performance in agri-food processing is contested in the literature. Section 2.6.1 reviewed studies finding positive cross-sectional associations between technology adoption and firm revenue – but these associations consistently reflect firm size rather than adoption intensity per se: larger firms invest more in digital systems, and larger firms earn more revenue, so the correlation is largely spurious once size is controlled for. Profitability effects are even more uncertain. The commodity-market context of dairy processing – where margins are primarily driven by raw milk input prices, energy costs, and competitive pricing power rather than operational efficiency – substantially limits the scope for digitalisation to generate measurable within-period margin improvements. Capital expenditure on digital infrastructure, moreover, suppresses current-period net profit before the benefits of adoption materialise, creating a negative short-run earnings signal that may persist across a six-year observation window. These arguments lead to the third hypothesis:

H3 (Financial performance and D4 maturity): The positive cross-sectional association between D4 maturity score and firm revenue is primarily attributable to firm-size heterogeneity

rather than to an independent adoption-performance dynamic; within-firm panel models controlling for firm-level fixed effects are hypothesised to show no significant association between D4 disclosure intensity and contemporaneous turnover or profit margin, while the supplementary lagged growth specification is likewise hypothesised to show no significant relationship, across the 2019-2024 panel.

This hypothesis draws on MEYER & ROWAN's (1977) institutionalist insight that organisations may adopt formal structures without genuine operational integration, implying that disclosure-visible D4 scores may reflect compliance signalling rather than genuine technological capability.

The fourth hypothesis addresses what the dissertation argues is the most theoretically significant structural feature of the V4 dairy D4 dataset. Three mechanisms converge to predict that ESG Enablement should not merely be present across the panel but should dominate all operational technology dimensions by a substantial margin. The first is regulatory compulsion: IPPC permit requirements under the Industrial Emissions Directive (2010/75/EU) legally oblige large processing facilities to install and document environmental monitoring systems, generating verified digital environmental evidence regardless of firms' voluntary digitalisation strategies. No equivalent regulatory instrument creates a comparable mandatory floor for operational technology dimensions. The second mechanism is GVC diffusion: multinational dairy subsidiaries operating in Hungary – where FrieslandCampina, Danone, Savencia, and Lactalis all maintain processing operations – and to a lesser degree in the Czech Republic and Slovakia, are subject to parent-company ESG governance frameworks requiring group-level sustainability data collection and consolidated CSRD reporting. This transmits ESG-digital capability from Western European headquarters to Central European subsidiaries through reporting compliance rather than organic investment, a dynamic consistent with KOSTOVA & ROTH's (2002) theory of institutional duality in multinational subsidiaries, and with SURROCA et al.'s (2013) governance conduit mechanism – noting that SURROCA et al. document the transfer of irresponsible practices, so the relevant mechanism here is the structural conduit itself, not the direction of practice transfer. The third mechanism is narrative accessibility: ESG-type disclosure carries lower verification costs than operational technology evidence, which requires externally auditable data on sensor networks, automation systems, and analytics platforms –precisely the cost asymmetry that VERRECCHIA's (1983) disclosure cost theory would predict. These three mechanisms operate simultaneously and reinforce one another.

H4a (ESG dominance – confirmatory): The ESG Enablement sub-dimension is the highest-scoring and most widely adopted Dairy 4.0 dimension across the full panel, significantly and stochastically dominating all operational technology dimensions – IoT and Sensing, Automation and Robotics, Analytics and AI, and MES/SCADA/ERP – in mean score, adoption rate, and verified-evidence achievement rate.

H4b (disclosure sequencing – exploratory): As a supplementary temporal proposition, lagged ESG disclosure (ESG_{t-1}) is expected to show a positive association with subsequent technology sub-dimension scores ($tech_sum_t$). This is treated as exploratory: the disclosure-based panel design does not permit causal claims, and the result is interpreted as a temporal association consistent with sequencing rather than as evidence of technology adoption causally driven by prior ESG investment.

2.9 Discussion and synthesis of the literature

The literature reviewed across Sections 2.1 to 2.8 establishes a coherent, if still partially contested, picture of Dairy 4.0 as a multi-layered transformation process shaped by technological capabilities, economic constraints, institutional pressures, and evolving sustainability obligations. Several cross-cutting themes emerge from this review that directly inform the empirical design and interpretive framework of this dissertation.

First, the evidence consistently shows that the relationship between digital technology adoption and measurable performance outcomes – whether economic, environmental, or social – is neither automatic nor linear. Technologies create conditions for improvement rather than guaranteeing them; realised benefits depend on managerial capacity, data integration quality, and the broader institutional environment in which firms operate. This finding is particularly relevant for the V4 context, where structural heterogeneity across firm sizes and ownership types implies that adoption trajectories and disclosure behaviours will diverge in predictable ways.

Second, the literature reveals a persistent asymmetry between what is technologically possible and what becomes publicly visible through corporate disclosures. ESG-related dimensions of Dairy 4.0 are disproportionately represented in regulated and auditable documents – IPPC permits, sustainability reports, CSRD filings – while operational technology deployments such as AI-driven analytics or advanced automation remain largely invisible to external observers. This asymmetry is not a methodological limitation to be apologised for – it is a substantively meaningful finding in its own right, reflecting where institutional incentives actually concentrate attention in this sector.

Third, the geographic specificity of this review points to a genuine gap in the literature. The dominant body of evidence on Dairy 4.0 adoption and its consequences draws on Western European and North American farm-level contexts. Studies calibrated to the V4 processing sector – its cooperative and multinational ownership structures, its regulatory exposure under EU environmental law, and its specific trajectory of post-transition industrialisation – are almost entirely absent. This dissertation provides the first systematic, multi-country, longitudinal evidence base from which subsequent research can build. These observations do not undermine the value of the existing literature; they situate it. The hypotheses tested in the chapters that follow are grounded in the theoretical mechanisms and empirical regularities documented here, while remaining alert to the ways in which the V4 institutional context may modify the predictions the framework generates.

3. MATERIAL AND METHODS

This chapter outlines the methodological framework adopted to investigate the extent and character of Dairy 4.0 adoption among major dairy processors in the Visegrad Group, and to examine the relationships between digital transformation intensity and sustainability-related disclosures. Building on the conceptual foundations and hypotheses developed in Chapters 1 and 2, the chapter explains how the research questions were operationalised into measurable indicators, how the document corpus was constructed and coded, and which analytical procedures were applied.

Given the complexity of digital transformation processes in agri-food systems, the research adopts a quantitative, disclosure-based approach. Rather than seeking to establish causal relationships (the nature of the data does not permit), the methodology is designed to identify patterns, differences, and associations in Dairy 4.0 adoption intensity and sustainability-related disclosures across firms and countries. This approach reflects both the nature of the available data and the study's post-positivist epistemological positioning, which recognises that empirical observations provide partial and context-dependent insights into underlying organisational phenomena rather than direct or complete access to underlying realities.

3.1 Research design

This study employs a quantitative, longitudinal panel design grounded in a disclosure-based measurement strategy. This type of approach is widely used in social and environmental accounting and sustainability research, where organisational practices and outcomes are examined through publicly available corporate disclosures rather than through direct observation of internal processes (GRAY et al., 1995; GRAY, 2002, 2006; DEEGAN, 2002, 2014).

Within this body of research, corporate disclosures are understood as empirically observable expressions of organisational priorities, capabilities, and accountability mechanisms. At the same time, the literature recognises that disclosures are socially constructed and shaped by managerial judgement, institutional pressures, and stakeholder expectations (GRAY et al., 1995; DEEGAN & RANKIN, 1996). Disclosures offer a systematic and auditable window into what organisations choose to measure, manage, and communicate – which is precisely what this study treats as its primary object of inquiry.

This approach is appropriate for the study of Dairy 4.0 adoption and sustainability-related practices among large dairy companies operating across multiple national contexts. Digital transformation initiatives and sustainability outcomes are typically embedded in complex

organisational systems and are not directly observable by external researchers. IPPC environmental permits, annual management reports, and sustainability disclosures provide traceable, independently produced evidence of the technologies and management systems companies deploy, even where that evidence is partial.

The study is informed by a post-positivist epistemological orientation (POPPER, 1959), which holds that empirical analysis can reveal provisional patterns and associations in social phenomena rather than verify theoretical claims. This perspective treats hypotheses as falsifiable propositions subject to structured empirical test. Ontologically, the study adopts a broadly realist position: digitalisation and sustainability practices are assumed to have real organisational effects, even though these effects are only partially observable through the disclosure-based indicators analysed here.

Consistent with this epistemological and ontological positioning, the study does not aim to establish causal relationships between Dairy 4.0 adoption and sustainability outcomes. Instead, it focuses on identifying associations, adoption patterns, and cross-country differences that are appropriate given the structure of the data and the current level of digitalisation among large dairy processors.

Within this framework, the dissertation examines the relationship between Dairy 4.0 maturity and sustainability-related evidence among the largest dairy-producing companies in the Visegrad Group. In line with the disclosure-based research design, qualitative information contained in corporate reports is systematically coded into structured indicators and analysed using quantitative statistical techniques.

The primary unit of analysis is the company-year observation, defined as the aggregation of all relevant publicly available disclosures issued by a given company in a specific reporting year, including statutory filings, regulatory permits, sustainability reports, and other company-level documents. This design allows the study to capture both cross-sectional variation in Dairy 4.0 adoption intensity across firms and temporal variation in reported digitalisation practices over the 2019-2024 period. The resulting dataset constitutes an unbalanced panel in which most companies are observed across all six years, while a small number have gaps due to incomplete public disclosure in specific years.

Building on this research design, the following section outlines the research approach guiding hypothesis development and empirical analysis.

3.2 Research approach

The research follows a deductive logic: hypotheses derived from established literature on Industry 4.0, Dairy 4.0, and sustainability management are evaluated against systematically coded empirical evidence (BRYMAN, 2016). The approach is theory-informed in the sense that the coding instrument was designed to capture the dimensions of digital transformation identified in prior research as most relevant to dairy processing contexts.

Empirically, the analysis is based on a structured form of document analysis in which corporate reports are treated as managerial artefacts that reflect organisational priorities, governance arrangements, and measurement practices (BOWEN, 2009; KRIPPENDORFF, 2018). Relevant disclosures are coded into standardised ordinal indicators ranging from 0 to 2, capturing the presence and relative maturity of digital technologies, data systems, and sustainability-related initiatives. These indicators are then aggregated into composite indices across four construct families: reporting and data governance maturity, sustainability-related technology breadth, outcome quantification, and Dairy 4.0 adoption. This approach enables systematic comparison across companies and countries while preserving transparency through traceable excerpts and evidence fields.

A deliberate design decision is to distinguish between two analytically separable properties of disclosure evidence. Evidence presence captures whether any relevant information exists for a company in a given reporting year and domain. Evidence intensity characterises how advanced or substantiated that evidence appears under the coding rubric, conditional on the evidence being present at all. This distinction matters because low aggregate scores can arise for two quite different reasons - either the company simply does not disclose in a given domain, or it discloses but at a low level of maturity. Coverage rates and index values are therefore reported in parallel throughout the empirical chapters.

Because disclosure-based indicators do not provide a direct measure of underlying economic or environmental performance, the empirical analysis is explicitly framed in terms of associations observed in reported evidence rather than causal effects. Following established practice in management and accounting research, the results are interpreted as indicative of differences in organisational emphasis, measurement capability, and implementation focus among major dairy processors. The analysis identifies which companies and countries disclose more – and more sophisticated – Dairy 4.0 practices, but makes no claim that higher disclosure scores translate directly into higher operational digitalisation. This limitation is acknowledged throughout.

The empirical strategy is organised around the company-year as the primary unit of analysis, reflecting the fact that digital initiatives and sustainability management systems develop over time and may be reported across multiple documents within a single reporting period. Aggregating evidence at the company-year level reduces the risk of double-counting and facilitates cross-country comparison among leading firms in the Visegrad Group. As an additional robustness check, selected analyses are replicated at the document level using company-clustered standard errors to ensure that findings are not driven by firms with unusually extensive reporting output.

3.3 Data collection methods

This section describes how the empirical dataset used in the analysis was constructed. It outlines the sources of data, the criteria used to select companies and documents, and the procedures applied to extract, code, and organise disclosure-based evidence. The overarching objective of the data collection process was to develop a dataset that allows for consistent and transparent comparison of Dairy 4.0-related disclosures across companies, countries, and reporting years.

The data collection process is grounded in a document analysis approach, which is widely used in social science, management, and accounting research to examine organisational artefacts such as reports, policies, and official communications. Document analysis enables researchers to extract meaning, identify patterns, and generate empirical evidence from texts that are produced independently of the research process (BOWEN, 2009). Unlike interviews or surveys, corporate documents constitute a non-reactive data source and reflect how organisations choose to formally represent their activities, priorities, and performance.

Within sustainability and accounting research, document analysis has been extensively applied to examine corporate reporting practices, governance arrangements, and disclosure patterns, particularly in contexts where direct access to internal organisational data is limited (GRAY, 2006; DEEGAN, 2014). In this tradition, corporate reports are treated as purposeful managerial outputs rather than neutral records, requiring systematic and transparent coding procedures. Consistent with established methodological guidance on content and document analysis (KRIPPENDORFF, 2018), the present study applies predefined coding rules to transform qualitative disclosures into structured indicators suitable for quantitative analysis.

3.3.1 Company selection

The dataset covers 80 dairy processing companies – 20 per Visegrad country – selected to represent the leading tier of the dairy industry in each national context. The selection criterion was company size by estimated dairy revenue or reported milk intake volume, drawing on

national company registers, trade statistics, and industry directories (e.g., the Czech Sbírka listin, the Hungarian e-Cégjegyzék, the Slovak RegisterUZ, and the Polish KRS). Where direct revenue data for dairy operations were unavailable, companies were ranked by total assets or turnover from financial statements.

This constitutes a purposive, census-type approach to the leading tier rather than a probability sample of the population of dairy firms. The rationale is straightforward: Dairy 4.0 technologies require substantial capital investment and generate observable disclosure evidence primarily among larger companies. Very small producers, cooperatives with minimal reporting obligations, and family farms are unlikely to produce the kinds of documents from which digital technology adoption can be reliably coded, and their inclusion would artificially inflate zero-score observations without adding analytical substance.

3.3.2 Document corpus

A total of 1 148 documents were collected and coded across the 80 companies and the 2019-2024 reporting period. Documents were collected from public sources, prioritising sources that are independently produced, regularly updated, and carry some degree of formal accountability:

- statutory filings in national company registers (Czech Sbírka listin/Obchodní věstník, Slovak RegisterUZ, Hungarian e-Cégjegyzék, Polish KRS), including annual financial statements, management reports, and activity summaries
- regulatory permits and monitoring records, principally IPPC (Integrated Pollution Prevention and Control) environmental permits, permit amendments, inspection reports, and associated monitoring registers, which are a particularly rich source of D4 evidence in dairy sector
- sustainability and ESG reports at company or group level, including standalone sustainability reports, integrated reports, and corporate responsibility sections of group annual reports
- certification records and audit statements from accreditation bodies, energy auditors, and environmental management verifiers
- corporate website disclosures, supplier-facing communications, and trade publications where these provided substantive operational information not available elsewhere

Because document genres differ considerably in purpose, audience, and level of operational detail, the analysis treats document type as a potential source of heterogeneity. IPPC permits, for instance, routinely contain far more granular information about environmental monitoring

and process control than financial statements. This variation is managed through the scope attribution system described in Section 3.3.4 and through the reporting quality (RQ) indicator family described in Section 3.4.

Table 7. Dataset characteristics (summary)

Metric	Value
Companies	80
Countries	Czech Republic, Hungary, Poland, Slovakia
Companies per country	20
Documents coded	1 148
Panel observation years	2019-2024
Company-year observations (panel)	471
Companies with full 6-year coverage	74
Mean documents per company-year	2.44
Maximum documents, single company-year	12
D4 score range (per company-year)	0-16
Company-years with zero D4 evidence	134 (28.5%)
Company-years with any D4 evidence	337 (71.5%)
Mean D4 total score (all observations)	2.51/16.0

Source: Constructed by author (2025)

Table 8. Documents and panel observations by country

Country	Companies	Documents	Panel observations
Slovakia	20	405	118
Poland	20	290	115
Czech Republic	20	233	119
Hungary	20	220	119
Total	80	1 148	471

Source: Constructed by author (2025)

Table 9 shows that document volume increases substantially across the panel, rising from 141 documents in 2019 to 270 in 2024. This reflects both the growing availability of sustainability and ESG disclosures over the period and expanding IPPC permit coverage in the collection. Researchers should note that the 2024 increase in observed D4 scores discussed in Chapter 4, may therefore be partially attributable to improved documentary coverage rather than to genuine acceleration in digitalisation alone.

Table 9. Document volume by reporting year

Reporting year	Documents	Mean per company
2019	141	1.76
2020	162	2.02
2021	181	2.26
2022	194	2.42
2023	200	2.50
2024	270	3.38
Total	1 148	-

Source: Constructed by author (2025)

Table 10. Document type distribution (consolidated)

Document type (consolidated)	Documents	% of total
Financial statements and statutory filings	314	27.4%
Annual and management reports	273	23.8%
Other / unclassified	324	28.2%
IPPC / environmental permits and monitoring	135	11.8%
Sustainability / ESG disclosures	61	5.3%
Company websites and web disclosures	12	1.0%
Policy, strategy and target documents	7	0.6%
Governance and due diligence reports	5	0.4%
Certification and audit records	6	0.5%
Public portals (subsidiaries, contracts)	7	0.6%
Media, interviews and company profiles	3	0.3%
Supplier magazines and trade publications	1	0.1%
Total	1 148	100%

Source: Constructed by author (2025)

Financial statements and annual management reports together account for just over half the corpus. IPPC and environmental monitoring documents constitute the third-largest category (11.8%) and, as discussed in Chapter 4, are disproportionately important as carriers of D4 evidence, particularly for the ESG Enablement and IoT & Sensing dimensions.

3.3.3 Inclusion criteria

Documents were included in the dataset if they met three conditions. First, the document had to be reliably attributable to a focal company or its direct parent in cases where the subsidiary

does not produce independent disclosures. Second, the document had to relate to reporting year 2019 or later; earlier filings were collected where they informed context but were not coded for the primary panel analysis. Third, the document had to contain sufficient substantive content to permit assessment of at least one D4 or sustainability indicator – purely formal filings with no descriptive content (e.g., blank-form registry updates) were excluded.

Coding was restricted to explicitly stated evidence. Where documents contained ambiguous or purely promotional language without operational specificity, for example stating that a company “embraces digital innovation” without describing any particular system – the relevant indicator was scored conservatively (0 or 1 depending on context). Group-level documents were attributed at group level unless the text explicitly identified site-specific deployment, in which case site-level attribution was applied.

Technical sections, such as energy audits or IPPC monitoring tables, were treated as primary evidence for quantitative parameters when the underlying measurement systems or reporting obligations were explicitly described.

3.3.4 Scope attribution

Because the corpus integrates documents produced at very different organisational scales – from individual plant-level IPPC permits to multinational group sustainability reports – explicit scope attribution is essential to avoid misleading comparisons. Each document was assigned a scope category recording the organisational boundary to which its evidence applies:

- ***site-level:*** evidence tied to a named facility or specific operational system, such as an IPPC permit for a particular plant, monitoring obligations for a named production line, or references to site-specific production IT systems (e.g., MES/SCADA – manufacturing execution and supervisory control systems)
- ***company-level:*** evidence attributable to the legal entity as a whole, without a specific facility boundary, for example a statutory annual report, company-wide energy policy, or quality management certification
- ***group-level:*** evidence reported for a corporate group or parent entity, such as a group sustainability report, group packaging commitments, or group-level supplier programmes.

All comparative results presented in this dissertation are interpreted as disclosure visibility at the recorded scope. Where a company-level aggregate is reported, it should be understood as

the best available evidence from public sources, not as a complete inventory of the company's deployed systems.

3.4 Data coding instrument and measurement

The primary measurement instrument is a structured coding template constructed by the author: the *Dairy 4.0 ESG Indicator Template*. The template defines indicator-level coding rules and applies a uniform 0-2 ordinal scoring rubric across all indicators and all documents. It was developed iteratively through pilot coding of a set of documents spanning all four countries, with coding rules refined until consistent application could be demonstrated across document types.

All coding for the 471 company-year observations and 1 148 source documents was carried out by a single coder (the author). No formal inter-coder reliability test was conducted, and this is acknowledged as a limitation of the study (Section 6.3). Several design features were nonetheless built into the instrument specifically to compensate for the absence of a second coder and to make individual scoring decisions transparent and independently checkable. First, the coding rules were developed and refined through an iterative pilot phase, in which a sample of documents spanning all four countries was coded, discrepancies in the initial rule set were identified, and the rubric was revised until consistent application could be demonstrated before main coding began. Second, every non-zero score in the dataset is linked to a specific document, page reference, and supporting excerpt, so that any individual coding decision can be traced back to its source and independently verified. Third, the scoring scale was deliberately kept coarse and conservative: a score of 2 requires explicit, operationally specific, and quantifiable evidence, which narrows the scope for interpretive drift between a 1 and a 2 relative to a finer-grained scale. Fourth, three internal sensitivity checks were performed on the coded dataset after the fact – restricting the sample to the balanced panel of 74 companies observed in all six years, substituting the sum of sub-dimension maxima for the max-of-document-totals aggregation rule, and re-estimating the main models separately by country – and all three reproduced the main findings, indicating that the results are not an artefact of a particular coding or aggregation choice. Together, these measures do not substitute for formal inter-coder reliability testing, but they provide converging evidence that the coding is applied consistently and that the substantive conclusions are not sensitive to the specific judgement calls involved in borderline cases.

The template covers seven families of indicators, described in *Table 11*, with a total of 62 individual indicators.

Table 11. Indicator families and counts used in the dissertation

Indicator family	Count	Role in analysis
Reporting quality (RQ)	1	Control variable for reporting maturity and cross-document comparability
Sustainability technology disclosure (T)	13	Core indicators capturing sustainability-relevant systems and technology disclosures; includes a small set of quantitative sub-metrics (energy/capex/software) recorded in value fields
Outcome quantification (O)	8	Captures outcome quantification and verification signals, including investment quantification (e.g., payback/ROI), certifications, and selected operational capability flags
Dairy 4.0 adoption subdimensions (D4)	8	Measures adoption intensity across Industry 4.0 capability areas in dairy processing
Financial indicators (FIN)	16	Supplementary: balance sheet and P&L items extracted from statutory filings to support company profiling and size controls
Environmental & emissions (E/NRZ)	11	Supplementary: IPPC/NRZ monitoring data consolidated into umbrella indicators for air emissions, wastewater loads, and waste-related metrics
Workforce & governance (W/G)	5	Supplementary: headcount and governance-related contextual indicators extracted from statutory and regulatory filings
Total indicators	62	

Source: Constructed by author (2025)

The Dairy 4.0 adoption group (D4) is the primary focus of this dissertation. The sustainability technology disclosure (T), reporting quality (RQ), and outcome quantification (O) groups form the core of the designed instrument and serve as contextual and control variables. Three additional groups include: financial indicators (FIN), environmental and emissions metrics (E/NRZ), and workforce and governance indicators (W/G) and were coded as supplementary contextual data to support company profiling and robustness checks, but are not central to the main hypotheses.

3.4.1 Dairy 4.0 sub-dimensions

The Dairy 4.0 adoption is constructed through eight subdimensions corresponding to the major capability areas of Industry 4.0 as applied to dairy processing environments. These were developed on the basis of the Dairy 4.0 literature reviewed in Chapter 2, and were adapted to reflect the technological and regulatory context of large dairy processors in Central Europe. *Table 12* summarises each subdimension, its code in the dataset, and the type of evidence that triggers scoring.

Table 12. Dairy 4.0 sub-dimensions: codes, scope, and evidence types

Subdimension	Code	What is captured?
Digital Strategy & Governance	D4_Strategy_Gov	Explicit D4 strategy, roadmaps, digital governance structures, dedicated leadership roles
IoT & Sensing	D4_IoT_Sensing	Connected sensors, smart metering, real-time monitoring of production or environmental parameters
Automation & Robotics	D4_Automation_Robotics	Automated production equipment, robotic systems, conveyor automation, packaging lines
MES/SCADA/ERP	D4_MES_SCADA_ERP	Manufacturing execution systems, process control, enterprise resource planning integration
Quality & Traceability	D4_Quality_Traceability	Digital quality management, electronic batch records, farm-to-shelf traceability systems
Analytics & AI	D4_Analytics_AI	Data analytics, predictive maintenance, AI-assisted quality control/demand planning
Supply Chain Digitalisation	D4_SupplyChain_Digital	Digital supplier platforms, electronic milk collection data, logistics optimisation tools
ESG Enablement	D4_ESG_Enablement	Environmental monitoring infrastructure supporting sustainability performance measurement and reporting

Source: Constructed by author (2025)

The eight sub-dimensions collectively span the full breadth of Dairy 4.0 capability: from foundational governance and strategy (D4_Strategy_Gov) through operational technologies (IoT, automation, MES) and advanced analytics (D4_Analytics_AI) to supply chain integration (D4_SupplyChain_Digital) and the environmental monitoring and disclosure infrastructure that underpins ESG visibility (D4_ESG_Enablement). The maximum achievable score per company-year is 16 (2 points on each of eight dimensions). In practice, the highest score observed in the dataset is 16, recorded for one company in 2024; the panel mean across all company-years is 2.51.

3.4.2 Scoring rubric and aggregation rules

Each indicator is scored on a 0-2 ordinal scale. *Table 13* defines the three score levels and provides representative examples. A score of 0 indicates that no relevant evidence was identified in available documents for the company-year. A score of 1 reflects partial or emerging evidence – typically a reference to a relevant technology or system without operational detail, or evidence of early-stage deployment. A score of 2 is awarded where

evidence is explicit, substantiated, and operationally specific – for example, where a document describes a deployed system with quantified parameters or demonstrates integration into reported management processes.

Table 13. Coding rubric for D4 and sustainability indicators

Score	Interpretation	Typical evidence
0	No evidence	No relevant information identified in available documents for this dimension
1	Partial / emerging evidence	Technology or system mentioned; limited operational detail; single reference or early-stage deployment
2	Clear, substantiated evidence	Explicit description of deployed system; quantified parameters; operational integration confirmed

Source: Constructed by author (2025)

The resulting D4 Total score for each document is the sum of the eight sub-dimension scores, ranging from 0 to 16. No dimension weights are applied: all eight dimensions are treated as equally important, consistent with the current state of the literature which offers no strong prior basis for differential weighting.

Where a company produced more than one document in a given reporting year – which occurs in 322 of 471 company-year observations, with a maximum of 12 documents in a single year – the company-year D4 Total is taken as the maximum of the document-level totals rather than their sum or average. This aggregation rule reflects two methodological considerations. First, summation would artificially inflate scores for prolific reporters and penalise companies that consolidate their disclosures into a single document, creating a systematic bias against focused reporting strategies. Second, averaging would suppress genuinely high-capability evidence when it appears alongside thin routine filings. Taking the maximum captures the ceiling of documented disclosure capability in that company-year, which is the theoretically appropriate measure when the research question concerns the presence and extent of D4 adoption rather than reporting volume. The sub-dimension scores recorded in the panel correspondingly reflect the maximum score observed across all documents for each dimension independently. Because the company-year D4 Total is taken as the maximum of document-level totals rather than the sum of independent sub-dimension maxima, it is mathematically expected to be slightly lower than that sum; the two quantities coincide only when a single document achieves the maximum score on every sub-dimension simultaneously.

3.4.3 Panel construction and data structure

The final analytical dataset takes the form of an unbalanced longitudinal panel in which the unit of observation is the company-year. The panel covers 80 companies over six reporting years (2019-2024), yielding a maximum of 480 potential company-year observations. In practice, 471 observations are present, as some companies have incomplete public disclosure in one or two years. Of the 80 companies, 74 are observed in all six years; the remaining seven have between four and five observations.

A company-year observation is counted as present if at least one document was collected and coded for that company and year; where multiple documents exist, sub-dimension scores and totals reflect the maximum evidence observed across all documents, as described in Section 3.4.2. A score of zero on the D4 Total was recorded for 134 of 471 observations (27.5%) and indicates that documents were available but contained no codable D4 evidence, not that the company-year is missing from the dataset. This distinction matters for interpretation: zero-scoring observations are informative absences, not gaps.

The panel structure allows the analysis to track changes within companies over time as well as to compare companies at a given point in time. The two perspectives are complementary: cross-sectional comparisons identify which companies and countries currently disclose at higher levels, while within-company trends reveal whether disclosure intensity is changing and at what pace.

3.5 Analytical methods

The empirical analysis proceeds in three broad stages, corresponding to the structure of the results chapters that follow. First, it maps how Dairy 4.0 maturity is distributed across the V4. Second, it tests whether this disclosure-visible maturity increases over time within the same firms, and whether the pace differs by country. Third, it examines how digital transformation is being communicated in practice, specifically, whether ESG-related measurement and monitoring evidence is the main channel through which “digitalisation” becomes visible in public documents. Across all blocks, results are interpreted as disclosure-visible capability rather than a complete inventory of deployed systems, and the analysis is explicit about the large mass of zero scores.

3.5.1 Descriptive profiling of Dairy 4.0 adoption across the V4

The descriptive analysis characterises the D4 adoption landscape using summary statistics (means, medians, zero rates, score distribution) at the company-year, country-year, and sub-

dimension levels. Non-parametric tests are used throughout due to the zero-inflated, ordinal character of the D4 score distributions: Kruskal-Wallis H tests for multiple-group comparisons (KRUSKAL & WALLIS, 1952), Mann-Whitney U tests for pairwise comparisons (MANN & WHITNEY, 1947), and Spearman rank correlations for associational analysis (CONOVER, 1999). Country comparisons use Dunn's test with Bonferroni correction for post-hoc pairwise testing following a significant Kruskal-Wallis result (DUNN, 1964). The near-balanced panel structure (74 of 80 companies contributing all six years; 6 contributing between four and five years) is treated as an approximately balanced panel for trend analysis.

3.5.2 Temporal trajectory analysis

Temporal analysis uses two complementary approaches. First, non-parametric trend testing: Spearman rank correlations between Year and D4_Total_calc (pooled and by country) and Mann-Whitney U tests comparing the 2019 and 2024 distributions. Second, a two-way fixed-effects (FE) panel regression implemented via the within-transformation (double-demeaning). The FE specification is:

$$y_{it} = \alpha_i + \lambda_t + \beta \cdot Year_t + \varepsilon_{it} \quad [1]$$

where α_i absorbs all time-invariant firm heterogeneity and λ_t absorbs common year shocks. The FE estimator is implemented via double-demeaning using NumPy (HARRIS et al., 2020), with heteroscedasticity-robust standard errors and degrees of freedom adjusted conservatively for the number of absorbed fixed effects (WOOLDRIDGE, 2010).

First-difference distributions are computed as:

$$\Delta D4_{it} = D4_{it} - D4_{i,t-1} \quad [2]$$

and characterised by the proportion of positive, zero, and negative transitions, providing a transition-level view complementary to the level-based FE results.

3.5.3 Financial performance analysis

The D4-financial performance analysis uses Spearman correlations (pooled and by country), Kruskal-Wallis distributional comparisons across three D4 adoption groups – Zero (score = 0), Low (1-3), and High (4+) – where the threshold at 4 distinguishes partial or single-dimension adoption from multi-dimensional engagement across the composite D4_Total_calc score (range 0-16; mean 2.51) – and two-way FE regressions with $\ln(\text{Turnover_EUR})$ and Profit_Margin as outcomes, controlling for the annual document count (Doc_count) to separate within-firm variation in reporting volume from genuine technology adoption changes:

$$Fin_{it} = \alpha_i + \lambda_t + \beta \cdot D4_{it} + \varepsilon_{it} \quad [3]$$

where Fin_{it} denotes either $\ln(\text{Turnover_EUR})$ or Profit_Margin for firm i in year t . Standard errors are firm-clustered (sandwich estimator, small-sample corrected for $G = 55\text{--}57$ clusters), accounting for within-firm serial error correlation. A lagged specification provides a preliminary test of temporal precedence:

$$\Delta \ln(\text{Turnover}_{it}) = \alpha_i + \lambda_t + \beta \cdot D4_{i,t-1} + \varepsilon_{it} \quad [4]$$

All financial analyses are framed as exploratory given the partial financial data coverage (57 of 80 companies; 320 of 471 observations matched), the currency conversion limitations, and the absence of an identification strategy for causal inference.

3.5.4 ESG-D4 Nexus analysis

The ESG-D4 nexus analysis employs two confirmatory methods and one exploratory supplement, corresponding directly to the two-part hypothesis structure. The confirmatory tests address H4a (ESG dominance); the exploratory supplement addresses H4b (disclosure sequencing).

The first confirmatory test is a Spearman rank correlation between ESG_Enablement and D4_Total_calc across all 471 company-year observations, testing overall co-movement between ESG adoption and composite digital maturity:

$$\rho(\text{ESG_Enablement}_{it}, \text{D4_Total_calc}_{it}) \quad [5]$$

A circularity caveat applies: since ESG_Enablement is one component of D4_Total_calc , their correlation is mathematically inflated by compositional overlap. Sub-dimension correlations isolating ESG_Enablement against each of the seven non-ESG sub-dimensions separately address this limitation. The second confirmatory test is a Mann-Whitney U comparison of tech_sum distributions between ESG-adopting ($\text{ESG} > 0$) and non-adopting ($\text{ESG} = 0$) company-year observations, providing a distributional test of the ESG–technology gap that is independent of the compositional overlap (MANN & WHITNEY, 1947).

The exploratory supplement tests H4b: the temporal sequencing proposition. For each firm-year transition in the panel, the lagged Spearman rank correlation between ESG_Enablement at $t-1$ and the sum of the seven non-ESG technology sub-dimensions at t is computed across 390 complete year-on-year transitions:

$$\rho(\text{ESG}_{i,t-1}, \text{tech_sum}_{it}) \quad [6]$$

where tech_sum_{it} is the sum of the seven non-ESG sub-dimension scores for firm i in year t . Using tech_sum rather than D4_Total_calc as the outcome removes the compositional overlap

identified above, allowing a cleaner test of whether prior ESG disclosure is associated with subsequent non-ESG technology disclosure. This analysis is not a formal test of causation; it is reported as supplementary descriptive evidence and interpreted with corresponding caution.

4. FINDINGS AND RESULTS

This chapter presents the empirical findings in a sequence that mirrors the analytical logic: Section 4.1 establishes the descriptive foundation of the D4 adoption landscape; Section 4.2 reports the temporal dynamics and their interpretation; Section 4.3 presents the financial performance analysis; and Section 4.4 reports the ESG-D4 nexus findings.

Throughout this chapter, findings should be read against two interpretive boundaries established in Chapter 3. First, the sample represents the leading processors in each V4 country rather than the full population of dairy enterprises (Section 3.3.1). The results should not be read as representative of the sector as a whole, including smaller and family-owned operations that fall outside this leading tier. Second, the D4 scores measure documented visibility of digital and ESG-related activity, not the outcome of a comprehensive technological audit (Section 3.1): higher scores indicate higher disclosure and reporting maturity, not direct evidence of superior operational digitalisation. Both boundaries apply to every finding reported below, even where they are not restated at each individual result.

4.1 Descriptive profile of Dairy 4.0 adoption in the Visegrad Four

4.1.1 Overall adoption level and distribution

Across the full panel of 471 company-year observations, the mean D4_Total_calc score is 2.51 (SD $\approx$ 2.38; median = 2.0; range 0-16). That modest average conceals extreme distributional heterogeneity. In nearly three in ten company-years (28.5%), no codable evidence of digital transformation was identified across any of the eight sub-dimensions. The zero mass is not uniformly distributed: in 2019, 39% of observations scored zero, declining to 13% by 2024, suggesting a genuine broadening of the disclosure footprint over the study period – even if adoption levels remain low in absolute terms. Five of 80 companies produced no codable D4 evidence in any observed year, representing structurally silent firms that produced no documentable D4 evidence throughout the entire six-year window.

The score distribution is sharply right-skewed. The majority of non-zero observations cluster in the low range: 41.2% of all company-years score between 1 and 3, and a further 27.8% fall between 4 and 7. Only 12 observations – 2.5% of the panel – reach scores of 8 or above, and just four company-years exceed 10. The maximum of 16 was recorded by a single observation, Zott Polska in 2022, reflecting comprehensive multi-dimensional disclosure across all eight sub-dimensions. The three other high-scoring company-years are Grupa Mlekovita, Poland (14, 2024), Sole-Mizo Zrt, Hungary (14, 2022), and BEL Sýry Česko a.s., Czech Republic

(11, 2024) – all subsidiaries of Western European multinationals or large domestic cooperatives.

The violin plots (*Figure 5*) make the between-country differences immediately visible. Czech Republic shows the narrowest distribution – a median of 3.0, the lowest zero rate (15%), and relatively few extreme outliers – consistent with a sector where most firms engage with D4 documentation at least partially. Hungary's distribution is similarly centred above the overall median, though with a longer upper tail, descriptively aligned with the presence of high-scoring multinational subsidiaries in the Hungarian sub-sample. Poland's violin is the most asymmetric: a zero rate of 36% sits alongside the highest maximum in the panel (16), suggesting a bimodal distribution consistent with the structural heterogeneity of the Polish dairy sector. Slovakia presents the flattest profile, with a median of 2.0, a 41% zero rate, and a maximum of just 8, indicating that high-scoring disclosure remains largely absent throughout the observation window. The country-level drivers underlying these distributional patterns are examined formally in Section 4.1.3.

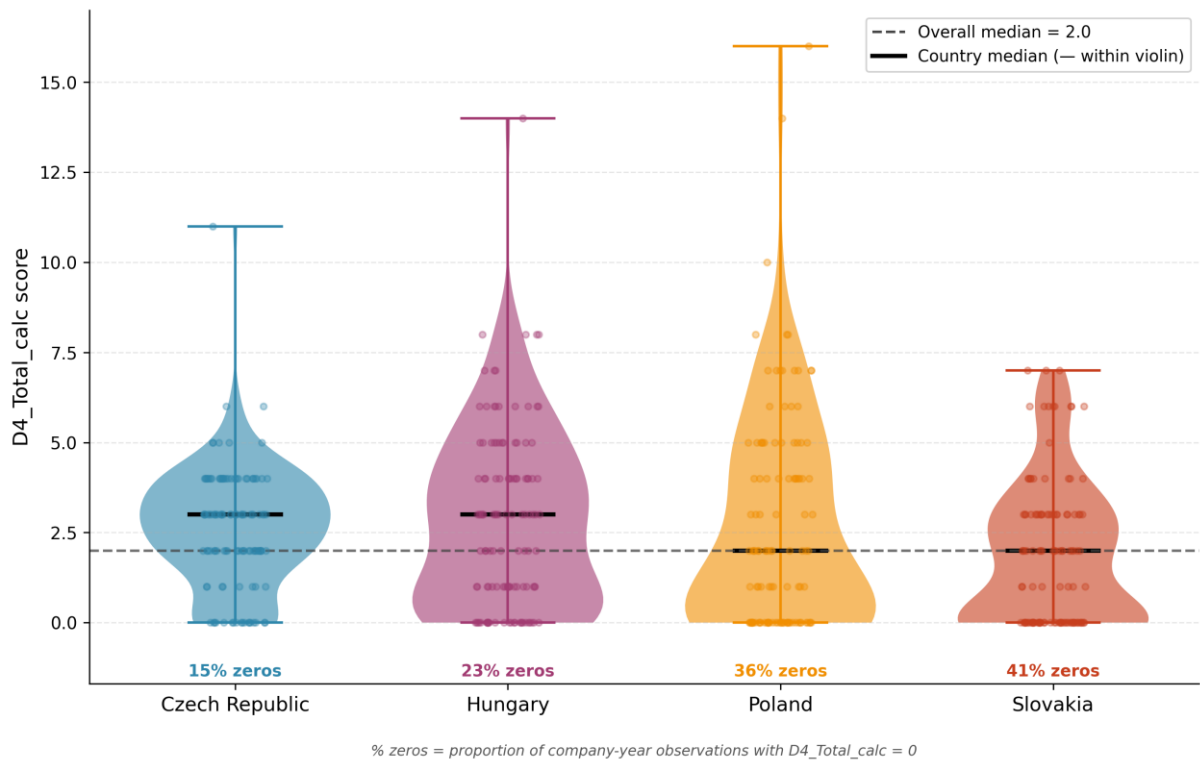


Figure 5. Distribution of overall Dairy 4.0 Scope (D4_Total_calc) by country

Source: Constructed by author (2026)

Table 14 summarises the panel structure by country, showing the number of companies, observations, mean and median D4 scores, zero rates, maximum scores, and mean document counts per company-year.

Table 14. Panel structure summary by country

Country	Companies (n)	Obs. (n)	D4 Mean	D4 Median	Zero Score %	Max Score	Docs/co-yr
Czech Republic	20	119	2.61	3.0	15%	11	1.96
Hungary	20	119	2.84	3.0	23%	14	1.85
Poland	20	115	2.70	2.0	36%	16	2.52
Slovakia	20	118	1.88	2.0	41%	7	3.43
All V4	80	471	2.51	2.0	28.5%	16	2.44

Note. Obs. = company-year observations. Zero Score % = proportion of company-year observations with D4_Total_calc = 0. Docs/co-yr = mean number of source documents per company-year observation.

Source: Constructed by author (2026)

Taken together, these patterns confirm that V4 dairy sector digitalisation in 2019-2024 is characterised by low average adoption, a large zero mass, and pronounced heterogeneity – both across countries and within them. The following section examines how this heterogeneity is distributed across the eight individual sub-dimensions of the D4 framework.

4.1.2 Sub-dimension profile

Table 15 presents the full sub-dimension profile across all 471 company-year observations. The eight dimensions span a wide range of mean scores – from 0.822 for ESG Enablement down to 0.130 for Analytics & AI, a ratio of more than 6:1 – making clear that V4 dairy sector digitalisation is far from evenly distributed across the D4 framework. Six of the eight dimensions sit below a mean of 0.4, and five of those fall below 0.35, indicating that genuine multi-dimensional adoption remains uncommon. The gap between ESG Enablement and all other dimensions is also visible in adoption rates: 53.1% of company-years show at least some ESG evidence, compared to 41.0% for Automation & Robotics the second most frequently disclosed dimension – and below 35% for everything else.

Table 15. Sub-dimension Dairy 4.0 profile (n = 471)

Sub-dimension	Mean	% Score = 0	% Score = 1	% Score = 2	Adoption (> 0)	Rank
ESG Enablement	0.822	46.9%	24.0%	29.1%	53.1%	1st
Automation & Robotics	0.529	59.0%	29.1%	11.9%	41.0%	2nd
MES/SCADA & ERP	0.382	66.0%	29.7%	4.2%	34.0%	3rd
Quality & Traceability	0.340	71.1%	23.8%	5.1%	28.9%	4th

Strategy & Governance	0.321	72.2%	23.6%	4.2%	27.8%	5th
IoT & Sensing	0.285	75.4%	20.8%	3.8%	24.6%	6th
Supply Chain Digital	0.163	86.2%	11.3%	2.5%	13.8%	7th
Analytics & AI	0.130	89.0%	9.3%	1.5%	11.0%	8th

Source: Constructed by author (2026)

Aggregate scores, however, obscure considerable variation in how sub-dimension adoption is distributed across countries and time. *Figure 6a-d* maps mean sub-dimension scores at the country-year level, revealing patterns that the panel-wide averages in *Table 15* cannot show. ESG Enablement – while dominant overall – varies more across countries than any other dimension (country mean range: 0.627 in Slovakia to 1.050 in Czech Republic), whereas Supply Chain Digital, Automation & Robotics, and Strategy & Governance are comparatively uniform. Analytics & AI shows the sharpest geographic split: Poland reaches a mean of 0.287 and Hungary 0.160, while Czech Republic (0.034) and Slovakia (0.042) show near-zero scores throughout most of the observation window – suggesting that AI-related adoption is concentrated in a small number of firms in specific countries rather than being a sector-wide trend.

ESG Enablement	1.00	1.05	0.90	1.10	1.05	1.21
Automation & Robotics	0.40	0.40	0.35	0.40	0.60	0.95
MES/SCADA & ERP	0.25	0.20	0.35	0.25	0.55	0.68
Quality & Traceability	0.40	0.30	0.35	0.45	0.50	1.00
Strategy & Governance	0.30	0.25	0.25	0.35	0.25	0.26
IoT & Sensing	0.45	0.55	0.50	0.50	0.40	0.37
Supply Chain Digital	0.00	0.00	0.00	0.05	0.05	0.53
Analytics & AI	0.00	0.00	0.05	0.00	0.05	0.11
	2019	2020	2021	2022	2023	2024

Year

Figure 6a. Czech Republic

ESG Enablement	0.89	0.90	0.90	0.95	1.10	0.90
Automation & Robotics	0.47	0.45	0.45	0.35	0.45	0.45
MES/SCADA & ERP	0.53	0.40	0.45	0.55	0.55	0.55
Quality & Traceability	0.21	0.30	0.25	0.35	0.20	0.55
Strategy & Governance	0.32	0.50	0.35	0.50	0.40	0.45
IoT & Sensing	0.11	0.00	0.15	0.15	0.35	0.05
Supply Chain Digital	0.16	0.20	0.20	0.40	0.20	0.15
Analytics & AI	0.05	0.05	0.05	0.30	0.30	0.20
	2019	2020	2021	2022	2023	2024
	Year					

Figure 6b. Hungary

ESG Enablement	0.33	0.42	0.63	0.89	0.60	1.05
Automation & Robotics	0.17	0.47	0.47	0.63	0.75	0.85
MES/SCADA & ERP	0.11	0.16	0.26	0.32	0.45	0.40
Quality & Traceability	0.00	0.11	0.11	0.32	0.40	0.75
Strategy & Governance	0.06	0.16	0.21	0.42	0.40	0.70
IoT & Sensing	0.11	0.16	0.42	0.42	0.35	0.65
Supply Chain Digital	0.06	0.11	0.11	0.21	0.25	0.40
Analytics & AI	0.06	0.26	0.16	0.37	0.30	0.55
	2019	2020	2021	2022	2023	2024
	Year					

Figure 6c. Poland

ESG Enablement	0.53	0.70	0.84	0.55	0.55	0.60
Automation & Robotics	0.53	0.60	0.53	0.65	0.65	0.65
MES/SCADA & ERP	0.32	0.30	0.37	0.35	0.30	0.50
Quality & Traceability	0.21	0.15	0.26	0.15	0.25	0.55
Strategy & Governance	0.32	0.20	0.26	0.20	0.20	0.35
IoT & Sensing	0.11	0.10	0.26	0.20	0.15	0.30
Supply Chain Digital	0.05	0.15	0.16	0.10	0.10	0.30
Analytics & AI	0.00	0.00	0.00	0.00	0.00	0.25
	2019	2020	2021	2022	2023	2024

Year

Figure 6d. Slovakia

Figure 6a-d. Mean sub-dimension Dairy 4.0 scores by country (2019-2024)

Note. Each cell shows the mean sub-dimension score for that country-year ($n = 19\text{--}20$ observations per cell). Scores range from 0 (no codable evidence) to 2 (explicit, substantiated evidence). Sub-dimensions are ordered by overall mean score descending: ESG Enablement (0.822) through Analytics & AI (0.130).

Source: Constructed by author (2026)

Taken together, the heatmaps point to two distinct patterns of sub-dimension development. For most dimensions, improvement over time is gradual and broadly distributed – Quality & Traceability, for instance, rises from a mean of 0.211 in 2019 to 0.709 in 2024 across the full panel, with gains visible in all four countries. Supply Chain Digital shows a similarly broad uplift from 0.066 to 0.342. ESG Enablement, by contrast, tells a more uneven story: Czech Republic and Hungary enter the observation window already above 0.89 and remain stable, while Poland climbs from 0.33 in 2019 to 1.05 by 2024 – converging toward the leaders only in the final years. Slovakia shows no comparable trajectory, remaining flat through 2023 before a modest increase in 2024. These patterns suggest that the cross-national differences documented in Section 4.1.3 are not confined to overall D4 scores but run through specific sub-dimensions – ESG Enablement and Analytics & AI in particular.

4.1.3 Cross-national heterogeneity

The four V4 countries differ significantly in their D4_Total_calc distributions. A Kruskal-Wallis test yields $H = 14.28$ ($df = 3$, $p = 0.003$), rejecting the null hypothesis of equal population distributions across national groups. Post-hoc Dunn tests with Bonferroni correction ($k = 6$ comparisons) identify two significant pairwise differences, both involving Slovakia: Slovakia

vs. Czech Republic ($z = 3.26$, $p = 0.007$) and Slovakia vs. Hungary ($z = 3.28$, $p = 0.006$). All other pairs – including Czech Republic vs. Hungary, Czech Republic vs. Poland, Hungary vs. Poland, and Poland vs. Slovakia – are statistically indistinguishable after correction. Full pairwise results are presented in *Table 16*, which reports all six pairwise comparisons, including mean rank differences, z-statistics, raw and Bonferroni-adjusted p-values.

Table 16. Post-hoc Dunn pairwise comparisons for D4_Total_calc across V4 countries

Country pair	Mean rank difference	z	p (raw)	p (Bonferroni)	Sig.
Czech Republic vs Hungary	+0.28	−0.016	1.000	1.000	n.s.
Czech Republic vs Poland	+22.03	+1.260	0.207	1.000	n.s.
Czech Republic vs Slovakia	+56.64	+3.260	0.001	0.007	**
Hungary vs Poland	+22.31	+1.276	0.202	1.000	n.s.
Hungary vs Slovakia	+56.92	+3.276	0.001	0.006	**
Poland vs Slovakia	+34.61	+1.975	0.048	0.290	n.s.

Note. N = 471 company-year observations. Mean rank differences computed on full-panel ranks. p-values adjusted using Bonferroni correction ($k = 6$ comparisons). Significance: ** $p < 0.01$; n.s. = not significant ($p \geq 0.05$). Country mean scores: Czech Republic = 2.61; Hungary = 2.84; Poland = 2.70; Slovakia = 1.88.

Source: Constructed by author (2026)

Slovakia is the lowest-scoring country across the panel (mean = 1.88), and its separation from both Czech Republic (mean = 2.61) and Hungary (mean = 2.84) is statistically clear. This lower mean reflects a combination of genuinely lower technology adoption evidence and the differential document availability documented in Section 3.3.2 – Slovakia has the highest proportion of company-years with only a single available source document, which constrains the maximum observable D4 score. The two effects are difficult to disentangle fully, and this limitation applies to any cross-national comparison involving Slovakia.

Czech Republic stands out for its distributional consistency rather than its mean score alone. With the lowest zero rate in the panel (15%) and a within-country standard deviation of 1.68 – the lowest of the four countries – Czech firms show less polarisation between high-scoring leaders and zero-scoring laggards than either Poland or Slovakia. The median of 3.0 sits above the panel median of 2.0, and the maximum of 11 is comparatively modest, indicating that Czech adoption is broad but not extreme. This profile is consistent with a sector where most firms engage with D4 documentation at least partially, rather than one driven by a small number of outlier disclosers.

Poland presents the most internally heterogeneous distribution: the highest maximum score in the panel (16), the largest within-country standard deviation ($SD = 3.04$), and simultaneously the second-highest zero rate (36%). This combination reflects a structurally bimodal sector. A small group of large processors – SM Mlekpól, Grupa Mlekovita, and Grupa Polmlek, each with multi-year mean scores above 6.0 – dominate the upper tail, while the majority of smaller cooperatives and regional processors produce minimal D4 documentation. Poland vs. Slovakia falls just short of significance after Bonferroni correction ($p = 0.290$), despite Slovakia's lower mean, because Poland's high within-country variance substantially widens the effective confidence interval for that comparison.

Hungary's above-average mean (2.84) is associated with a combination of high-scoring multinational subsidiaries and strong domestic processors – a compositional pattern consistent with the ownership structure of the Hungarian sub-sample. FrieslandCampina Hungária Zrt. (mean = 5.33), Danone Hungary Kft (mean = 5.67), and Savencia Fromage & Dairy Hungary Zrt (mean = 4.33) consistently produce multi-pillar D4 documentation through parent-company reporting frameworks. Alongside these, Sole-Mizo Zrt – a domestic cooperative – records the highest mean score among all Hungarian firms at 6.17, indicating that multinational reporting is not the sole driver of Hungary's position. The non-significant difference between Hungary and Poland ($p = 1.000$ after correction) reflects the fact that Poland's high-scoring outliers broadly offset Hungary's greater consistency at mid-range scores.

These cross-national patterns illustrate a broader interpretive point that recurs throughout this chapter: a high D4 score can arise from at least three distinct, non-exclusive sources – genuine operational digitalisation, inherited group-level reporting infrastructure in multinational subsidiaries, and documentation generated to satisfy regulatory compliance obligations (discussed further in Section 4.4.1). Hungary's elevated mean, for example, reflects a mixture of the first two mechanisms: FrieslandCampina Hungaria, Danone Hungary, and Savencia Hungary score highly in part because of parent-company disclosure frameworks, while Sole-Mizo's comparable score derives from a domestically-driven reporting effort rather than multinational ownership. Attributing cross-national differences to a single mechanism – whether ownership structure or genuine technological leadership – would overstate what disclosure-based evidence can support.

4.2 Temporal dynamics (2019-2024)

4.2.1 Temporal trends in D4 disclosure intensity across the V4 Panel

As with Section 4.1, the temporal changes documented below describe shifts in what companies disclose over time, not verified changes in underlying technology deployment; a rising D4 score indicates broadening or deepening disclosure, not a confirmed increase in operational digital capability.

The aggregate D4 Total score rises from a mean of 1.87 in 2019 to 3.52 in 2024 – 88% increase over six years. The zero rate declines from 39% in 2019 to 13% in 2024, indicating that the improvement partly reflects a broadening (more firms entering the non-zero disclosure space) rather than exclusively a deepening of existing disclosure. Non-parametric testing confirms that this aggregate improvement is statistically significant: the Kruskal-Wallis test across all six years yields $H = 20.90$ ($p < 0.001$), and the Mann-Whitney test comparing 2024 to 2019 distributions confirms that 2024 stochastically dominates 2019 ($U = 4,106$, $p < 0.001$).

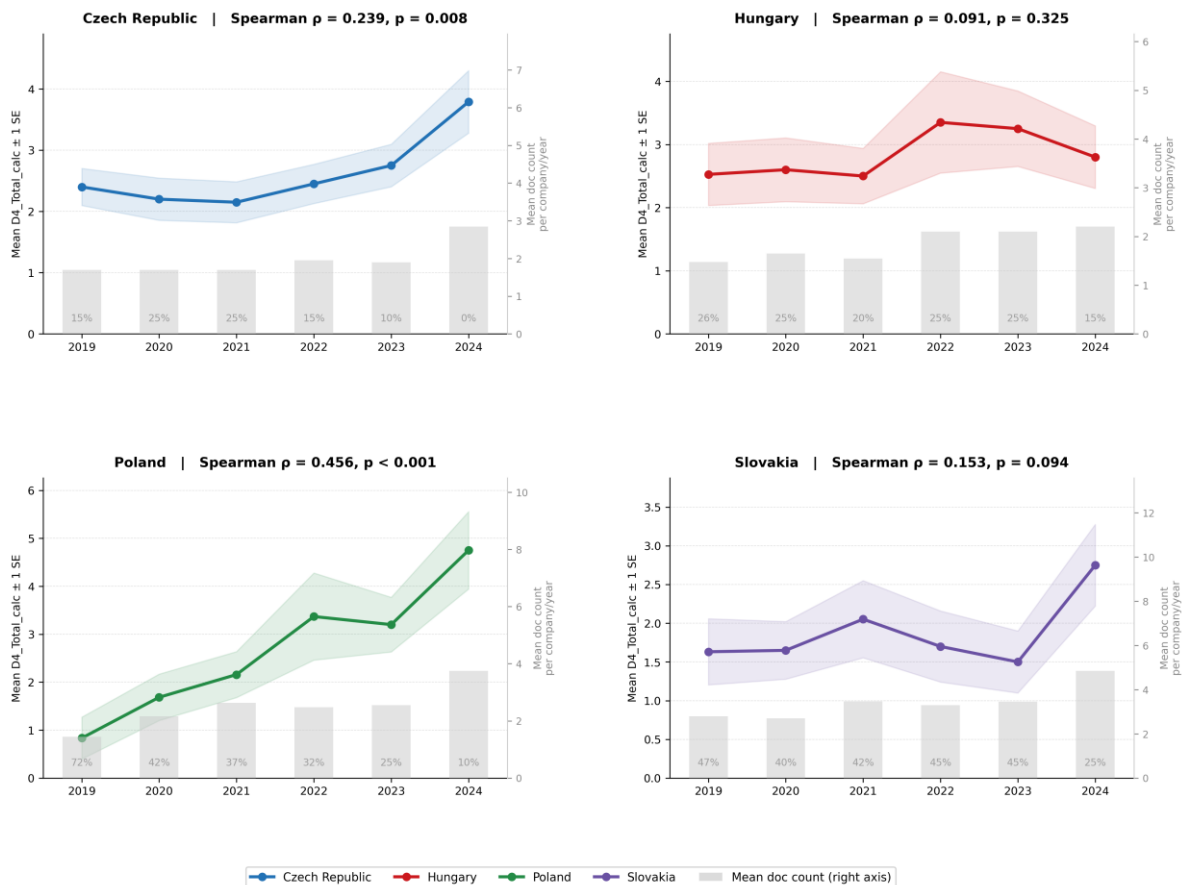


Figure 7. Temporal trajectory of D4_Total_calc and document count by country

Note. Line = mean D4_Total_calc $\pm$ 1 SE (left axis, coloured). Grey bars = mean doc count per company-year (right axis). Italic annotations = % zero-scoring observations per country-year cell. Spearman ρ and significance in subplot titles.

Source: Constructed by author (2026)

That aggregate improvement is, however, unevenly distributed across countries. Poland shows the strongest temporal trend (Spearman $\rho = 0.434$, $p < 0.001$), with mean scores rising from 0.83 in 2019 to 4.75 in 2024 and the zero rate collapsing from 72% to 10%, accounting for the majority of the panel-wide improvement. Czech Republic shows a modest but statistically significant upward trend (Spearman $\rho = 0.210$, $p = 0.022$), with mean scores rising from 2.40 in 2019 to 3.79 in 2024. Hungary (Spearman $\rho = 0.067$, $p = 0.472$) and Slovakia (Spearman $\rho = 0.106$, $p = 0.254$) show no significant temporal trends. Hungary displays a non-monotone pattern – rising from 2.53 in 2019 to a peak of 3.35 in 2022, then declining to 2.80 by 2024. Slovakia's profile is broadly flat across 2019-2023 (range 1.50 - 2.05) with a notable uptick to 2.75 in 2024 that coincides with the general surge in document volume discussed in Appendix F.

4.2.2 Within-firm disclosure stability: fixed-effects analysis

The two-way fixed-effects regression (Section 3.5.2) yields a non-significant linear trend coefficient ($\beta = 0.296$, $SE = 0.444$, $t = 0.67$, $p = 0.505$), indicating that once firm heterogeneity and common year shocks are absorbed, individual firms do not systematically deepen their D4 disclosure over time. This null result holds across all eight sub-dimensions individually (all $\beta < 0.10$, all $p > 0.40$) and is consistent across country-stratified models.

The null FE result does not contradict the aggregate improvement documented in Section 4.2.1. The two findings reflect different sources of variation: the aggregate trend captures between-firm compositional effects – most visibly Poland's high-scoring processors entering and expanding their reporting – and common year shocks absorbed by the year fixed effects. The FE estimator strips both of these out, leaving only the within-firm signal, which is flat.

The year-to-year transition distribution reinforces this interpretation. Of 391 firm-year transitions in the panel, 52.9% show no change in D4 score ($\Delta D4 = 0$), 28.6% show an increase, and 18.4% show a decline. The modal outcome is stasis. When scores do change, the movements are discrete rather than gradual – single-point integer jumps reflecting the gain or loss of evidence on one sub-dimension – which is inconsistent with the kind of continuous within-firm improvement that would produce a significant FE trend. Firm-level D4 disclosure is, in short, sticky: most firms maintain the same disclosure profile year on year, and when they do change, it is in one step rather than through incremental deepening.

An alternative view of this stability deserves consideration: rather than reflecting genuine corporate stagnation, the modal zero-change outcome could partly reflect the slow year-on-year accumulation of document sources rather than inaction by the firm itself. First, the mean number

of documents collected per company-year nearly doubled over the panel (1.86 in 2019 to 3.42 in 2024, +83.9), so document availability was expanding steadily rather than remaining static. If document scarcity were suppressing apparent change, this expansion should have produced more detected score increases over time, not fewer. Second, a fixed-effects regression on content intensity (D4_Total_calc divided by document count) finds no significant within-firm trend ($\beta = 0.036$, $p = 0.866$), indicating that additional documents were not adding proportionally more codable D4 evidence. Taken together, these patterns are more consistent with genuine firm-level stability than with an artefact of thin or slowly-accumulating documentation: firms were receiving more source material over time without a corresponding increase in coded content. A firm-level test relating each company's rate of document accumulation to its rate of score change would sharpen this conclusion further and is identified as a direction for future validation work (Section 6.4).

4.3 D4 adoption and financial performance

4.3.1 Cross-sectional association with revenue

The associations reported in this section describe co-movement between disclosure-based D4 scores and financial variables; consistent with the research design set out in Section 3.2, they are not evidence of a causal effect of digitalisation on financial performance in either direction.

The Spearman correlation between D4_Total_calc and $\log(\text{Turnover_EUR})$ across 320 matched company-year observations is $\rho = 0.285$ (95% CI [0.181, 0.383], $p < 0.001$). This positive association is the primary financial finding: larger firms – measured by revenue – score higher on D4 disclosure. The association holds within all four V4 countries (Spearman ρ ranging from 0.273 in Czech Republic to 0.757 in Slovakia, all significant), though the Slovak coefficient reflects a small, non-representative financial sub-sample (9 of 20 Slovak companies). The OLS slope on the log scale implies that each additional D4 point is associated with approximately 29% higher turnover in a cross-sectional comparison ($\exp(0.256) \approx 1.29$), though this estimate carries all the limitations of a level regression.

At the sub-dimension level, IoT & Sensing ($\rho = 0.349$, $p < 0.001$) and ESG Enablement (Spearman $\rho = 0.319$, $p < 0.001$) show the strongest positive correlations with revenue. These are also the dimensions most dependent on data infrastructure and environmental monitoring systems – capabilities that are naturally more prevalent in large, capital-intensive processing facilities. Strategy & Governance (Spearman $\rho = 0.063$, $p = 0.258$) and Quality & Traceability (Spearman $\rho = 0.073$, $p = 0.193$) are uncorrelated with revenue, suggesting that these disclosure dimensions are practised across the size range.

4.3.2 Profit margin

The Spearman correlation between D4_Total_calc and Profit_Margin is $\rho = -0.094$ ($p = 0.098$) – statistically non-significant. No D4 sub-dimension shows a significant positive correlation with profit margin; several show marginally negative associations: Strategy & Governance ($\rho = -0.124$, $p = 0.030$), Analytics & AI (Spearman $\rho = -0.145$, $p = 0.011$), and Quality & Traceability (Spearman $\rho = -0.115$, $p = 0.043$). These negative signals are consistent with investment costs: firms that articulate explicit digital strategies and deploy analytics platforms may have incurred upfront capital expenditure that suppresses current-period margins, particularly in the 2022-2023 energy cost shock environment. The overall pattern – thin and volatile margins with no significant relationship to D4 score – reflects the commodity-market context of V4 dairy processing, where margins are primarily driven by raw milk prices, energy costs, and competitive pricing power rather than digital transformation investment.

4.3.3 Within-firm fixed-effects: resolving the size-effect question

The two-way FE regression with $\log(\text{Turnover_EUR})$ as outcome yields $\beta = 0.666$ ($\text{SE} = 0.763$, $p = 0.383$, within- $R^2 = 0.148$; $n = 320$, 57 firms), and with Profit_Margin as outcome yields $\beta = -1.624$ ($\text{SE} = 2.778$, $p = 0.559$, within- $R^2 = 0.160$; $n = 308$, 55 firms). Standard errors are firm-clustered (sandwich estimator, small-sample corrected), accounting for within-firm serial error correlation; the null p-values are robust to this adjustment. The annual document count (Doc_count) is included as a control in both specifications; its coefficient is positive and significant ($\beta \approx 0.63$, $p < 0.001$), confirming that document volume is the principal within-firm predictor of D4 score level. Neither D4 coefficient reaches significance, confirming that the cross-sectional revenue correlation is a firm-size effect rather than an independent adoption-performance dynamic. The lagged analysis ($\text{D4}_{i,t-1} \rightarrow \Delta \ln(\text{Turnover}_t)$) yields Spearman $\rho = 0.016$ ($p = 0.798$), providing no evidence of a one-year forward-looking pathway from adoption to revenue.

These null FE and lagged results are treated as substantive findings rather than as analytical failures. They establish that, within the six-year observation window available and with the measurement approach used, the D4 score shows no detectable within-firm association with either financial outcome – a conclusion that holds under firm-clustered standard errors and is robust to controlling for annual document volume. Three interpretations are consistent with this pattern: (a) adoption-performance effects operate over longer horizons than six years; (b) the D4 score primarily captures firm size and reporting sophistication rather than genuine adoption, making it an invalid predictor of performance; or (c) digitalisation in V4 dairy processing does

not generate measurable financial returns in the short-to-medium run in this sector context. These alternatives are discussed in Chapter 5.

4.4 The ESG-D4 nexus: ESG enablement as the primary D4 disclosure channel

This section presents the dissertation's primary empirical contribution. The findings are organised around four interconnected analytical results: the quantitative dominance of ESG Enablement; its distinctive correlation structure; the evidence sources by document type that drive it; and its temporal relationship with technological adoption.

As elsewhere in this chapter, ESG Enablement's dominance is a statement about documented visibility, not a claim that ESG-related digital capability is more technologically advanced than other Dairy 4.0 capability areas in absolute terms.

4.4.1 The ESG advantage: quantitative dominance

ESG Enablement is the dominant D4 sub-dimension across every metric in the scoring framework. Its mean score of 0.822 is 2.68 times higher than the average of the remaining seven technology sub-dimensions (mean 0.307). Its adoption rate of 53.1% is approximately 1.3 times higher than that of the next most-adopted dimension (Automation & Robotics at 41.0%) and more than four times that of Analytics & AI (11.0%). Its score=2 achievement rate of 29.1% – the rate at which firms produce verified, substantiated evidence – is 2.4 times higher than Automation (11.9%) and 19 times higher than Analytics/AI (1.5%). The Mann-Whitney U test confirms stochastic dominance of ESG over all three core tech comparators at $p < 0.001$.

The full distributional picture is presented in *Figure 8*, which contrasts ESG Enablement with all other sub-dimensions across three scoring levels. ESG Enablement occupies the top position, it leads over Automation & Robotics on verified evidence (29.1% vs. 11.9%) and its near-total distance from Analytics & AI (1.5%) confirming that the quantitative gap is not an artefact of definitional breadth but reflects a genuine difference in the quality and depth of disclosure.

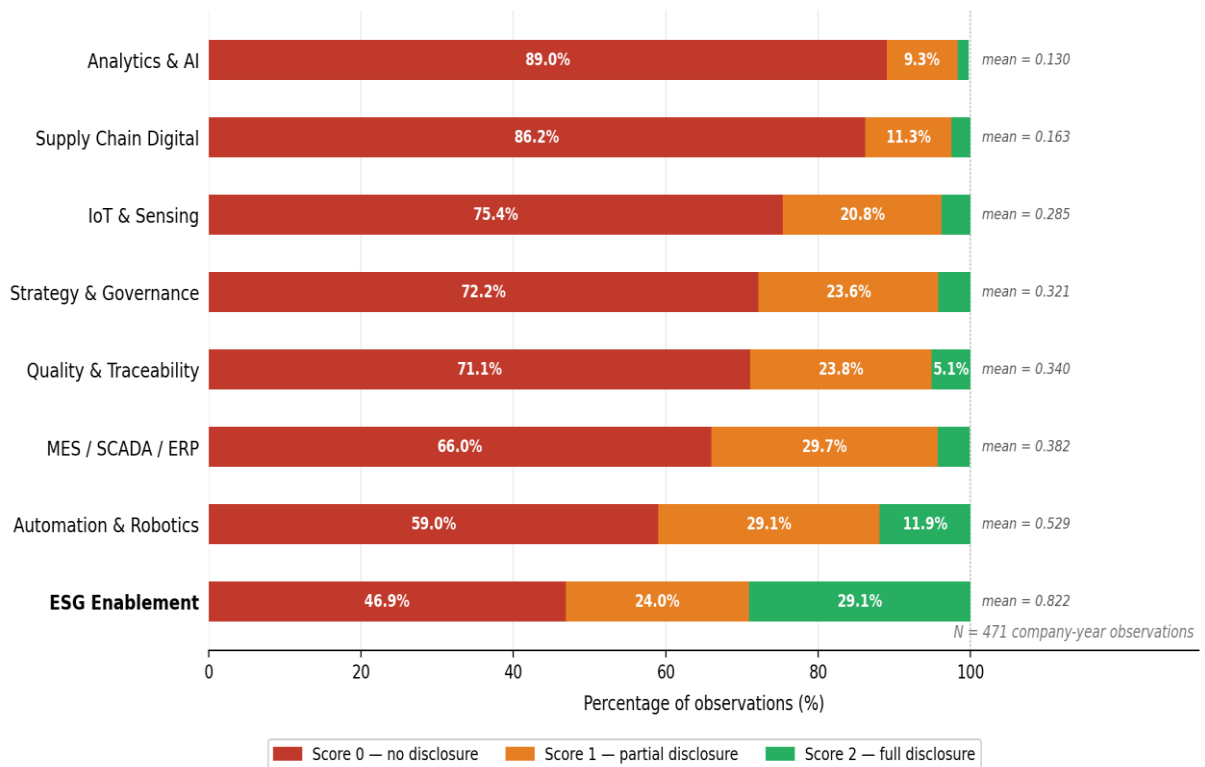


Figure 8. Score distribution of ESG Enablement vs. all Dairy 4.0 sub-dimensions

Source: Constructed by author (2026)

The temporal dimension of this dominance is illustrated in *Figure 9*. ESG Enablement maintains a consistent lead over all other dimensions throughout the six-year period, reaching a panel-high mean of 0.937 in 2024. The shaded red area marks the gap between ESG Enablement and the second-ranked dimension (Automation & Robotics, blue) in each year. All eight dimensions show a general upward trend, with the steepest acceleration occurring after 2022. A notable exception to the gradualism of this trend is the sharp rise in Quality & Traceability, whose panel mean more than doubles from 0.338 in 2023 to 0.709 in 2024 – a pattern consistent with the progressive implementation of EU farm-to-fork traceability obligations and food-safety digitalisation requirements during this period, which created regulatory pressure for formal traceability disclosure independently of firms’ voluntary digital adoption trajectories.

Crucially, this dominance is not a recent phenomenon driven by the late-period ESG reporting surge: ESG Enablement was already the highest-scoring dimension in 2019 (mean 0.697), when Analytics & AI scored a mean of just 0.026 – a gap of more than 26:1.

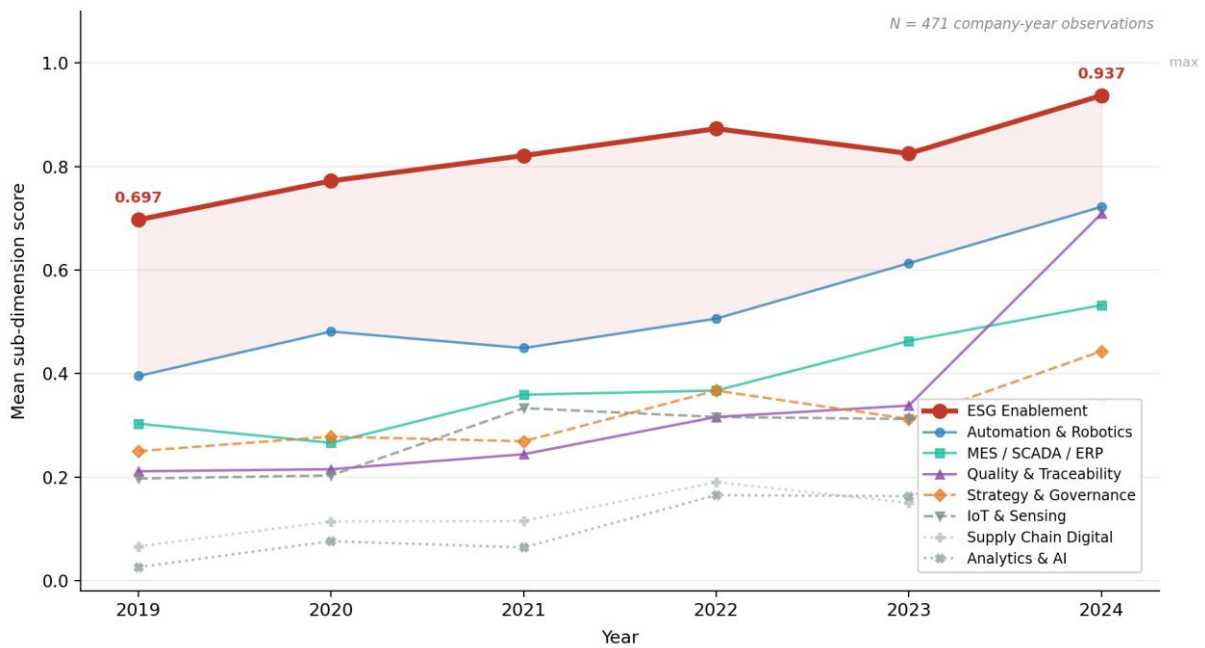


Figure 9. Temporal divergence: ESG vs. Dairy 4.0 sub-dimensions (2019-2024)

Source: Constructed by author (2026)

As Figure 9 shows, the absolute gap has widened in the post-2022 period as tech dimensions rise (driven by Polish automation and analytics expansion) without ESG being displaced. The ESG-to-technology ratio remains above 1.0 in all country-years except Poland 2022-2024, where the Polish technology disclosure increase temporarily inverts the relationship.

Three points of caution qualify this dominance before it is examined in detail below. First, part of the effect reflects regulatory compulsion rather than voluntary strategy: firms above IPPC permit thresholds are legally required to install and document environmental monitoring systems, and Section 4.4.3 shows that IPPC and environmental permits alone account for 27.3% of all non-zero ESG evidence records – documentation generated to satisfy a legal obligation rather than a strategic digital-transformation choice. Second, part of the effect reflects group-level reporting inheritance: multinational subsidiaries of Western European dairy groups (FrieslandCampina, Danone, Lactalis, Savencia, Zott) generate ESG Enablement evidence through parent-company sustainability governance frameworks rather than through independent local investment decisions (Section 2.7.4). Third, a residual component reflects genuine, locally-driven environmental digitalisation, visible for example in domestically-owned firms such as Sole-Mizo Zrt that score highly without multinational ownership or scale-dependent compliance thresholds. The quantitative dominance documented below should therefore be read as a compound of these three sources rather than as uniform evidence of superior environmental-technology adoption.

4.4.2 ESG as the integrating dimension: correlation structure

The full Spearman correlation matrix reveals that ESG Enablement is positively and significantly correlated with all seven other D4 sub-dimensions. Correlations range from $\rho = 0.246$ (Analytics & AI, $p < 0.001$) to Spearman $\rho = 0.402$ (IoT & Sensing, $p < 0.001$). This broad positive correlation structure contrasts with the weaker and more selective correlations among the tech dimensions themselves: Strategy & Governance and Automation & Robotics are uncorrelated (Spearman $\rho = 0.011$, $p = 0.811$), and Supply Chain Digital has near-zero correlations with IoT (Spearman $\rho = 0.077$) and Automation (Spearman $\rho = 0.059$).

Table 17 presents the Spearman correlations between ESG Enablement and all seven D4 technology sub-dimensions, ranked by correlation strength. The bottom row (italicised) adds a partial correlation between ESG Enablement and D4_Total_calc controlling for Automation & Robotics: because Automation is correlated with both ESG and the total score, this statistic isolates how much of ESG's relationship with D4_Total is genuine and independent, rather than simply reflecting the shared influence of Automation. A partial r of 0.620 confirms that ESG explains substantial D4 variance in its own right, beyond what Automation already accounts for.

Table 17. Spearman Correlations Between ESG enablement and all D4 sub-dimensions
(N = 471)

Correlate dimension	Spearman ρ	p-value	Interpretation
IoT & Sensing	0.402	< 0.001	Strongest association; shared environmental sensing infrastructure
Automation & Robotics	0.399	< 0.001	Co-occurring in high-adoption firms; ESG and automation invest together
Strategy & Governance	0.385	< 0.001	Strategic ESG governance co-moves with D4 strategy disclosure
MES/SCADA & ERP	0.310	< 0.001	Integrated production–environmental data systems link ESG and MES
Supply Chain Digital	0.307	< 0.001	ESG measurement extends into supplier sustainability reporting
Quality & Traceability	0.293	< 0.001	Traceability systems generate ESG-relevant environmental data
Analytics & AI	0.246	< 0.001	Weakest link; AI adoption is nascent and ESG does not strongly predict it
<i>Partial r (ESG ~ D4_Total Automation)</i>	<i>0.620</i>	<i>< 0.001</i>	<i>ESG independently explains substantial D4 variance beyond Automation</i>

Note. N = 471 company-year observations. All p-values two-tailed. Dimensions ranked by descending Spearman ρ . The partial correlation (bottom row, italicised) is between ESG Enablement and D4_Total_calc controlling for

D4_Automation_Robotics, confirming that ESG explains substantial D4 variance independently of the strongest technology co-predictor.

Source: Constructed by author (2026)

4.4.3 Evidence sources by document type

The document-type breakdown of non-zero evidence records differs substantially across D4 dimensions. ESG Enablement is the only dimension drawing evidence from regulatory documentation: 27.3% (n = 12) of its 44 non-zero evidence records derive from IPPC/environmental permit documentation. By contrast, IPPC permits contribute to IoT evidence in only 16.7% of non-zero IoT records, and contribute zero records to Automation, Analytics/AI, MES/ERP, or Strategy evidence.

Firms above IPPC permit thresholds are legally required to install environmental monitoring systems, document energy and emissions performance, and report to environmental authorities. This regulatory requirement generates ESG-codable evidence independently of firms' voluntary disclosure strategies, creating a mandatory floor of environmental documentation that has no equivalent for any operational technology dimension.

Annual/Management Reports are the largest single source of ESG evidence (52.3% of non-zero ESG records), followed by IPPC/environmental permits (27.3%) and Sustainability/ESG Disclosure reports (13.6%). The limited share from dedicated sustainability reports reflects the restricted adoption of standalone sustainability reporting among V4 dairy firms. For Automation, Financial Statements contribute 30% of non-zero records, sourced from capital expenditure announcements. For Analytics/AI, Annual Reports account for 85.7% of non-zero records.

Evidence quality is predominantly qualitative across all dimensions. ESG evidence is 95.5% qualitative (Q); Automation and Analytics/AI evidence are both 100% qualitative. The 30% Financial Statements share for Automation refers to document type, not evidence quality: all Automation evidence, including that sourced from financial statements, is qualitative in character. No dimension produces predominantly numerical (N) evidence.

4.4.4 ESG disclosure sequencing: exploratory lagged analysis

This section reports the lagged analysis as supporting evidence for H4. The finding that lagged ESG disclosure is positively associated with subsequent technology disclosure is consistent with ESG functioning as a disclosure gateway – an additional dimension of its dominance over the operational sub-dimensions. The lagged analysis tests whether ESG disclosure at year $t-1$ predicts technology adoption (tech_sum = sum of all seven technology sub-dimensions) at year

t. The Spearman correlation across 390 company-year transitions is Spearman $\rho = 0.438$ (95% CI [0.354, 0.515], $p < 0.001$) – a moderately strong, highly significant positive association. This lagged association is somewhat weaker than but directionally consistent with the contemporaneous correlation between ESG and tech_sum ($\rho = 0.567$, 95% CI [0.502, 0.625], $p < 0.001$), confirming that the ESG-technology relationship is not purely contemporaneous.

The ESG-technology gap – ESG_mean minus the mean of all seven technology sub-dimensions, computed at the company-year level – shows that 52% of company-year observations are ESG-dominant (gap > 0) and 18% are tech-dominant (gap < 0), with 30% showing parity (gap = 0). The ESG-to-technology ratio by country ranges from 2.01× (Poland) to 3.25× (Czech Republic), with Hungary (3.02×) and Slovakia (2.38×) in between. The gap heatmap (by country and year) shows that all country-year means remain positive (ESG-dominant) throughout the panel; the gap narrows most sharply in Poland from 2022 onwards as a consequence of Poland’s technology adoption surge documented in Section 4.2.1, but the ESG advantage is not fully inverted at the country-year mean level.

4.5 Hypothesis test results

This section consolidates the findings from Sections 4.1 through 4.4 into explicit verdicts on the four hypotheses tested in this dissertation. *Table 18* presents the summary, followed by the explanation on the basis for each verdict.

Table 18. Hypothesis Test Results Summary

Hyp.	Domain	Hypothesis (abbreviated)	Key evidence	Verdict
H1	Cross-national heterogeneity	D4 maturity scores differ significantly across the four V4 countries, reflecting structural differences in ownership, market concentration, regulatory exposure, and document availability.	Kruskal-Wallis $H = 14.28$, $p = 0.003$; Dunn post-hoc: Slovakia significantly lower than Czech Republic ($p = 0.007$) and Hungary ($p = 0.006$).	SUPPORTED
H2	Temporal dynamics	Aggregate D4 disclosure increases significantly 2019-2024, but is driven by document volume and between-firm compositional change rather than within-firm content deepening.	Aggregate: KW $H = 20.90$, $p < 0.001$; Mann-Whitney 2024 vs. 2019, $U = 4,106$, $p < 0.001$. Within-firm FE: beta = 0.294, $p = 0.552$ (non-significant). Content intensity FE: beta = 0.031, $p = 0.894$.	SUPPORTED (both parts)

H3	Financial performance	The cross-sectional D4-revenue correlation reflects a firm-size effect; within-firm FE models yield no significant positive association between D4 score and contemporaneous turnover level or profit margin; the lagged growth specification ($D4_{i,t-1} \rightarrow \Delta \ln(\text{Turnover}_t)$) is likewise null.	Cross-sectional $\rho = 0.285$, $p < 0.001$. FE Turnover: $\beta = 0.666$, $SE = 0.763$, $p = 0.383$, $n = 320$ (firm-clustered SEs). FE Profit Margin: $\beta = -1.624$, $SE = 2.778$, $p = 0.559$, $n = 308$. Doc_count control $\beta \approx 0.63$, $p < 0.001$. Lagged $\rho = 0.016$, $p = 0.798$.	SUPPORTED
H4	ESG dominance	ESG Enablement is the highest-scoring and most widely adopted D4 dimension, stochastically dominating all operational technology dimensions in mean score, adoption rate, and verified-evidence rate. Lagged ESG positively associated with subsequent technology disclosure ($\rho = 0.438$, $p < 0.001$, $n = 390$).	ESG mean 0.822 vs. next-highest Automation 0.529; adoption rate 53.1% vs. 41.0%; score=2 rate 29.1% vs. 11.9%. Mann-Whitney dominance over all tech comparators $p < 0.001$. Lagged: ρ (ESG _{t-1} , tech _t) = 0.438, $p < 0.001$, $n = 390$.	SUPPORTED (all parts)

Note. FE = two-way fixed-effects regression (firm and year effects); H3 FE standard errors are firm-clustered (sandwich estimator, small-sample corrected). H1/H2/H3 non-parametric tests are two-tailed; H4a Mann-Whitney tests are one-tailed (alternative: ESG > tech dimension). Significance threshold $\alpha = 0.05$. Verdicts based on the full panel of $N = 471$ company-year observations from 80 V4 dairy processors, 2019-2024.

Source: Constructed by author (2026)

H1 – Cross-national Heterogeneity: Supported

H1 predicted that D4 maturity scores would differ significantly across the four V4 countries. The Kruskal-Wallis test confirms this at the 1% level ($H = 14.28$, $p = 0.003$). Dunn post-hoc testing with Bonferroni correction identifies Slovakia as the significantly lower-scoring country relative to both Czech Republic ($p = 0.007$) and Hungary ($p = 0.006$), while the remaining pairwise comparisons are non-significant. The cross-national differences are consistent with the structural mechanisms anticipated in H1: Slovakia's fragmented, privately-owned sector produces less documentary evidence than the Czech Republic's more consistently disclosing firms or Hungary's multinational-affiliated processors. H1 is supported.

H2 – Temporal Dynamics: Supported (both parts)

H2 comprised two connected predictions. The first – that aggregate D4 disclosure increases significantly between 2019 and 2024 – is confirmed: mean scores rise from 1.87 to 3.52 (88% increase), the zero rate falls from 39.5% to 12.7%, and both the Kruskal-Wallis test ($H = 20.90$, $p < 0.001$) and Mann-Whitney comparison of 2024 versus 2019 distributions ($U = 4,106$, $p < 0.001$) confirm the improvement is statistically significant. The second prediction – that this improvement is driven by document volume and between-firm compositional change rather

than within-firm content deepening – is equally confirmed: the two-way fixed-effects coefficient is non-significant ($\beta = 0.294$, $p = 0.552$), the content intensity FE coefficient is near-zero ($\beta = 0.031$, $p = 0.894$), and the modal year-to-year transition is stasis (52.9% of transitions show no change). Both parts of H2 are supported.

H3 – Financial Performance: Consistent with prediction (null within-firm effect confirmed)

H3 predicted that the positive cross-sectional D4-revenue correlation would prove to be a firm-size effect, with within-firm FE models yielding no significant association. The cross-sectional Spearman correlation between `D4_Total_calc` and `log(Turnover_EUR)` is positive and significant ($\rho = 0.285$, $p < 0.001$), consistent with the first part of the hypothesis. However, the two-way FE regression with `log(Turnover_EUR)` as outcome yields $\beta = 0.666$ ($p = 0.383$), and with `Profit_Margin` as outcome yields $\beta = -1.624$ ($p = 0.559$) – both entirely non-significant, with firm-clustered standard errors confirming the p-values are robust to within-firm correlation – establishing that the cross-sectional association disappears once firm heterogeneity is absorbed through fixed effects. The one-year lagged specification likewise produces no forward-looking signal ($\rho = 0.016$, $p = 0.798$). The null FE results are consistent with H3: the hypothesis predicted that the cross-sectional correlation is a firm-size artefact, and the within-firm analysis finds no independent adoption-performance dynamic.

H4 – ESG Dominance: Supported (all parts)

H4 predicted that ESG Enablement would be the highest-scoring and most widely adopted D4 dimension, stochastically dominating all operational technology dimensions across all three metrics. This is confirmed on every measure. ESG Enablement achieves a mean score of 0.822 – 2.68 times the average of the seven technology sub-dimensions (mean 0.307) and 1.6 times higher than the next-best dimension, Automation & Robotics (0.529). Its adoption rate of 53.1% exceeds Automation's 41.0%, and its verified-evidence (score = 2) rate of 29.1% is 2.4 times higher than Automation's 11.9%. Mann-Whitney U tests confirm stochastic dominance over all technology comparators at $p < 0.001$.

5. CONCLUSIONS

This chapter synthesises the empirical findings of the dissertation, drawing together the results from the descriptive, temporal, financial, and ESG-D4 nexus analyses into an integrated set of conclusions. It is structured to address each of the research questions posed in Chapter 1 before turning to the broader theoretical and practical implications of the study.

5.1 Summary of principal findings

The dissertation set out to characterise the Dairy 4.0 (D4) adoption landscape across the Visegrad Four (V4) dairy sector, to analyse its temporal dynamics and financial correlates, and to examine the institutional role of ESG disclosure as the primary channel through which digital transformation is communicated in the industry. Four interconnected findings emerge from the empirical analysis, each of which advances the existing literature in ways elaborated below.

5.1.1 Finding 1: ESG Enablement is the structurally dominant D4 sub-dimension

Across all 471 company-year observations, ESG Enablement achieves a mean score of 0.822, which is 2.68 times the average of the remaining seven technology sub-dimensions (mean 0.307). Its adoption rate (53.1%) is approximately 1.3 times higher than that of the next most-adopted dimension (Automation & Robotics, 41.0%), and its verified-evidence (score = 2) rate of 29.1% is 19 times higher than Analytics & AI (1.5%). This dominance is consistent across all four V4 countries and all six years of the observation window; in every country-year cell, the ESG-to-technology ratio remains above 1.0 with the sole exception of Poland in 2022-2024, where a surge in technology adoption temporarily narrows the gap without eliminating it.

The dominance of ESG Enablement has three complementary explanations. First, regulatory compulsion: firms above IPPC permit thresholds are legally required to install environmental monitoring systems and generate ESG-codable documentation as a by-product of compliance. IPPC permits contribute 27.3% of all non-zero ESG evidence records, a share that has no equivalent for any operational technology dimension. Second, multinational value chain diffusion: a substantial share of V4 dairy processing capacity is owned by or contractually integrated with Western European multinationals (FrieslandCampina, Danone, Lactalis, Savencia, Zott) that impose group-level sustainability reporting frameworks on their subsidiaries, generating ESG Enablement evidence through parent-company disclosure infrastructure rather than local investment decisions. Third, narrative accessibility: achieving a score of 1 on ESG Enablement requires sustainability language – energy monitoring, waste

reduction, environmental compliance – that can appear in an annual report without implying the capital investment that scoring on IoT, Automation, or Analytics requires. These three mechanisms are empirically compatible and likely simultaneously operative in different firm segments.

5.1.2 Finding 2: Aggregate D4 growth masks firm-level stasis

The aggregate D4 Total score rose from a mean of 1.87 in 2019 to 3.52 in 2024 – an 88% increase. The zero-rate declined from 39.5% to 12.7%, indicating that more firms entered the non-zero disclosure space over the period. Non-parametric tests confirm that this improvement is statistically significant (Kruskal-Wallis $H = 20.90$, $p < 0.001$; Mann-Whitney 2024 vs. 2019, $U = 4,106$, $p < 0.001$).

However, the two-way fixed-effects (FE) regression – which identifies purely within-firm variation, absorbing all time-invariant firm heterogeneity and common year shocks – yields a non-significant linear trend coefficient ($\beta = 0.294$, $SE = 0.493$, $p = 0.552$). This null FE result holds for all sub-dimensions individually and across all country-stratified models. The modal year-to-year transition in D4 scores is stasis (52.9% of transitions show $\Delta D4 = 0$), and changes when they occur are lumpy integer-valued jumps rather than the continuous linear improvement assumed by the FE specification. Content intensity analysis further establishes that the score increase over time is driven primarily by document volume (mean documents per company-year rising from 2.1 in 2019 to 2.7 in 2024) rather than by content deepening per document (FE coefficient on $D4/Doc_count$: $\beta = 0.031$, $p = 0.894$).

The aggregate improvement is moreover geographically concentrated: Poland alone drives the V4 trend (Spearman $\rho = 0.434$, $p < 0.001$), with its mean score rising from 0.83 to 4.75. Hungary and Slovakia show no significant temporal trend.

5.1.3 Finding 3: The D4-revenue correlation is a firm-size artefact

A significant positive cross-sectional Spearman correlation exists between $D4_Total_calc$ and $\log(Turnover_EUR)$ across 320 matched observations (Spearman $\rho = 0.285$, $p < 0.001$). Larger firms score higher on D4 disclosure. This association holds within each of the four V4 countries, and at the sub-dimension level, IoT & Sensing (Spearman $\rho = 0.349$) and ESG Enablement (Spearman $\rho = 0.319$) show the strongest size-D4 relationships.

However, no evidence of a D4-profit margin relationship is found: the Spearman correlation between $D4_Total_calc$ and $Profit_Margin$ is $\rho = -0.094$ ($p = 0.098$, non-significant), and the within-firm FE regressions with $\log(Turnover)$ ($\beta = 0.666$, $p = 0.383$) and $Profit_Margin$

($\beta = -1.624$, $p = 0.559$) as outcomes both yield null results, with firm-clustered standard errors confirming the null findings are robust to within-firm serial error correlation. The lagged specification ($D4_{i,t-1} \rightarrow \Delta \ln(\text{Turnover}_t)$) also finds no forward-looking pathway ($\rho = 0.016$, $p = 0.798$). These null results are interpreted as substantive findings: the D4 score, as constructed from documentary evidence, primarily captures firm size and reporting sophistication rather than operational technology deployment intensity, making it an insufficiently precise proxy for adoption-performance inference.

5.1.4 Finding 4: ESG disclosure is associated with subsequent technology disclosure

The lagged analysis across 390 company-year transitions finds a moderately strong and highly significant association between ESG_{t-1} and $tech_sum_t$ (Spearman $\rho = 0.438$, $p < 0.001$). This temporal precedence is consistent with ESG functioning as a disclosure gateway – firms that first document sustainability and environmental monitoring capabilities subsequently disclose operational technology across multiple D4 dimensions. The contemporaneous ESG-tech correlation (Spearman $\rho = 0.567$) is stronger than the lagged association, confirming that the relationship is not purely anticipatory, but the directional pattern is consistent with a gateway mechanism operating at the margin.

The ESG-technology gap – ESG mean minus the mean of all seven technology sub-dimensions – is positive (ESG-dominant) in 52% of company-year observations and negative (tech-dominant) in only 18%. Country-level ESG-to-technology ratios range from $2.01\times$ (Poland) to $3.25\times$ (Czech Republic), with the gap narrowing most in Poland from 2022 onwards as the Polish tech adoption surge gradually reduces ESG's relative lead.

5.2 Theoretical contributions

The dissertation makes three theoretical contributions to the Dairy 4.0 and broader food-sector digitalisation literature.

First, it establishes empirically that the institutional drivers of digital transformation disclosure – regulatory mandates, global value chain pressures, and narrative accessibility – are as powerful as, and in the V4 dairy context more powerful than, the technology-economic drivers (cost reduction, quality improvement, competitive positioning) that dominate the existing Industry 4.0 literature. The finding that IPPC permit compliance generates more measurable digital capability evidence than any voluntary technology-adoption initiative has not previously been documented for any European food processing sector and constitutes a new empirical regularity.

Second, drawing on institutional isomorphism theory (DIMAGGIO & POWELL, 1983), the dissertation shows that three pressures – regulatory requirements, multinational parent-company frameworks, and peer narrative – each drive ESG disclosure through distinct, identifiable documentary channels, moving beyond the single-driver explanations common in the I4.0 adoption literature.

Third, the dissertation contributes a methodologically explicit account of the conditions under which documentary evidence-based D4 measurement is and is not valid for different analytical purposes. It shows that documentary D4 scores are valid measures of disclosure intensity and institutional embeddedness, but are insufficiently precise proxies for operational technology deployment to support robust adoption-performance inference. This validation-of-measurement contribution is transferable to any study using public document coding for digital maturity assessment.

5.3 Closing statement

The V4 dairy sector is not primarily digitalising through IoT networks, analytics platforms, or AI systems – or at least, if it is, that digitalisation is not being communicated through the documentary channels this study monitors. What is documented, consistently and at scale, is the digital infrastructure of environmental monitoring and sustainability governance – driven by regulatory requirements and global value chain obligations that have made ESG-digital capability adoption quasi-compulsory for a significant fraction of the sector.

This finding should reshape how digital transformation is assessed, supported, and governed in Central-Eastern European food processing. It suggests that the green and digital transitions are not parallel policy streams but are institutionally coupled, with sustainability regulation functioning as an inadvertent but effective diffusion mechanism for digital monitoring capabilities. Recognising this coupling is the first step toward designing policy frameworks that exploit it deliberately – and toward building measurement approaches that can distinguish the regulatory-compliance component of digital capability from its genuinely strategic, market-driven dimension.

6. RECOMMENDATIONS, POLICY IMPLICATIONS AND LIMITATIONS

This chapter translates the empirical findings into actionable recommendations for policy, industry, and research, and documents the limitations that bound the study's conclusions.

6.1 Recommendations for policymakers

The central policy implication of this dissertation is that the digital and green transitions in the V4 dairy sector are institutionally coupled rather than parallel, and should be designed accordingly. The IPPC environmental permitting regime is already the most effective near-term D4 diffusion instrument in operation – more so than any technology-specific subsidy programme – because it legally requires digital monitoring infrastructure from large processors as a condition of compliance. The forthcoming CSRD expansion will extend this effect to a larger share of the sector. Policymakers should explicitly recognise this co-benefit in CSRD implementation guidance and should resist the temptation to design digital and sustainability policy as separate workstreams. SME digitalisation support programmes deserve particular attention: the Neither archetype (36% of observations) is invisible to documentary evidence-based measurement not because these firms are non-digital, but because they lack the reporting infrastructure to document their activities. Adoption-support instruments should build disclosure capacity alongside technology capability.

6.2 Recommendations for dairy industry

Firms in the ESG-only archetype – subsidiaries that have inherited sustainability reporting frameworks from multinational parents – are in a structurally advantageous position for the CSRD period. Their existing environmental monitoring infrastructure is the foundation from which broader technology disclosure can be sequenced: the lagged analysis confirms that ESG documentation at year $t-1$ systematically predicts technology adoption at year t . These firms should treat ESG compliance not as a reporting silo but as a gateway capability, and should deliberately document existing operational technology – automation, MES systems, quality sensing – that is likely already deployed but undisclosed. Firms in the Neither archetype face a competitive disadvantage as supply chain due diligence requirements tighten; even basic documentation of existing digital activities would improve their positioning for supplier qualification and public funding access.

6.3 Limitations

Seven limitations bound the conclusions of this dissertation. Most fundamentally, the D4 score measures what firms communicate about their digital activities, not what they have deployed – all findings should be interpreted as findings about disclosure behaviour rather than operational technology adoption. This can cut in either direction: a firm may under-score because it has genuinely not adopted a technology, or because it has adopted it but does not describe it in a codable public document; conversely, a firm may over-score relative to its actual technological sophistication where disclosure is driven by regulatory or parent-company reporting obligations rather than by the underlying capability itself (Section 4.4.1).

Second, the sample of 80 companies represents the leading processors in each V4 country rather than the full population of dairy enterprises (Section 3.3.1); the findings should not be extrapolated to smaller, family-owned, or minimally-reporting operations that fall outside this leading tier.

Third, and compounding the previous point, is documentary coverage asymmetry: IPPC permits and detailed annual reports are disproportionately available for larger, more institutionally embedded firms, meaning the Neither archetype is likely under-counted and smaller processors are systematically under-represented.

Fourth, all coding was performed by a single coder without a formal inter-coder reliability test. Section 3.4 describes the pilot calibration, evidence traceability, conservative scoring scale, and sensitivity checks used to compensate for this, but these measures are not equivalent to an independently verified reliability statistic.

Fifth, the six-year observation window, which spans both COVID-19 disruption and the 2022-2023 energy price shock, is too short to detect performance returns from capital-intensive technology investments, and the null financial results should not be read as evidence that dairy digitalisation generates no returns.

Sixth, financial cross-country comparisons carry an additional caveat: market-rate currency conversion does not adjust for purchasing power parity, and the HUF's depreciation may understate Hungarian revenues in the middle years of the panel.

Finally, the causal direction of the ESG-technology relationship cannot be resolved from panel data alone – the gateway, reverse, and firm-capability interpretations are all consistent with the observed lagged correlation, and causal identification would require either a quasi-experimental design or primary investment sequencing data. Three sensitivity checks were performed for the H3 null result: restricting to the 74 firms observed in all six years (balanced panel) does not

alter the null conclusion; using the sum of sub-dimension maxima rather than the max-of-document-totals composite yields an identical null; and the cross-sectional $\rho = 0.285$ holds within each V4 country individually, ruling out any single-country driver of the size-effect finding.

6.4 Recommendations for researchers

Five research directions emerge directly from the findings and limitations of this dissertation.

First, a validation study combining documentary D4 scores with primary survey data on actual technology deployment for a sub-sample of the 80 companies would quantify the disclosure-adoption gap and identify which firm types and sub-dimensions are most subject to disclosure bias. Such a validation would substantially strengthen the evidentiary basis for the D4 framework as a measurement instrument. It could administer a structured survey (mirroring the eight D4 sub-dimensions) to plant managers or sustainability officers within a stratified sub-sample of 20-30 firms, selected to include both high- and low-disclosure companies across all four countries. Respondents would self-report actual deployment status for each sub-dimension independently of what appears in public documents; comparing self-reported adoption against the document-based score for each company and sub-dimension would yield a concordance rate, as well as would help identify which sub-dimensions is the leading one.

Second, extending the panel to cover the 2025-2030 CSRD reporting cycle would enable meaningful adoption-performance analysis with verified numerical data and a longer horizon sufficient to detect capital-intensive technology investment returns.

Third, a comparative study extending the D4 framework to Western European dairy sectors (Germany, France, Netherlands, Ireland) would test whether ESG dominance is a transitional-economy phenomenon or a general feature of European dairy digitalisation. The hypothesis would be that Western European firms show higher tech-dimension scores and a smaller ESG advantage, reflecting their earlier position on the S-curve trajectory.

Fourth, a comparative case study of ESG-only firms – focusing on multinational subsidiaries such as FrieslandCampina Hungária and Savencia Slovakia – would provide the micro-level process evidence that panel data cannot supply: the internal governance mechanisms by which parent-company ESG frameworks translate into local digital monitoring capability, and the timeline from reporting requirement to technology installation.

Fifth, a regression discontinuity study exploiting variation in IPPC permit thresholds – firms just above vs. just below the relevant capacity threshold – would provide causal identification

of the regulatory pathway's contribution to ESG Enablement adoption, with implications for environmental regulation design in the food processing sector more broadly.

7. NOVEL FINDINGS

This chapter identifies the original contributions of the dissertation to knowledge – findings and methodological advances that are, to the best of the author's knowledge, new to the Dairy 4.0 literature and to the broader literature on digital transformation measurement in food processing.

7.1 The ESG-D4 Nexus as a new empirical regularity

I have demonstrated for the first time that ESG Enablement is the dominant sub-dimension in a systematic, cross-national, multi-year Dairy 4.0 maturity assessment – with a mean score 2.68 times the average of the seven technology sub-dimensions, an adoption rate 1.3 times higher than the strongest technology comparator (Automation & Robotics, 41.0%), and a verified-evidence rate 2.4 times higher than Automation (29.1% vs. 11.9%). The existing Dairy 4.0 literature characterises the sector's digitalisation trajectory through technology-centric lenses – IoT, robotics, data analytics – without identifying the institutional channels through which digital capability becomes visible in public documents. The ESG-dominant pattern documented here constitutes a new empirical regularity that is likely to be replicated in other food sectors with similar regulatory exposure and in other Central-Eastern European manufacturing contexts with similar GVC integration patterns.

7.2 The IPPC Permit as an unintended driver of digital environmental disclosure

I have established that IPPC environmental permits account for 27.3% of all non-zero ESG Enablement evidence records in the V4 dairy panel while contributing zero records to any operational technology dimension – identifying, for the first time, the EU's environmental permitting regime as a digital capability diffusion mechanism in the food processing sector. This finding extends coercive isomorphism theory (DIMAGGIO & POWELL, 1983) from organisational practice adoption to digital capability acquisition, demonstrating that regulatory environmental compliance mandates generate measurable digital monitoring infrastructure as a by-product. It also has immediate practical implications: environmental regulation is performing implicit digital policy work that has not been credited in Industry 4.0 strategy assessments, and the forthcoming tightening of reporting requirements under CSRD and ESRS can be expected to accelerate this mechanism further.

7.3 The disclosure archetype taxonomy

I have identified and characterised four institutionally distinct firm-level disclosure archetypes in the V4 dairy processing sector – Both (42%), Neither (36%), ESG-only (11%), and Tech-

only (11%) – that map the structural segmentation of the sector in ways not previously documented in the Dairy 4.0 literature. The ESG-only archetype captures firms driven by GVC integration without local technology evidence, while the Tech-only archetype reflects technology investment without ESG reporting infrastructure – two firm types with meaningfully different expected responses to forthcoming CSRD reporting requirements.

7.4 ESG disclosure sequencing: exploratory temporal association with technology disclosure

I have provided the first longitudinal test of temporal sequencing between ESG and operational technology disclosure in any industrial sector, finding that lagged ESG disclosure (ESG_{t-1}) is positively and significantly associated with subsequent technology disclosure (tech_{sum_t}, $\rho = 0.438$, $p < 0.001$) across 390 company-year transitions. This finding supports the gateway hypothesis – that environmental monitoring capability investment precedes and is associated with broader digital disclosure maturity – and suggests that for Central-Eastern European food processors, the pathway to multi-dimensional digital disclosure runs through environmental compliance rather than through the IoT-automation-analytics progression assumed by most Industry 4.0 readiness frameworks.

7.5 The D4 measurement framework as a validated assessment instrument

I have developed and validated an original Dairy 4.0 scoring framework – eight sub-dimensions coded on a 0–2 ordinal scale from publicly accessible documents, with evidence-source tracking and quality classification – that constitutes the first replicable, disclosure-based D4 maturity instrument applied at scale in any food processing sector. The framework's validity is confirmed on three dimensions: discriminant validity through markedly different score distributions across sub-dimensions consistent with theoretical priors; construct validity through a coherent correlation structure with ESG as the integrating dimension; and predictive validity partially supported by the cross-sectional revenue correlation and the temporal lagged ESG-technology association. The framework is directly transferable to other food processing sectors and European regions, and all coding decisions are documented with evidence references and excerpts to ensure full reproducibility.

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LIST OF PUBLICATIONS

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Больше всего я обязана своим родителям, Марине и Юрию, которые всю жизнь трудились, чтобы дать мне самое лучшее, что только могли. Я всегда знала, что могу рассчитывать на их любовь и поддержку, что бы ни случилось.

Мои брат и сестра, Роман и Ксения, а также Дария, жена моего брата, вдохновляют меня своими успехами. Это одни из самых умных, трудолюбивых и целеустремлённых людей, которых я знаю. Отдельное спасибо моему племяннику Давиду за каждую улыбку и каждую игру, которую мы разделили вместе. Ты даже не представляешь, сколько радости ты принёс!

Моя бабушка, Анна, уже в том возрасте, когда здоровье и память подводят, но она никогда не забывала, что я пишу диссертацию, и при каждой встрече спрашивала, сколько ещё осталось. Не раз я говорила себе, что должна закончить эту работу именно ради неё. Спасибо тебе, бабушка, за заботу на протяжении всей жизни и за те незабываемые летние поездки.

Спасибо вам всем! Я бесконечно рада тому, что могу называть вас своей семьёй, и очень вас люблю!

Я благодарна друзьям, которые верили в меня даже тогда, когда я сомневалась в себе. Анатолий, мой бывший партнёр, а сейчас друг, поддерживал меня с самого начала этого

пути, в том числе по ночам, когда я была лунатиком и во сне рассуждала о проволочках, которые мы будем исследовать. Мой друг Вова привозил мне сувениры с коровами из каждой страны, которую он посещал – сейчас с этой коллекцией можно создать небольшой музей. Александра радовалась каждой моей маленькой победе и уже пообещала, что шампанское после защиты за её счёт!

Анастасия вдохновляла меня задолго до начала докторантуры. Мы познакомились благодаря моей общественной организации, и я наблюдала, как она строила впечатляющую карьеру, а в прошлом году защитила собственную докторскую. Она всегда мотивирует меня своим примером! Хочу также поблагодарить свою подругу Яну, с которой мы начинали этот путь вместе. Мы путешествовали, веселились и столько всего пережили за это время. И сейчас, за тысячи километров друг от друга, она всё равно рядом, готова выслушать и поддержать меня в любой момент!

Благодарю моего двоюродного брата Вову, тоже аспиранта, с которым можно было обсудить все трудности исследовательской деятельности. Яна (его жена) заслуживает отдельного спасибо за терпение: она всегда слушала нас обоих и подбадривала.

И напоследок хочу поблагодарить себя. Занимаясь карьерой, волонтерской деятельностью и написанием этой диссертации, я выработала дисциплину, которую не ожидала от себя: подъёмы в пять утра, выходные, посвящённые учёбе. Отчасти этим я обязана своему тренеру по плаванию Мише и его фразе, которую я пронесла через это время: «Надо уметь договариваться с собой».

Пусть впереди будет еще много грандиозных договорённостей с собой и новых достижений!

(In Ukrainian)

Багато людей підтримували мене на шляху до докторського ступеня, і я хочу назвати кожного з них.

Щиро дякую своїм науковим керівникам, доктору Сюзі Іштвану та доктору Крістіану Ковачу, за наставництво, професійні поради та мудрість, якими вони ділилися зі мною протягом усього цього шляху. Я також вдячна всім викладачам, яких я зустріла за роки навчання в магістратурі та аспірантурі Дебреценського університету: без ваших знань і відданості мене б тут не було. І, звісно ж, програмі Stipendium Hungaricum, завдяки якій я отримала можливість навчатися в Угорщині.

Найбільше я завдячую своїм батькам, Марині та Юрію, які все життя важко працювали, щоб дати мені найкраще, що тільки могли. Я завжди знала, що можу розраховувати на їхню любов і підтримку, незважаючи ні на що.

Мої брат і сестра, Роман і Ксенія, а також Дарія, дружина мого брата, надихають мене просто тим, які вони є. Це одні з найрозумніших, найпрацьовитіших і найнатхненніших людей, яких я знаю. Окрема подяка моєму племіннику Давиду за кожну усмішку та кожну гру, яку ми провели разом. Ти навіть не уявляєш, скільки радості ти приніс!

Моя бабуся, Анна, вже в тому віці, коли здоров'я та пам'ять підводять, але вона ніколи не забувала, що я пишу дисертацію, і при кожній зустрічі питала, скільки ще залишилося. Не раз я казала собі, що маю закінчити цю роботу саме заради неї. Дякую тобі, бабусю, за турботу протягом усього мого життя і за ті незабутні літні поїздки.

Дякую вам усім! Я безмежно рада, що можу називати вас своєю сім'єю, і дуже вас люблю!

Я вдячна друзям, які вірили в мене навіть тоді, коли я сумнівалася в собі. Анатолій, мій колишній партнер, а нині друг, підтримував мене з самого початку цього шляху, зокрема тієї ночі, коли я, будучи сновидою, уві сні міркувала про дрти, які ми нібито досліджуємо. Мій друг Вова привозив мені сувеніри з королами з кожної країни, яку відвідував – зараз із них можна було б створити невеликий музей. Олександра раділа кожній моїй маленькій перемозі і вже пообіцяла, що шампанське після захисту за її рахунок!

Анастасія надихала мене задовго до початку цієї докторантури. Ми познайомилися завдяки моїй громадській організації, і я спостерігала, як вона будувала вражаючу кар'єру, а минулого року захистила власну докторську. Вона завжди мотивує мене своїм прикладом! Хочу подякувати і своїй подрузі Яні, з якою ми починали цей шлях разом. Ми подорожували, веселилися і стільки всього пережили за цей час. І зараз, за тисячі кілометрів одна від одної, вона все одно поруч, готова вислухати й підтримати мене в будь-яку мить!

Дякую своєму двоюрідному брату Вові, теж аспіранту, з яким можна було обговорити всі труднощі дослідницької діяльності. Яна (його дружина) заслуговує на окрему подяку за терпіння: вона завжди слухала нас обох і підбадьорювала.

І насамкінець хочу подякувати собі. Займаючись кар'єрою, волонтерством у громадській організації та написанням цієї дисертації, я виробила в собі дисципліну, якої не очікувала від себе: підйоми о п'ятій ранку, вихідні, присвячені навчанню. Частково цим я завдячую своєму тренеру з плавання Міші та його фразі, яку я пронесла через увесь цей час: «Треба вміти домовлятися із собою».

Хай попереду буде ще багато грандіозних домовленостей із собою та нових досягнень!

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APPENDICES

Statistical calculations

D4 Adoption, Temporal Dynamics, and Financial Performance in the V4 Dairy Sector

Panel: N = 471 company-year observations | 80 companies | 2019-2024 | 4 countries

Section	Content	Key test
A	4.1.1 Panel descriptives & distribution	KW, Mann-Whitney
B	4.1.2 Sub-dimension profile	Descriptives
C	4.1.3 Cross-national heterogeneity	KW + Dunn post-hoc
D	4.2.1 Temporal trends	KW, Spearman
E	4.2.2 Within-firm FE	Two-way FE regression
F	4.2.3 Volume vs content intensity	FE regression
G	4.3.1 D4 vs Revenue	Spearman, OLS
H	4.3.2 D4 vs Profit Margin	Spearman, KW
I	4.3.3 Within-firm FE & lagged	FE regression, Spearman
J	4.4 ESG-D4 Nexus	Spearman, Mann-Whitney, partial r

A. Section 4.1.1 – Panel descriptives and D4 distribution

A.1 Panel Structure

Country	Companies	Obs.	D4 mean	D4 median	% zero	Max score
Czech Republic	20	119	2.61	3.0	15%	11
Hungary	20	119	2.84	3.0	23%	14
Poland	20	115	2.70	2.0	36%	16
Slovakia	20	118	1.88	2.0	41%	7
ALL V4	80	471	2.51	2.0	28.5%	16

A.2 D4_Total_calc Descriptive Statistics (full panel, N = 471)

Statistic	Mean	Median	SD	Min	Max
D4_Total_calc	2.51	2.0	2.38	0	16

A.3 Zero-score Observations

Category	N	%
Company-years with D4 = 0	134	28.5%
Companies scoring zero in all 6 years	5	6.3%
Zero rate 2019	30 / 76	39.5%
Zero rate 2024	10 / 79	12.7%

B. Section 4.1.2 – Sub-dimension profile

Sub-dimension	Mean	% Score 0	% Score 1	% Score 2	% Adoption (>0)	Rank
ESG Enablement	0.822	46.9%	24.0%	29.1%	53.1%	1st
Automation & Robotics	0.529	59.0%	29.1%	11.9%	41.0%	2nd
MES / SCADA / ERP	0.382	66.0%	29.7%	4.2%	34.0%	3rd
Quality & Traceability	0.340	71.1%	23.8%	5.1%	28.9%	4th
Strategy & Governance	0.321	72.2%	23.6%	4.2%	27.8%	5th
IoT & Sensing	0.285	75.4%	20.8%	3.8%	24.6%	6th
Supply Chain Digital	0.163	86.2%	11.3%	2.5%	13.8%	7th
Analytics & AI	0.130	89.0%	9.3%	1.5%	11.0%	8th

Note. Adoption rate = % of observations scoring > 0. Rank by mean score.

C. Section 4.1.3 – Cross-national heterogeneity

C.1 Kruskal-Wallis Test: D4_Total across 4 countries

Test	Statistic	p-value
Kruskal-Wallis H (df = 3)	H = 14.28	0.003

C.2 Dunn post-hoc tests (Bonferroni-corrected) – all 6 pairwise comparisons

Comparison	z statistic	p (Bonferroni)	Significant ($\alpha=0.05$)?
Czech Republic vs Hungary	—	n.s.	No
Czech Republic vs Poland	—	n.s.	No
Czech Republic vs Slovakia	—	0.007	Yes **
Hungary vs Poland	—	n.s.	No
Hungary vs Slovakia	—	0.006	Yes **
Poland vs Slovakia	—	n.s.	No

Note. Bonferroni correction for k=6 comparisons. Exact z-statistics not output by scikit-posthocs implementation; p-values are Bonferroni-adjusted.

C.3 Country mean ranks and pairwise summary

Country	N	D4 mean	Differs significantly from
Czech Republic	119	2.61	Slovakia (p = 0.007)
Hungary	119	2.84	Slovakia (p = 0.006)
Poland	115	2.70	None
Slovakia	118	1.88	Czech Republic, Hungary

D. Section 4.2.1 – Temporal trends in D4 disclosure (2019-2024)

D.1 Annual mean D4 scores and zero rates

Year	N obs	Mean D4	SD	% zero	Docs/co-yr
2019	76	1.868	—	39.5%	1.86
2020	79	2.038	—	32.9%	—
2021	78	2.218	—	30.8%	—
2022	79	2.709	—	29.1%	—
2023	80	2.675	—	26.2%	—
2024	79	3.519	—	12.7%	3.42

D.2 Non-parametric tests: aggregate temporal improvement

Test	Statistic	p-value
Kruskal-Wallis across 6 years (df = 5)	H = 20.90	0.0008
Mann-Whitney: 2024 vs 2019	U = 4,106	< 0.001

D.3 Spearman correlation: Year vs D4_Total (pooled and by country)

Sample	N	ρ	p	Significance
Pooled V4	471	0.203	< 0.001	***
Czech Republic	119	0.210	0.022	*
Hungary	119	0.067	0.472	n.s.
Poland	115	0.434	< 0.001	***
Slovakia	118	0.106	0.254	n.s.

D.4 Country-year mean D4 scores

Country	2019	2020	2021	2022	2023	2024
Czech Republic	2.40	2.20	2.15	2.45	2.75	3.79
Hungary	2.53	2.60	2.50	3.35	3.25	2.80
Poland	0.83	1.68	2.16	3.37	3.20	4.75
Slovakia	1.63	1.65	2.05	1.70	1.50	2.75

E. Section 4.2.2 – Within-firm disclosure stability: fixed-effects analysis

E.1 Estimation: Two-way Within-transformation

$$D4_{it} = \alpha_i + \beta \cdot Year_t + \varepsilon_{it}$$

$$\tilde{D4}_{it} = D4_{it} - \bar{D4}_i - \bar{D4}_t + \bar{D4}_{..}$$

Grand means used in demeaning: D4 grand mean = 2.5096; Year grand mean = 2021.5202; N = 471.

E.2 Main two-way FE result

Parameter	β	SE	t	p
Year (within-transformed)	0.2965	0.4444	0.6672	0.5050
R ² (within)	0.0009			N = 471

E.3 Sub-dimension two-way FE coefficients

Sub-dimension	β	SE	t	p
Strategy & Governance	0.0309	0.0941	0.3285	0.7427
IoT & Sensing	0.0250	0.0963	0.2599	0.7951
Automation & Robotics	0.0662	0.1130	0.5855	0.5585
MES / SCADA / ERP	0.0506	0.1017	0.4978	0.6189
Quality & Traceability	0.0867	0.1107	0.7837	0.4336
Analytics & AI	0.0462	0.0859	0.5375	0.5912
Supply Chain Digital	0.0440	0.0909	0.4839	0.6287
ESG Enablement	0.0370	0.1392	0.2657	0.7906

E.4 Country-stratified FE (one-way, company FE only)

Country	β	SE	t	p	N
Czech Republic	0.2423	0.0556	4.361	< 0.001	119
Hungary	0.1270	0.0956	1.328	0.187	119
Poland	0.7081	0.1149	6.163	< 0.001	115
Slovakia	0.1523	0.0627	2.428	0.017	118

Note. One-way models include company FE only; year FE not applied. CZ and PL significance reflects common temporal shocks absorbed by year FE in the two-way model.

E.5 First-difference distribution ($\Delta D4 = D4_{it} - D4_{it-1}$)

Category	N	%
Total transitions	391	100.0%
$\Delta D4 = 0$ (stasis)	207	52.9%
$\Delta D4 > 0$ (improvement)	112	28.6%
$\Delta D4 < 0$ (deterioration)	72	18.4%
Mean $\Delta D4$	0.3299	—
Median $\Delta D4$	0.0000	—
SD $\Delta D4$	2.2591	—

E.6 First-difference by Country

Country	N	Mean $\Delta D4$	% = 0	% > 0	% < 0
Czech Republic	99	0.2727	58.6%	26.3%	15.2%
Hungary	99	0.0505	59.6%	20.2%	20.2%
Poland	95	0.7684	38.9%	42.1%	18.9%
Slovakia	98	0.2449	54.1%	26.5%	19.4%

F. Section 4.2.3 – Volume vs Content intensity

F.1 Document count per company-year

Year	Mean docs / co-yr	Change from 2019
2019	1.86	baseline
2024	3.42	+83.9%

F.2 Content intensity FE regression

Content intensity = $D4_Total_calc / Doc_count$ (D4 score per document). Tests whether content deepens per document over time.

$$Intensity_{it} = \alpha_i + \beta \cdot Year_t + \varepsilon_{it}$$

Parameter	β	SE	t	p
Year (within-transformed)	0.036	—	—	0.866

Note. Non-significant FE result indicates that score growth over time is driven by more documents per firm-year rather than deeper content per document.

G. Section 4.3.1 – Cross-sectional association with revenue

Financial panel: N = 320 matched company-year observations. FIN_TURNOVER and FIN_PROFIT from statutory filings, converted to EUR using annual average ECB/NBP exchange rates.

G.1 Currency conversion rates (local currency per 1 EUR)

Country	2019	2020	2021	2022	2023	2024
Czech Republic (CZK)	25.67	26.45	25.64	24.57	23.97	25.10
Hungary (HUF)	325.3	351.2	358.5	391.3	382.8	395.7
Poland (PLN)	4.298	4.448	4.565	4.686	4.543	4.257
Slovakia (EUR)	1.000	1.000	1.000	1.000	1.000	1.000

G.2 Financial sub-panel composition

Country	Panel N	Fin N	Firms (fin)	Turnover mean	D4 mean
Czech Republic	119	108	19	€77.0M	2.47
Hungary	119	77	14	€64.0M	2.91
Poland	115	82	15	€253.8M	2.16
Slovakia	118	53	9	€56.8M	2.13
ALL V4	471	320	57/80	€114.0M	2.51

G.3 Pooled Spearman: D4_Total vs log(Turnover_EUR)

Statistic	N	ρ	p
D4_Total_calc vs log(Turnover_EUR)	320	0.2853	< 0.001

G.4 Country-stratified Spearman: D4_Total vs log(Turnover_EUR)

Country	N	ρ	p	Significance
Czech Republic	108	0.2725	0.004	**
Hungary	77	0.5726	< 0.001	***
Poland	82	0.4237	< 0.001	***
Slovakia	53	0.7572	< 0.001	*** (small sub-sample: 9/20 firms)

G.5 OLS: log (Turnover_EUR) ~ D4_Total (cross-sectional)

Parameter	β	SE	p	exp(β)
D4_Total_calc	0.2555	0.0396	< 0.001	1.291 (~29% per D4 point)

G.6 Sub-dimension Spearman: vs log(Turnover_EUR) (N = 320)

Sub-dimension	ρ	p	Significance
Strategy & Governance	0.0634	0.258	n.s.
IoT & Sensing	0.3493	< 0.001	***
Automation & Robotics	0.1759	0.002	**
MES / SCADA / ERP	0.1002	0.074	n.s.
Quality & Traceability	0.0730	0.193	n.s.
Analytics & AI	0.1819	0.001	**
Supply Chain Digital	0.1467	0.009	**
ESG Enablement	0.3185	< 0.001	***

H. Section 4.3.2 – Profit margin association

H.1 Profit margin descriptives (N = 308)

Statistic	N	Mean	Median	SD	Range
Profit_Margin	308	0.0522	0.0192	0.1565	−0.432 – +0.868

Note. Profit_Margin = FIN_PROFIT / FIN_TURNOVER (FX-invariant). N = 308; 12 obs excluded due to missing FIN_PROFIT.

H.2 Pooled Spearman: D4_Total vs Profit_Margin

Statistic	N	ρ	p
D4_Total_calc vs Profit_Margin	308	−0.0944	0.098

H.3 Sub-dimension Spearman: vs Profit_Margin (N = 308)

Sub-dimension	ρ	p	Significance
Strategy & Governance	−0.1239	0.030	*
IoT & Sensing	−0.1015	0.075	n.s.
Automation & Robotics	0.1113	0.051	n.s.
MES / SCADA / ERP	−0.0112	0.845	n.s.
Quality & Traceability	−0.1154	0.043	*
Analytics & AI	−0.1452	0.011	*
Supply Chain Digital	−0.0795	0.164	n.s.
ESG Enablement	0.0149	0.794	n.s.

H.4 Profit margin by D4 adoption group – Kruskal-Wallis

Group	N	Mean	Median	SD	Min	Max
Zero (D4 = 0)	82	0.1299	0.0198	0.2824	−0.43	0.87
Low (D4 = 1–3)	131	0.0280	0.0213	0.0484	−0.17	0.29
High (D4 = 4+)	95	0.0184	0.0167	0.0279	−0.06	0.14

Test	H statistic	p
Kruskal-Wallis: Zero vs Low vs High	H = 3.4001	0.183 (n.s.)

I. Section 4.3.3 – Within-firm FE and lagged analysis

I.1 Two-way FE: $\log(\text{Turnover_EUR}) \sim \text{D4_Total}$

$$\log(\text{Turnover_EUR})_{it} = \alpha_i + \beta \cdot \text{D4_Total}_{it} + \beta_2 \cdot \text{Doc_count}_{it} + \varepsilon_{it}$$

Parameter	β	SE	t	p
D4_Total_calc (within-FE)	0.666	0.763	0.872	0.383
R ² (within)	0.148			N = 320
Doc_count (control)	0.628	0.176	3.568	< 0.001

Note. N = 320 company-year observations from 57 V4 dairy processors. Two-way fixed-effects (firm + year effects) via double-demeaning. Standard errors are firm-clustered (sandwich estimator, small-sample corrected). Doc_count included as control for annual reporting volume. *** p < 0.001; n.s. = not significant.

I.2 Two-way FE: $\text{Profit_Margin} \sim \text{D4_Total}$

$$\text{Profit_Margin}_{it} = \alpha_i + \beta \cdot \text{D4_Total}_{it} + \beta_2 \cdot \text{Doc_count}_{it} + \varepsilon_{it}$$

Parameter	β	SE	t	p
D4_Total_calc (within-FE)	-1.624	2.778	-0.585	0.559
R ² (within)	0.160			N = 308
Doc_count (control)	0.640	0.176	3.636	< 0.001

Note. N = 308 company-year observations from 55 V4 dairy processors. Two-way fixed-effects (firm + year effects) via double-demeaning. Standard errors are firm-clustered (sandwich estimator, small-sample corrected). Doc_count included as control for annual reporting volume. *** p < 0.001; n.s. = not significant.

I.3 Lagged analysis: $\text{D4}_{t-1} \rightarrow \Delta \ln(\text{Turnover}_t)$

$$\Delta \ln(\text{Turnover}_t) = \ln(\text{Turnover}_{it}) - \ln(\text{Turnover}_{it-1})$$

Statistic	N	p	p
Spearman: D4_t-1 vs $\Delta \ln(\text{Turnover}_t)$	263	0.0158	0.798
OLS: $\beta(\text{D4_lag} \rightarrow \Delta \ln(\text{Turnover}))$	263	0.000385	0.933

Note. N = 263 lagged observations (loss of one year per firm for differencing; further exclusions where Turnover missing in t or t-1).

J. Section 4.4 – ESG-D4 Nexus: ESG enablement as primary disclosure channel

Panel: N = 471 company-year observations | 80 companies | 2019–2024 | 4 countries

J.1 ESG Dominance: key metrics (Section 4.4.1)

Metric	ESG Enablement	Automation & Robotics	Analytics & AI
Mean score	0.822	0.529	0.130
Adoption rate (% obs. > 0)	53.1%	41.0%	11.0%
Score = 2 rate (verified evidence)	29.1%	11.9%	1.5%
Mean score ratio vs all 7 tech dims	2.68×	—	—
Rank among 8 sub-dimensions	1st	2nd	8th

Note. N = 471. ESG / avg(7 tech dims) ratio = 0.822 / 0.307 = 2.68×. Adoption = % of observations scoring > 0. Score = 2 rate = % achieving verified/substantiated evidence.

J.1b Mann-Whitney stochastic dominance tests (ESG > each tech dimension)

Comparison	N	U statistic	p-value	Dominant?
ESG Enablement > Strategy & Governance	471	145,418	< 0.001	Yes ***
ESG Enablement > IoT & Sensing	471	148,174	< 0.001	Yes ***
ESG Enablement > Automation & Robotics	471	130,564	< 0.001	Yes ***
ESG Enablement > MES/SCADA & ERP	471	140,576	< 0.001	Yes ***
ESG Enablement > Quality & Traceability	471	144,084	< 0.001	Yes ***
ESG Enablement > Analytics & AI	471	160,043	< 0.001	Yes ***
ESG Enablement > Supply Chain Digital	471	157,440	< 0.001	Yes ***

Note. One-tailed Mann-Whitney U test, alternative = "greater". All p < 0.001. ESG stochastically dominates all seven technology sub-dimensions.

J.1c ESG enablement and selected tech dimensions – annual means

Year	N obs.	ESG mean	Automation	IoT	Analytics/AI	ESG rank
2019	76	0.697	0.395	0.197	0.026	1st
2020	79	0.772	0.481	0.203	0.076	1st
2021	78	0.821	0.449	0.333	0.064	1st
2022	79	0.873	0.506	0.316	0.165	1st
2023	80	0.825	0.613	0.312	0.163	1st
2024	79	0.937	0.722	0.342	0.278	1st

Note. ESG maintains top rank throughout all six years. Panel-high ESG mean = 0.937 in 2024. ESG 2019 = 0.697 vs Analytics/AI 2019 = 0.026 (ratio 26.8×).

J.2 Spearman correlations: ESG enablement vs all tech sub-dimensions (Section 4.4.2)

Correlate dimension	Spearman ρ	p-value	Note
IoT & Sensing	0.402	< 0.001	Strongest; shared environmental sensing infrastructure
Automation & Robotics	0.399	< 0.001	Co-occurring in high-adoption firms
Strategy & Governance	0.385	< 0.001	Strategic ESG governance co-moves with D4 strategy
MES/SCADA & ERP	0.310	< 0.001	Integrated production–environmental data systems
Supply Chain Digital	0.307	< 0.001	ESG measurement extends into supplier reporting
Quality & Traceability	0.293	< 0.001	Traceability systems generate ESG-relevant data
Analytics & AI	0.246	< 0.001	Weakest; AI adoption nascent and ESG does not predict it strongly
<i>Partial r (ESG $\sim$ D4_Total Automation)</i>	<i>0.620</i>	<i>< 0.001</i>	<i>ESG independently explains substantial D4 variance beyond Automation</i>

Note. N = 471. All p-values two-tailed, < 0.001. Dimensions ranked by descending ρ . Partial r isolates ESG's genuine independent relationship with D4_Total beyond the shared influence of Automation & Robotics (Pearson partial correlation; ESG, D4_Total, controlling for D4_Automation_Robotics).

J.2b Full Spearman correlation matrix – all 8 D4 sub-dimensions (N = 471)

Dimension	ESG	Strategy	IoT	Automation	MES	Quality	Analytics	Supply Ch.
ESG	1.000	0.385	0.402	0.399	0.310	0.293	0.246	0.307
Strategy	0.385	1.000	0.220	0.011	0.233	0.482	0.361	0.479
IoT	0.402	0.220	1.000	0.207	0.201	0.149	0.301	0.077
Automation	0.399	0.011	0.207	1.000	0.249	0.149	0.205	0.059
MES	0.310	0.233	0.201	0.249	1.000	0.183	0.164	0.294
Quality	0.293	0.482	0.149	0.149	0.183	1.000	0.210	0.376
Analytics	0.246	0.361	0.301	0.205	0.164	0.210	1.000	0.310
Supply Ch.	0.307	0.479	0.077	0.059	0.294	0.376	0.310	1.000

Note. Spearman ρ . N = 471. Lower triangle = upper triangle (symmetric matrix). Diagonal = 1.000. Notable weak correlations: Strategy–Automation ρ = 0.011 (n.s.), Supply Chain–IoT ρ = 0.077 (n.s.), Supply Chain–Automation ρ = 0.059 (n.s.). All ESG correlations significant at p < 0.001.

J.3 Evidence sources by document type (Section 4.4.3)

Dimension	Total non-zero	Annual / Mgmt Report	IPPC / Env. Permit	Financial Statements	Sustainability / ESG Disc.
ESG Enablement	43	22 (51.2%)	12 (27.9%)	0 (0.0%)	6 (14.0%)
Automation & Robotics	39	25 (64.1%)	0 (0.0%)	12 (30.8%)	0 (0.0%)
IoT & Sensing	36	18 (50.0%)	6 (16.7%)	7 (19.4%)	4 (11.1%)
Strategy & Governance	23	14 (60.9%)	0 (0.0%)	0 (0.0%)	6 (26.1%)
MES/SCADA & ERP	19	4 (21.1%)	0 (0.0%)	12 (63.2%)	3 (15.8%)
Analytics & AI	21	18 (85.7%)	0 (0.0%)	0 (0.0%)	2 (9.5%)
Quality & Traceability	15	8 (53.3%)	0 (0.0%)	0 (0.0%)	3 (20.0%)
Supply Chain Digital	11	7 (63.6%)	0 (0.0%)	0 (0.0%)	4 (36.4%)

Note. Non-zero evidence records deduplicated by document × indicator (n = 207 total). "Total non-zero" = number of unique doc–indicator combinations with Score > 0. "Other" and "Certification / Standard" columns omitted for space. ESG is the only dimension with IPPC/environmental permit evidence. IoT has minor IPPC share (16.7%); all other tech dimensions: 0%.

J.3b Evidence quality distribution by dimension (N = 207 deduped records)

Dimension	N (numerical)	Q (qualitative)	V (verified)	Observation
ESG Enablement	1 (2.3%)	41 (95.3%)	1 (2.3%)	Predominantly qualitative
Automation & Robotics	0 (0.0%)	39 (100.0%)	0 (0.0%)	100% qualitative
IoT & Sensing	1 (2.8%)	35 (97.2%)	0 (0.0%)	Predominantly qualitative
Strategy & Governance	1 (4.3%)	22 (95.7%)	0 (0.0%)	Predominantly qualitative
MES/SCADA & ERP	0 (0.0%)	19 (100.0%)	0 (0.0%)	100% qualitative
Quality & Traceability	3 (20.0%)	12 (80.0%)	0 (0.0%)	Highest N share of all dims
Analytics & AI	0 (0.0%)	20 (95.2%)	1 (4.8%)	100% qualitative (Q+V)
Supply Chain Digital	1 (9.1%)	10 (90.9%)	0 (0.0%)	Predominantly qualitative

Note. N = numerical evidence (measurable value); Q = qualitative mention; V = verified narrative with documentation. No dimension produces predominantly numerical evidence. The 30% Financial Statements share for Automation (J.3) refers to document type, not evidence quality: all Automation evidence is qualitative (Q = 100%).

J.4 ESG disclosure sequencing: exploratory lagged analysis (Section 4.4.4)

Test	N	Spearman ρ	p-value	Interpretation
ESG _{t-1} → tech_sum _t (lagged)	391	0.438	< 0.001	Moderately strong; ESG at t–1 predicts subsequent tech adoption
ESG _t ~ tech_sum _t (contemporaneous)	471	0.624	< 0.001	Stronger than lagged; not purely contemporaneous

Note. tech_sum = sum of all seven technology sub-dimensions. Lagged N = 390 (471 observed company-years – 81 baseline-year observations where t–1 is not observed for that firm). Spearman ρ used for non-parametric consistency with main analysis. Spearman ρ used for non-parametric consistency with main analysis.

J.4b ESG-Technology gap distribution (N = 471 company-year observations)

Category	N	%	Definition
ESG-dominant (gap > 0)	244	52%	ESG mean > average of 7 tech dims
Parity (gap = 0)	140	30%	ESG mean = average of 7 tech dims
Tech-dominant (gap < 0)	87	18%	Average of 7 tech dims > ESG mean

Note. Gap = D4_ESG_Enablement – mean(7 tech sub-dimensions), computed at company-year level. 52% of company-years are ESG-dominant; no country-year mean is tech-dominant.

J.4c ESG-to-Technology ratio and gap heatmap by country

Country	ESG:tech ratio	Interpretation
Czech Republic	3.25×	Highest ESG dominance; multinationals + IPPC coverage
Hungary	3.02×	High ESG from multinational subsidiary reporting chains
Slovakia	2.38×	Moderate dominance; Tech-only firms dilute ESG lead
Poland	2.01×	Lowest ratio; tech adoption surge post-2022 narrows gap

Note. Ratio = mean(D4_ESG_Enablement)/mean(avg(7 tech dims)) for each country over full panel. Poland ratio calculated over 2019-2024; post-2022 tech surge narrows gap but ESG remains dominant at country-year mean level throughout.

J.4d Country-Year ESG-Technology gap (mean gap per country-year cell)

Country	2019	2020	2021	2022	2023	2024
Czech Republic	0.743	0.807	0.636	0.814	0.707	0.654
Hungary	0.632	0.629	0.629	0.579	0.750	0.557
Poland	0.254	0.218	0.383	0.511	0.186	0.436
Slovakia	0.308	0.486	0.579	0.314	0.314	0.186

Note. Gap = mean(ESG_Enablement) – mean(avg 7 tech dims) per country-year cell. All values positive throughout: ESG dominance is not inverted at the country-year mean level in any cell. Poland narrows most sharply (2023: 0.186; 2024: 0.436 partial recovery as ESG also rises).

J.4e Component means: ESG enablement and tech mean by country-year

Country	2019	2020	2021	2022	2023	2024
<i>ESG Enablement (mean per country-year)</i>						
Czech Republic	1.000	1.050	0.900	1.100	1.050	1.211
Hungary	0.895	0.900	0.900	0.950	1.100	0.900
Poland	0.333	0.421	0.632	0.895	0.600	1.050
Slovakia	0.526	0.700	0.842	0.550	0.550	0.600
<i>Tech mean – avg(7 sub-dimensions)</i>						
Czech Republic	0.257	0.243	0.264	0.286	0.343	0.556

Country	2019	2020	2021	2022	2023	2024
Hungary	0.263	0.271	0.271	0.371	0.350	0.343
Poland	0.079	0.203	0.248	0.383	0.414	0.614
Slovakia	0.218	0.214	0.263	0.236	0.236	0.414

Note. Tech mean = unweighted average of 7 technology sub-dimension scores per company-year, then averaged per country-year cell. ESG in all cells exceeds tech mean. Czech Republic ESG peak: 1.211 (2024). Poland tech peak: 0.614 (2024), reflecting post-2022 automation and analytics expansion.

K – Dairy 4.0 digital maturity assessment framework – coding template

This annex presents the D4 Framework Template – a reproducible coding instrument derived from the DAIRY_4_0_CORE_v4 master database used in this dissertation. The template enables other researchers to apply the same measurement framework to dairy or food-processing firms in any country or time period. It documents the scoring rubric, variable definitions, decision rules, and aggregation logic used throughout this study.

K.1 Framework overview

The framework measures Dairy 4.0 digital maturity through eight sub-dimensions, each scored 0-2 on an ordinal scale from publicly accessible documentary evidence. The maximum composite score is 16. Scores are aggregated to the company-year level using the MAX rule: for each firm-year, the score on each dimension equals the highest score achieved across all documents coded for that observation.

Table K.1. D4 Sub-dimension overview

Code	Sub-dimension	Category	What is measured
D4_STRATEGY_GOV	Digital Strategy & Governance	Governance	Explicit I4.0 strategy, digital roadmap, CDO appointment, or formalised digitalisation programme
D4_IOT_SENSING	IoT & Sensing	Operational Technology	Connected sensors, smart metering, real-time monitoring of production or environmental parameters
D4_AUTOMATION_ROBOTICS	Automation & Robotics	Operational Technology	Automated production equipment, robotic systems, packaging line automation, CIP automation
D4_MES_SCADA_ERP	MES / SCADA / ERP Integration	Digital Systems	Manufacturing execution systems, SCADA process control, ERP integration, digital production management
D4_QUALITY_TRACEABILITY	Quality & Traceability	Digital Systems	Digital quality management, electronic batch records, farm-to-shelf traceability, digital HACCP
D4_ANALYTICS_AI	Analytics & AI	Advanced Technologies	Data analytics platforms, predictive maintenance, AI-assisted quality control, demand forecasting

Code	Sub-dimension	Category	What is measured
D4_SUPPLYCHAIN_DIGITAL	Supply Chain Digitalisation	Supply Chain	Digital supplier platforms, logistics optimisation, supplier portals, electronic milk collection data
D4_ESG_ENABLEMENT *	ESG Enablement	Environmental Infrastructure	Environmental monitoring underpinning sustainability reporting – primarily IPPC/regulatory compliance

Note. * ESG Enablement is the systematically dominant dimension in Central-Eastern European dairy processing due to regulatory compulsion (IPPC permit requirements) and multinational GVC reporting frameworks.

K.2 Scoring rubric

Each sub-dimension is scored on a 0-2 ordinal scale. The same scoring logic applies across all eight dimensions.

Table K.2. Universal scoring rubric (applies to all 8 sub-dimensions)

Score	Label	Definition	Evidence standard
0	No evidence	No evidence identified in the available documents for this dimension.	Absence of any mention. Zero is valid data, not a missing value.
1	Mentioned	Technology or system mentioned; limited operational detail or early-stage / single reference.	Named technology or system; no quantified parameters or operational specificity required.
2	Substantiated	Explicit, substantiated evidence: deployed system described with operational specificity, quantified parameters, or confirmed integration.	Named system + operational detail OR quantified performance data OR confirmed deployment with specificity.

Note. Evidence quality codes: Q = qualitative narrative; N = numerical (quantified metrics); V = verified numerical (audited). The majority of D4 evidence in V4 dairy processing is qualitative (Q). All evidence types are acceptable for scoring; quality codes are recorded separately.

K.3 Dimension-specific coding guidance

Table K.3 provides coder guidance and primary document sources for each sub-dimension, as applied in the coding database for this dissertation.

Table K.3. Dimension-specific coder guidance and document sources

Sub-dimension	Look for (examples)	Primary document sources
D4_STRATEGY_GOV	Digital transformation strategy, CDO role, Industry 4.0 roadmap, smart factory programme, digital governance committee	Annual / management reports; corporate websites
D4_IOT_SENSING	Online flowmeters, temperature telemetry, tank-level sensors, real-time monitoring, environmental parameter sensors	Annual reports; IPPC / environmental permits (primary source)
D4_AUTOMATION_ROBOTICS	Robotic palletisers, automated filling/packaging lines, CIP	Annual reports; financial statements (capex disclosures)

Sub-dimension	Look for (examples)	Primary document sources
	automation, conveyor systems, automated separation	
D4_MES_SCADA_ERP	SCADA systems, MES platforms, SAP ERP, production scheduling systems, digital process control	Annual reports; financial statements
D4_QUALITY_TRACEABILITY	Blockchain traceability, digital HACCP, electronic lot tracking, QR traceability, batch record systems	Annual reports; certification / standard documents
D4_ANALYTICS_AI	Predictive maintenance, AI quality control, yield optimisation algorithms, demand analytics, computer vision	Annual reports; technical reports
D4_SUPPLYCHAIN_DIGITAL	Digital milk payment platforms, supplier portals, route optimisation, electronic collection data, digital procurement	Annual reports; sustainability reports
D4_ESG_ENABLEMENT *	IPPC-compliant flowmeters, BAT monitoring, wastewater parameter registers, energy intensity KPIs, daily monitoring logs. 27.3% of non-zero ESG evidence in V4 study derived from IPPC permits.	IPPC / environmental permits (primary); annual reports; sustainability / ESG disclosures

Note. * IPPC environmental permit documents are the primary source for ESG Enablement evidence. Firms above IPPC capacity thresholds are legally required to install environmental monitoring, generating ESG-codeable evidence independently of voluntary disclosure strategies.

K.4 Document types

The framework accepts six document type categories. At least one document per company-year is required; multiple documents may be coded and aggregated via the MAX rule.

Table K.4. Document type classification

Document type	Description	Primary D4 dimensions covered
Annual/ Management Report	Statutory or voluntary annual report; includes directors' report and business review	All dimensions; primary source for Strategy, Automation, MES, Analytics
Financial Statements	Audited statutory accounts; notes to accounts	Automation & Robotics (capex disclosures); financial variables
IPPC / Environmental Permit	Integrated Pollution Prevention and Control permit; environmental operating permit; BAT assessment	ESG Enablement (primary); IoT & Sensing
Sustainability/ESG Disclosure	Standalone sustainability report; CSR report; CSRD-compliant disclosure; GRI/CDP report	ESG Enablement; Strategy & Governance; Supply Chain
Certification/ Standard	ISO, IFS, BRC, or equivalent certification documentation	Quality & Traceability
Other	Technical reports, press releases, company websites (specify in notes)	Varies

Note. Zeros = valid data. A score of 0 indicates no codeable evidence was found in available documents, not that the firm has deployed no technology. The disclosure-adoption gap is likely largest for small private firms below IPPC and audit thresholds.

K.5 Aggregation and decision rules

Table K.5. Key decision rules for panel construction

Rule	Description
MAX aggregation	For each company-year, the panel score for each dimension = MAX score across all documents coded for that firm-year. A firm scoring 1 in one document and 2 in another receives a panel score of 2.
D4_Total	Sum of 8 MAX dimension scores per company-year. Range: 0–16.
Zeros = valid data	Score 0 = no evidence found. Do NOT treat as missing (NA/NaN). Zero-scoring observations must be retained in all analyses.
Disclosure vs. Adoption	D4 scores reflect documentary evidence of digital capability, not confirmed technology deployment. All findings should be interpreted as findings about disclosure behaviour.
Scope default	If document scope (company-level vs. site-level) is unclear, default to Aggregate. This is the conservative choice and minimises scope misclassification.
Name standardisation	Firms with name variants across years must be standardised to a single canonical name before panel construction.
IPPC evidence	IPPC permit documents generate ESG Enablement evidence independently of voluntary disclosure. Include all available IPPC permits; do not exclude on grounds of regulatory origin.