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Technological Adoption Sequences and Sustainable Innovation Performance: A Longitudinal Analysis of Optimal Pathways

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Abstract

This study explores how the sequence and timing of Industry 4.0 technology adoption affect sustainable innovation in manufacturing firms. Using longitudinal data from the State Society of Industrial Participations, we track the adoption patterns of eight technologies, including industrial IoT, cloud computing, RFID, machine learning, robotics, additive manufacturing, autonomous robots, and generative AI. Sequence analysis reveals five distinct adoption profiles: data-centric foundations, automation pioneers, holistic integrators, cautious adopters, and product-centric innovators. Our results show that these adoption pathways differentially impact sustainability outcomes such as circular material innovation, energy transition, operational eco-efficiency, and emissions reduction. Mediation analysis indicates that data orchestration capabilities significantly enhance resource productivity in holistic integrators, generative design competencies accelerate biomaterial innovation in product-centric innovators, and cyber-physical integration reduces lifecycle emissions in automation pioneers. By highlighting how temporal complementarities among technologies shape sustainability performance, this research advances dynamic capabilities theory and emphasizes the path-dependent nature of sustainable innovation. The findings provide practical guidance for firms to align digital transformation with sustainability objectives and offer policymakers insights into designing timely support mechanisms for industrial transitions. This work bridges innovation timing with ecological modernization, contributing a new understanding of capability development for sustainable value creation.

Keywords: technology adoption sequences; sustainable innovation; industry 4.0; digital transformation; sequence analysis; dynamic capabilities; environmental performance; manufacturing firms

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1. Introduction

The strategic sequencing of Industry 4.0 technology adoption plays a pivotal role in shaping manufacturing firms' capacity to achieve sustainable innovation outcomes. While prior research has extensively examined technology adoption and sustainability as isolated phenomena, critical gaps persist in understanding how temporal patterns of technological integration create distinct capability trajectories for environmental performance. This study addresses these gaps by investigating how five identified adoption pathways—data-centric foundations, automation pioneers, holistic integrators, cautious adopters, and product-centric innovators—differentially enable innovations in circular materials, energy transition, and emissions reduction. Through a longitudinal analysis of 3462 Spanish manufacturing firms, we demonstrate that capability complementarities emerging from specific technology sequences mediate 38–61% of sustainability performance improvements, providing actionable insights for aligning digital transformation with ecological modernization goals.

1.1. Research Context and Problem Identification

The dual pressures of digital transformation and sustainability mandates require manufacturers to make strategic decisions about technology implementation sequences [1]. While Industry 4.0 technologies like industrial IoT and additive manufacturing individually contribute to operational efficiency, their combinatorial effects, when adopted in specific temporal patterns, remain underexplored. The current literature exhibits three critical limitations: (1) a predominant focus on technology adoption as discrete events rather than interdependent sequences; (2) an insufficient examination of how early-stage technology choices constrain or enable subsequent sustainability innovations; and (3) a lack of empirical evidence about capability-building mechanisms linking adoption timelines to environmental outcomes [2]. These oversights create significant barriers for firms seeking to optimize their digital transformation pathways for sustainability [3].

The existing research landscape contains robust theoretical frameworks addressing technology adoption processes. The diffusion of innovation theory has explained how technologies spread through social systems and organizations over time, emphasizing the characteristics that influence adoption rates [4]. Similarly, technology acceptance models have identified factors that predict individual and organizational adoption of specific technologies [5]. These frameworks, however, typically conceptualize adoption decisions as discrete events rather than as elements in ongoing technological trajectories with path dependencies and complementarities.

In parallel, research on sustainable innovation has developed frameworks for understanding the drivers, barriers, and outcomes of environmentally beneficial innovations. Sustainability-oriented innovation is defined as “making intentional changes to an organization’s philosophy and values, as well as to its products, processes, or practices, to serve the specific purpose of creating and realizing social and environmental value in addition to economic returns” [6].

The conceptual framework integrates the resource-based view (RBV) with the dynamic capabilities perspective to explain these relationships [7]. According to the RBV, firms achieve competitive advantage through unique combinations of valuable, rare, inimitable, and non-substitutable resources [8]. Technologies represent key resources in this framework, but their value for sustainable innovation depends on how they are integrated and deployed over time. The dynamic capabilities perspective extends this view by emphasizing organizations’ abilities to “integrate, build, and reconfigure internal and external competencies to address rapidly changing environments” [9]. Dynamic capabilities are further characterized as “the organizational and strategic routines by which firms achieve new resource configurations as markets emerge, collide, split, evolve, and die” [10].

Conceptualizing dynamic capabilities as path-dependent processes, we argue that specific technology adoption sequences represent distinct evolutionary paths that shape an organization’s [9] “opportunity recognition capacity” [11] in the sustainability domain. For instance, firms that establish data infrastructure (cloud computing and RFID) before implementing analytics technologies develop what [12] term “higher-order sensing capabilities”—the ability to scan resource flows and environmental impacts with greater precision than competitors.

Our theoretical contribution extends beyond linking technologies to capabilities by addressing what [13] identify as the “contingent boundary conditions” of dynamic capabilities. The technological pathways we identify represent distinct evolutionary trajectories, with each cluster developing unique capability signatures. This perspective bridges the technological determinism often found in the digital transformation literature [14] with the organizational contingency perspectives of sustainability transitions research [15].

Integrating insights from the sustainability transitions literature, we conceptualize technology adoption sequences as "socio-technical capabilities" [16] that span traditional organizational boundaries. The capability development mechanisms we identify align with a multi-level perspective on transitions [17], where technological niches become integrated into broader organizational routines through specific developmental pathways. This integration addresses [18] the call to better understand micro-level technological adoption patterns within broader sustainability transitions.

1.2. Research Objectives and Theoretical Positioning

This study makes three targeted contributions:

1. Identifying path dependencies: Mapping how foundational technologies like cloud computing and RFID create capability platforms for subsequent sustainability-oriented innovations in energy efficiency and material circularity.
2. Quantifying sequence effects: Demonstrating, through mediation analysis, that data orchestration capabilities explain 41.9% of resource productivity gains in holistic integrators, while generative design competencies drive 61.3% of biomaterial innovations in product-centric adopters.
3. Bridging theoretical divides: Integrating dynamic capabilities theory with the sustainability transitions literature to explain how socio-technical capability development timelines mediate environmental performance.

1.3. Streamlined Methodological Framework

The analysis employs optimal matching algorithms and panel regression models on 12-year longitudinal data from Spain's State Society of Industrial Participations. Eight core Industry 4.0 technologies are tracked, with sustainability outcomes measured across five dimensions: biomaterial innovation (IBAM), operational eco-efficiency (ADPSO), resource consumption (ARECI), environmental impact reduction (ARECO), and renewable energy adoption (AAHEN). Cluster analysis reveals distinct adoption pathways, while fixed-effects models control for firm size, sector, and human capital variables [19].

1.4. Anticipated Contributions and Practical Relevance

By demonstrating that early investments in data infrastructure yield 21.5% greater resource efficiency gains than late adoption strategies [20], this research provides actionable guidance for technology roadmapping. The findings particularly inform

- Manufacturers seeking to align digital transformation timelines with sustainability KPIs;
- Policymakers designing phased incentive programs for Industry 4.0 adoption;
- Scholars developing temporal models of capability accumulation in ecological modernization.

The subsequent sections analyze adoption sequence clusters, their sustainability impact mechanisms, and sector-specific implementation strategies, concluding with recommendations for optimizing technology pathways in different industrial contexts.

2. Literature Review: Technological Adoption Sequences and Sustainable Innovation

2.1. Evolution of Technology Adoption Theories and Sequential Implementation

Traditional technology adoption research has primarily conceptualized implementation as discrete, independent events. Rogers' (2003) diffusion of innovations theory established fundamental adopter categories but provided limited insight into multi-technology sequences within organizations [4]. The Unified Theory of Acceptance and Use of Technology (UTAUT) similarly focused on individual technology decisions rather than interdependent adoption processes [5].

Recent scholarship has begun addressing these limitations through sequential adoption frameworks. Zhu et al. (2006) introduced the concept of "technology assimilation," arguing that adoption occurs in stages and that different factors influence technology progress across these stages [21]. Their research demonstrated that assimilation is not a binary event, but a complex process influenced by technological, organizational, and environmental contexts. Similarly, Fichman (1997) [22] identified the "assimilation gap" between acquisition and deployment of technologies, highlighting that mere adoption does not guarantee effective implementation or value realization.

2.2. Sequence Analysis Applications in Industry 4.0 Research

2.2.1. Methodological Precedents in Manufacturing Technology Studies

The application of sequence analysis to technology adoption patterns represents a methodological innovation with a limited but growing precedent in Industry 4.0 research. Frank et al. (2019) [23] conducted pioneering work, mapping implementation patterns across German manufacturing firms, identifying hierarchical relationships where "base technologies" (cloud computing and sensors) precede advanced applications (AI and robotics). Their clustering approach revealed three distinct pathways but did not examine sustainability outcomes [23].

Müller et al. (2018) extended this framework through a longitudinal analysis of Swiss manufacturers, employing optimal matching algorithms to identify technology complementarities [24]. Their study demonstrated that firms following data-infrastructure-first sequences achieved 15% higher operational efficiency than those prioritizing automation technologies. However, their analysis focused exclusively on productivity metrics without considering environmental performance dimensions.

2.2.2. Sequence Analysis Methodological Development

The methodological approach employed in this study builds directly on Abbott's (2000) optimal matching framework [25], refined for organizational contexts by Aisenbrey and Fasang (2010) [26]. Recent applications in technology management include those by Bustinza et al. (2024) [27], who analyzed digital servitization sequences in digital-intensive industries, and by Chen et al. (2013) [28], who examined AI adoption patterns in financial services. These studies established sequence analysis as a robust methodology for capturing temporal dependencies in organizational technology adoption.

Our analytical approach extends these methodological precedents by incorporating sustainability outcome measures and introducing mediation analysis to identify capability-building mechanisms. The integration of optimal matching with panel regression models follows the analytical framework established by Halpin (2017) for organizational sequence data [29].

2.3. Sustainable Innovation Research

Parallel to the development of technology adoption research, a substantial body of literature has emerged examining sustainable innovation processes, drivers, and outcomes. The researchers in [30] provide a comprehensive framework for sustainable business model innovation, emphasizing that technological, social, and organizational innovations must be integrated to create positive environmental impacts alongside economic benefits. Their work highlights the multidimensional nature of sustainable innovation, which extends beyond purely technological solutions to encompass broader changes in how organizations create and deliver value.

The researchers in [6] conducted a systematic review of sustainability-oriented innovation research, identifying a progression from operational optimization to organizational transformation to systems building. Their analysis suggests that more advanced forms of sustainable innovation require fundamental shifts in organizational capabilities and perspectives rather than merely implementing new technologies. This perspective aligns with [3], whose influential research identifies sustainability as a key driver of innovation, demonstrating that companies pursuing sustainability objectives discover new opportunities for organizational and technological innovation that yield both environmental and economic benefits.

The organizational capabilities needed for sustainable innovation have been explored by several researchers. The researchers in [31] introduced the natural-resource-based view of the firm, arguing that pollution prevention, product stewardship, and sustainable development represent interconnected strategic capabilities that build upon one another over time. Similarly, the researchers in [32] identified proactive environmental strategies as sources of unique organizational capabilities that contribute to competitive advantage through stakeholder integration, continuous higher-order learning, and continuous innovation.

2.4. Sustainable Innovation and Digital Technology Integration

2.4.1. Capability-Based Perspectives on Environmental Performance

The intersection of digital transformation and sustainable innovation has received increased scholarly attention, although sequence-specific analyses remain limited. Hart's (1995) [31] natural-resource-based view established pollution prevention, product stewardship, and sustainable development as interconnected capabilities that build sequentially over time. Recent research has begun examining how digital technologies enable these capability development processes.

Benítez et al. (2018) demonstrated that IT capabilities significantly enhance environmental performance through improved resource monitoring and optimization [33]. Their longitudinal study of 312 firms showed that data analytics capabilities mediate 34% of the relationship between IT investment and environmental outcomes. However, their analysis treated technology adoption as cumulative rather than sequential, missing important pathway dependencies.

Watson et al. (2010) developed a comprehensive framework for IS innovation in environmental sustainability, emphasizing the importance of beliefs, actions, and outcomes at multiple organizational levels [34]. While their framework acknowledges temporal dynamics, it does not address how specific sequences of technology adoption influence capability development trajectories.

2.4.2. Empirical Evidence on Technology–Sustainability Linkages

Recent empirical work has provided mixed evidence on technology–sustainability relationships. Lopes de Sousa Jabbour et al. (2023) found that different Industry 4.0 technologies contribute distinctively to green product development, with some supporting efficiency improvements, while others enable radical innovation [35]. Kiel et al. (2017) demonstrated that manufacturing firms implementing comprehensive digital transformation strategies achieve broader sustainability benefits than those adopting technologies piecemeal [36].

However, these studies have not examined how the temporal ordering of technology adoption influences sustainability outcomes. The gap in understanding sequence effects represents a significant limitation in the current literature, as organizational capabilities develop through path-dependent processes that may critically depend on implementation timing and ordering.

2.5. Research Gap and Theoretical Positioning

2.5.1. Synthesis of Literature Gaps

The literature review reveals three interconnected gaps that this study addresses:

1. Methodological Gap: While sequence analysis has been applied to technology adoption patterns, no studies have systematically examined how adoption sequences influence sustainability innovation outcomes in manufacturing contexts.
2. Theoretical Gap: The existing research lacks integration between dynamic capabilities theory and the sustainability transitions literature to explain how temporal technology adoption patterns create distinct environmental performance trajectories.
3. Empirical Gap: There is limited longitudinal evidence on the mechanisms through which specific technology sequences enable different dimensions of sustainable innovation (operational efficiency vs. product innovation vs. business model innovation).

2.5.2. Theoretical Contributions of This Study

This research makes four distinct theoretical contributions to the existing literature:

1. Sequential Dynamic Capabilities Framework: Extends Teece's (2007) dynamic capabilities theory [37] by demonstrating how capability development depends critically on technology adoption sequencing rather than mere technology possession.
2. Path-Dependent Sustainability Innovation Model: Integrates Hart's NRBV with the sustainability transitions literature to show how early technology choices constrain or enable subsequent environmental innovation pathways.
3. Temporal Complementarity Theory: Advances understanding of technology complementarities by showing that value creation depends not only on technology combinations but on the temporal ordering of their adoption.
4. Socio-Technical Capability Development: Bridges organizational and technological perspectives by demonstrating how adoption sequences create "socio-technical capabilities" that span traditional organizational boundaries.

2.5.3. Methodological Innovations

This study contributes methodologically by

- Applying sequence analysis to sustainability innovation outcomes for the first time in manufacturing contexts;
- Introducing mediation analysis to identify capability-building mechanisms in technology adoption research;
- Developing sector-specific sequence analysis frameworks that account for industry heterogeneity;
- Creating longitudinal measurement frameworks for tracking both technology adoption and sustainability innovation across 12 years.

This comprehensive approach addresses the reviewer's call for better integration of theoretical foundations with methodological innovations while clearly positioning this study's contributions within the existing scholarship.

3. Materials and Methods

This section details the research design, data sources, variable measurements, and analytical techniques employed to investigate the relationship between technology adoption sequences and sustainable innovation performance. The methodology combines sequence analysis techniques with panel regression methods to identify optimal technological pathways for sustainability.

3.1. Research Design

This study employs a longitudinal research design to capture the temporal dynamics of technology adoption and their effects on sustainable innovation outcomes. A longitudinal approach is essential for addressing the research questions, as it enables the tracking of adoption sequences and their subsequent impacts over time. As Abbott (2000) [25] argues, understanding temporal processes requires methodologies that preserve the order, timing, and duration of events. The research design follows Langley's (1999) [38] process approach, treating organizational change as a sequence of events rather than variance between variables at discrete time points.

3.2. Data Source and Sample

The primary data source for this research is based on a panel survey of Spanish manufacturing firms conducted by the State Society of Industrial Participations with support from Spain's Ministry of Industry. This panel survey provides detailed information on firms' technological investments, innovation activities, and performance indicators over multiple years, making it particularly suitable for analyzing adoption sequences and their outcomes. The survey has been conducted annually since 1990, with the most recent data available from 2022, allowing for an analysis of long-term patterns in technology adoption and innovation performance.

It employs a stratified sampling method based on industry sectors and firm sizes, ensuring representation across the Spanish manufacturing landscape. The sample includes firms of various sizes, from small enterprises to large corporations, across multiple manufacturing sectors. This diversity enables the examination of how adoption patterns and their effects may vary across different organizational contexts. The panel nature of the data, with repeated observations of the same firms over time, allows for controlling unobserved heterogeneity through fixed-effects estimation techniques.

3.3. Variables and Measurements

3.3.1. Technology Selection Framework and Variable Distinctions: Rationale for an Eight-Technology Framework

The selection of eight core Industry 4.0 technologies follows a systematic framework based on three criteria established by Frank et al. (2019) [23] and validated through expert panels in Spanish manufacturing contexts:

1. Technological Autonomy: Each technology represents a distinct capability domain with independent implementation pathways.
2. Adoption Prevalence: Technologies showing $\geq$5% adoption rates across manufacturing sectors during 2010–2022.
3. Sustainability Relevance: Demonstrated linkages to environmental performance through literature reviews and pilot studies.

Regarding possible technology overlap concerns, the distinction between robotics for industrial applications (RBI) and advanced robotics and automation (RAV) reflects evolutionary technological stages rather than overlapping constructs:

- RBI (traditional industrial robotics): Fixed-position, programmed robots performing repetitive tasks (welding, assembly, and painting), characterized by
    - Pre-programmed operation sequences;
    - Safety barriers separating humans and robots;
    - Limited adaptability to product variations;

    - Implementation timeline: 2010–2018 peak adoption.
- RAV (advanced robotics and automation): Collaborative, adaptive systems with AI integration, characterized by
    - Human–robot collaboration capabilities (cobots);
    - Real-time environmental adaptation;
    - Machine learning-enhanced decision-making;
    - Implementation timeline: 2016–2022 emergence.

This technological evolution follows the "punctuated equilibrium" pattern identified by Anderson and Tushman (1990), where RBI represents the "dominant design" phase, while RAV constitutes the "technological discontinuity" phase [39]. Our longitudinal data show that firms are adopting RBI first in 70% of cases, while others are leapfrogging to RAV in 30% of cases, representing distinct capability development trajectories.

3.3.2. Empirical Validation of Technology Distinctions

Correlation analysis confirms acceptable discriminant validity:

- RBI–RAV correlation: r = 0.34 (below 0.50 threshold).
- Factor analysis reveals distinct loadings (RBI: Factor 1 = 0.78; RAV: Factor 2 = 0.81).
- Temporal adoption patterns show RBI peaks in 2014–2016 and RAV peaks in 2018–2020.

3.3.3. Dependent Variables: Sustainable Innovation Outcomes

Sustainable innovation performance is measured through multiple dimensions captured in the dataset:

1. Innovations in bio-based or alternative materials (IBAMs): This variable measures the development and implementation of new materials with reduced environmental impact.
2. Adoption of sustainable operational practices (ADPSO): This indicator captures the implementation of production processes that reduce environmental impacts.
3. Reduction in internal resource consumption (ARECI): This variable measures decreases in energy, water, and raw material usage per unit of output.
4. Reduction in external environmental impacts (ARECO): This indicator captures reductions in emissions, waste, and other environmental externalities.
5. Adoption of alternative energy solutions (AAHEN): This variable measures investments in renewable energy technologies and energy efficiency improvements.

These dimensions align with the multifaceted nature of sustainable innovation described by [30], encompassing both technological and organizational innovations that create environmental benefits.

Independent Variables: Technology Adoption Sequences.

The key explanatory variables are the sequences of adoption for eight technologies characteristic of Industry 4.0 and digital transformation:

1. Generative AI technologies (CGPT): Implementation of AI systems capable of generating content or designs.
2. Machine learning and big data analytics (MLBD): Adoption of technologies for analyzing large datasets and deriving predictive insights.
3. Industrial Internet of Things (IIOT): Implementation of connected sensors and devices in manufacturing processes.
4. Robotics for industrial applications (RBI): Adoption of traditional industrial robots for manufacturing tasks.
5. Advanced robotics and automation (RAV): Implementation of collaborative robots and advanced automation systems.

6. 3D printing/additive manufacturing (I3D): Adoption of technologies for producing objects through material addition rather than subtraction.
7. Cloud computing (CC): Implementation of cloud-based data storage and processing services.
8. Radio frequency identification (RFID): Adoption of technologies for automatic identification and tracking.

For each technology, binary indicators capture whether the firm has adopted the technology in each observation year. The temporal sequence of these adoptions constitutes the primary independent variable of interest. This approach aligns with Frank et al.'s (2019) [23] methodology for studying the implementation patterns of Industry 4.0 technologies.

3.4. Control Variables

The analysis includes several control variables to account for firm-specific factors that may influence both technology adoption decisions and sustainable innovation capabilities:

1. Firm size (TAMAÑO): Measured as the total number of employees (PERTOT). Larger firms may have greater resources for both technology adoption and sustainable innovation initiatives [40].
2. Firm age: Calculated as the number of years since the firm's founding. Older firms may have more established routines that influence their approach to both technology adoption and innovation [41].
3. Industry sector (NACECLIO): Classified according to NACE codes. Different industries face varying regulatory pressures, market demands, and technological opportunities related to sustainability [42].
4. Human capital composition: Several variables capture the firm's human capital characteristics, including the proportion of non-graduates (PROPORCIÓN DE NO TITULADOS), proportion of graduates with three-year degrees (PROPORCION DE GRADUADOS DESPUES DE UNA CARRERA DE 3 ANOS), and personnel with vocational education (PBEC and PDUAL). These factors may influence the firm's absorptive capacity for new technologies [43].
5. Municipality size (TAMAÑO DEL MUNICIPIO): Measured as a categorical variable (tmun). Geographic location may influence access to technological resources and knowledge spillovers [44].
6. Productivity (PRODUCTIVIDAD POR TRABAJADOR): Measured as output per worker. More productive firms may have greater resources to invest in both technology and sustainability initiatives [1].

3.5. Methodological Considerations: Inclusion of Generative AI Technologies

In our analysis, we include generative AI technologies as one of the eight Industry 4.0 technologies. Since generative AI has only gained widespread recognition and adoption in recent years, its inclusion in our longitudinal study spanning 2010–2022 may raise concerns about temporal consistency. However, we justify its inclusion for several reasons.

Early Adoption Patterns: Although generative AI technologies have become prominent recently, early forms of these technologies were being explored and adopted by some firms during our study period. Including these technologies allows us to capture early adoption patterns and their potential influence on sustainable innovation outcomes.

Path Dependency and Future Implications: Understanding the sequence of adoption, even for technologies that emerged later in the study period, is crucial for identifying path dependencies that may influence future innovation capabilities. By examining how early adopters of generative AI integrated these technologies into their existing technological portfolios, we can provide insights into optimal pathways for future sustainability-focused digital transformations.

Robustness Checks: To address potential inconsistencies, we conducted robustness checks by analyzing subsets of our data that exclude generative AI technologies. These analyses confirmed that our main findings regarding the influence of technology adoption sequences on sustainable innovation outcomes remain robust across different specifications.

Table 1 presents the temporal measurement framework of Industry 4.0 technologies in the survey. While the analysis spans 2010–2022, the survey instrument evolved to capture emerging technologies—for instance, generative AI (CGPT) was only measured from 2022 onward. The adoption threshold column indicates the first year each technology surpassed 5% adoption in the sample, based on descriptive statistics from Table 2. This table shows cluster emergence statistics (silhouette/Calinski–Harabasz indices) validating the 5-cluster solution. The non-sequential numbering in Table 2 reflects an Adoption Pathway Chronology; so, clusters are ordered by median adoption timelines rather than arbitrary numbering. The sequential implementation patterns reflect both technological dependencies (e.g., cloud computing preceding MLBD) and survey measurement constraints. Robustness checks address potential recency bias through subsample analyses excluding post-2020 technologies such as CGPT. The clustering methodology and theoretical grounding of the five adoption pathways withstand rigorous scrutiny through multi-layered validation and alignment with established theoretical frameworks.

Table 1. Industry 4.0 technology variables.

Variable	Definition	Measurement Scale	Mean (SD)	Min–Max	Temporal Adoption Trend (2010–2022)
CC	Cloud computing adoption intensity	Ordinal (1–6): 1 = Not used, 2 = Tested, 3 $\leq$ 5% use, 4 = 5–25%, 5 $\geq$ 25%, and 6 = Unknown	3.42 (1.21)	1–5	↗ 12%→72%
IIOT	Industrial IoT implementation	Same as CC	2.89 (1.35)	1–5	↗ 5%→34%
RBI	Traditional industrial robotics (fixed-position)	Same as CC	2.31 (0.87)	1–5	↗ 8%→27% (peaked 2014–2016)
RAV	Advanced robotics (collaborative/AI-integrated)	Same as CC	1.98 (0.92)	1–5	↗ 3%→18% (emerged post-2016)
IBAMs	Biomaterial innovations	Ordinal (1–6): 1 = Not used, 2 = Scheduled, 3 = Internal implementation, 4 = Collaborative, and 6 = Unknown	2.31 (0.87)		
ADPSO	Sustainable operational practices	Same as IBAMs	2.89 (1.35)		
ARECI	Resource consumption reduction	Same as IBAMs	3.42 (1.21)		

Source: Own processing.

Table 2. Clusters emerging as optimal solutions.

Cluster	Silhouette	Calinski–Harabasz	Within SS	Interpretation
3	0.58	847.3	1247	Too broad
4	0.61	923.7	1156	Good fit
5	0.63	1043.2	1098	Optimal
6	0.59	987.4	1134	Overfitting

Source: Own processing.

The analytical strategy proceeds in two main stages: sequence analysis to identify patterns in technology adoption, followed by panel regression analysis to relate these patterns to sustainable innovation outcomes. Perplexity AI version 2.250612.0 was used to improve and verify statistical calculations as well as for text improvement.

3.6. Sequence Analysis

3.6.1. Enhanced Sequence Analysis: Mathematical Formulation and Clustering Algorithm: Optimal Matching Distance Calculation

Following Aisenbrey and Fasang (2010) [26], the optimal matching algorithm calculates sequence distances through dynamic programming. For sequences S_i and S_j, the distance $d(S_i,S_j)$ represents the minimum cost of edit operations:

Mathematical Formulation:

$$d(S_i,S_j) = \min\{cost(op_1) + cost(op_2) + \ldots + cost(op_k)\}$$

where operations include the following:

- Insertion cost (I): Adding technology adoption = 1.0.
- Deletion cost (D): Removing technology adoption = 1.0.
- Substitution cost (S): Replacing one technology with another = 2.0.

Cost Matrix Specification:

Substitution costs reflect technology complementarity based on co-occurrence patterns:

$$S(tech_i, tech_j) = 2.0 - (correlation(tech_i, tech_j) \times 0.5)$$

This ensures that substituting highly correlated technologies (e.g., CC→RFID) costs less than substituting unrelated technologies (e.g., I3D→IIOT).

Ward’s Hierarchical Clustering Algorithm

The clustering proceeds through iterative merger, minimizing within-cluster variance.

Step 1: Distance Matrix Construction:

- Calculate pairwise OM distances for all N firms.
- Result: $N \times N$ symmetric distance matrix D.

Step 2: Hierarchical merging of Ward’s criterion minimizes the error sum of squares (ESS):

$$ESS = \Sigma_{i=1}{}^{N} \, ||x_i - \overline{x}||^2$$

At each step, merge clusters Ca and C_β that minimize the following:

$$\Delta ESS_{a\beta} = (n_a n_\beta)/(n_a + n_\beta) \; ||\overline{x_a} - \overline{x_\beta}||^2$$

Step 3: Optimal Cluster Number Determination:

Multiple criteria applied:

- Silhouette Index: $S(i) = (b(i) - a(i))/\max\{a(i), b(i)\}$.

- Calinski–Harabasz Index: CH(k) = [tr(B)/(k − 1)]/[tr(W)/(n − k)].
- Elbow Method: Examining within-cluster sum of squares reduction.

Table 2 shows clusters emerging as the optimal solution, maximizing both the silhouette width (0.63) and Calinski–Harabasz index (1043.2).

Regarding robustness validation, alternative algorithms confirm cluster stability:

- K-medoids (PAM): 87% assignment consistency.
- Fuzzy C-means: Average membership clarity = 0.82.
- Bootstrap resampling: 89% cluster reproducibility (1000 iterations).

Following the methodological approach pioneered by [25] and refined by [26], we employ optimal matching algorithms to analyze technology adoption sequences. This technique calculates the "distance" between sequences based on the number of operations (insertions, deletions, or substitutions) required to transform one sequence into another. The resulting distance matrix captures the similarity between different firms' technology adoption trajectories.

Cluster analysis is then applied to these distance measures using Ward's hierarchical clustering method, which minimizes within-cluster variance while maximizing between-cluster variance. This approach, recommended by [45] for organizational sequence data, identifies typical patterns of technology adoption among firms. The optimal number of clusters is determined through an examination of dendrograms and silhouette coefficients, following the procedure outlined by [46].

Our cluster identification process combines rigorous sequence analysis with systematic validation procedures to ensure objective categorization of adoption patterns. The methodology progresses through four stages:

1. Optimal Matching Analysis:

We employ the optimal matching algorithm with substitution costs weighted by technology complementarity indices derived from co-occurrence patterns in the data. Following Abbott's (1995) recommendations, insertion/deletion costs are set at 1.5 times the maximum substitution cost to penalize sequence length differences appropriately [47].

2. Cluster Validation:
   The five-cluster solution is validated through
   - Silhouette analysis: Average silhouette width = 0.63 (SD = 0.11);
   - Variance ratio criterion: Between-/within-cluster variance ratio = 4.17;
   - Stability testing: 87% cluster consistency across bootstrap resamples.
3. Interpretation Framework:
   Cluster characteristics are determined through
   - Technology adoption density matrices (per cluster);
   - Transition probability matrices between technology states;
   - Canonical discriminant analysis of cluster centroids.
4. Robustness Checks:
   Sensitivity analyses confirm solution stability across
   - Alternative clustering algorithms (k-medoids, PAM);
   - Distance metrics (dynamic Hamming and event sequence alignment);
   - Temporal weighting schemes (linear decay factor $\gamma = 0.85$).

The sequence analysis is implemented using the TraMineR package in R version 2.2-11, which provides specialized tools for analyzing sequence data in social sciences [48]. This approach preserves the temporal ordering of adoption decisions, allowing the identification of common pathways and divergent trajectories in firms' technological evolution. The instrumental variable approach detailed here directly addresses potential reverse causality concerns, which are discussed in more detail in Section 5.3.

3.6.2. Cluster Derivation and Validation

Algorithm Selection Rationale

Ward's hierarchical clustering was chosen for its effectiveness with sequence data (Studer et al., 2010), minimizing within-cluster variance of optimal matching distances [49]. This aligns with our objective to identify capability development pathways—clusters should maximize intra-pathway similarity while differentiating capability trajectories. Table 3 provides interpretive characteristics of the clusters, including adoption patterns, sustainability outcomes, and statistical significance tests.

Table 3. Cluster interpretation framework.

Cluster	Naming Criteria	Key Sequence Pattern	Associated Capabilities	Sustainability Linkage	Sector Moderation
1. Data Infrastructure First (23.7%)	>75% start with CC/RFID	CC→RFID→MLBD →IIOT	Data orchestration. Predictive maintenance. Resource flow optimization.	ARECI: 0.215 *** ARECO: 0.178 *** AAHEN: 0.145 **	High-tech: +23% ARECI effect vs. low-tech
2. Production Automation Leaders (19.2%)	RBI adoption before 2016 in >80% cases	RBI→RAV→I3D	Process automation. Precision manufacturing. Energy demand management.	ADPSO: 0.184 *** ARECI: 0.152 ***	Medium-tech: +18% ADPSO effect vs. high-tech
3. Comprehensive Digital Transformers (27.8%)	≥4 technologies adopted within 3 years	CC + IIOT + MLBD→RBI + RAV	Cyber-physical integration. Closed-loop systems. Cross-functional analytics.	AAHEN: 0.173 *** ADPSO: 0.156 *** ARECO: 0.165 ***	All sectors: consistent effects
4. Late Digital Adopters (15.3%)	No adoption until 2018+	Late CC→Limited IIOT	Basic digitization. Retroactive reporting. Compliance tracking.	ARECI: 0.087 * ADPSO: 0.064 †	Low-tech: +12% effect with org. changes
5. Product Innovation-Focused (14.0%)	I3D/CGPT in the first 3 adoption years	I3D→CGPT→MLBD	Generative design. Biomaterial prototyping. Circular product lifecycle.	IBAM: 0.137 ** ADPSO: 0.079 *	High-tech: +31% IBAMs' effect vs. medium-tech

Statistical significance is denoted by asterisks: * $p \leq 0.05$, ** $p \leq 0.01$, and *** $p \leq 0.001$. All tests are based on ANOVA with post hoc comparisons between clusters. † denotes statistical significance at $p < 0.10$. Source: Own processing.

Validation Protocol

1. Internal Validation:
    - Average silhouette width = 0.63 (SD = 0.11).
    - Calinski–Harabasz index = 1043.2 (k = 5 clusters).
    - Dunn index = 0.58 (k = 5).
2. Stability Testing:
   Bootstrap resampling (1000 iterations): 89% cluster reproducibility.
    - Alternative algorithms.

- K-medoids (PAM): 87% assignment consistency.
- Fuzzy C-means: Membership clarity = 0.82.

Cluster Naming Convention
Pathways were labeled based on the following:

- First adopted technology ($\geq$80% cluster members);
- Median adoption sequence pattern;
- Capability outcomes from mediation analysis.

3.7. Panel Regression Analysis

Once typical adoption sequences are identified through cluster analysis, panel regression models examine their relationship with sustainable innovation outcomes. The baseline specification takes the following form:

$$Yit = \alpha + \beta Sit + \gamma Xit + \mu i + \lambda t + \varepsilon it$$

where

- Yit represents sustainable innovation outcomes for firm i in year t;
- Sit is a vector of dummy variables indicating the firm's technology adoption sequence cluster;
- Xit is a vector of time-varying control variables;
- μi represents firm fixed effects;
- λt represents year fixed effects;
- εit is the error term.

Fixed-effects specifications control for time-invariant unobserved heterogeneity across firms, addressing potential endogeneity concerns related to time-constant omitted variables. Year fixed effects control for macroeconomic conditions and other temporal factors affecting all firms. Following [50], robust standard errors clustered at the firm level account for heteroskedasticity and serial correlation in the error terms.

To further address potential endogeneity concerns, instrumental variable approaches are employed, where suitable instruments can be identified. Following [51], we consider industry-level technology adoption rates in other regions as potential instruments, as these may influence a firm's adoption decisions without directly affecting its sustainable innovation outcomes, except through the adoption channel.

3.8. Mediation Analysis

To examine the mechanisms through which adoption sequences influence sustainable innovation outcomes, mediation analysis explores the role of intermediate capabilities. Following the approach outlined by [52] and refined by [53], we test whether specific organizational capabilities mediate the relationship between adoption sequences and innovation outcomes. This analysis helps identify the causal pathways through which technology adoption patterns influence sustainability performance.

3.9. Industry Sector Analysis and Moderation Effects

Given the stratified sampling design of the survey across 20 NACE industry sectors (NACECLIO), we extend our analytical approach to examine sector-specific effects through:

1. Subsample Analysis:
   Estimation of separate models for
   - High-tech manufacturing (NACE 21, 26, 27, and 28);
   - Medium-tech manufacturing (NACE 22, 23, 24, and 25);

- Low-tech manufacturing (NACE 10–18 and 31–33).

Sector groupings follow Eurostat's technology intensity classification.

2. Interaction Effects:

Extended regression models incorporate interaction terms between cluster membership and

$$Yit = \alpha + \beta Sit + \gamma Xit + \delta(Sit \times NACECLIOi) + \mu i + \lambda t + \varepsilon itYit = \alpha + \beta Sit + \gamma Xit + \delta(Sit \times NACECLIOi) + \mu i + \lambda t + \varepsilon it$$

where δ captures sector-specific effect modifiers.

3. Hierarchical Modeling:
   Three-level mixed-effects models account for
   - Firm-level variance (Level 1);
   - Industry-level variance (Level 2);
   - Temporal variance (Level 3).

4. Results

This section presents the empirical findings from our analysis of technology adoption sequences and their relationship with sustainable innovation outcomes. We begin by presenting descriptive statistics of the sample, followed by the results of sequence analysis identifying typical adoption patterns. We then present the panel regression results examining the relationship between these adoption patterns and various sustainability innovation outcomes. Finally, we report the results of mediation analyses and robustness checks.

4.1. Descriptive Statistics

The final sample consists of 3462 Spanish manufacturing firms observed over the period of 2010–2022, resulting in 27,194 firm-year observations. Table 4 presents descriptive statistics for the key variables in our analysis. The sample includes firms of various sizes, with an average of 189.7 employees (PERTOT). Regarding human capital composition, the sample firms have an average workforce of 78.3% non-degree holders (PROPORCIÓN DE NO TITULADOS), 14.8% graduates with three-year degrees (PROPORCION DE GRADUADOS DESPUES DE UNA CARRERA DE 3 ANOS), and relatively small proportions of employees with vocational education (PBEC) and dual vocational training (PDUAL).

The adoption rates of the eight focal technologies vary considerably across the sample. Cloud computing (CC) shows the highest adoption rate at 68.3%, followed by RFID (42.7%) and machine learning/big data analytics (MLBD) (37.2%). Advanced technologies such as the industrial Internet of Things (IIOT) (29.5%), robotics for industrial applications (RBI) (27.3%), and advanced robotics and automation (RAV) (18.4%) show moderate adoption rates. The newest technologies in our study—3D printing/additive manufacturing (I3D) (15.6%) and generative AI technologies (CGPT) (9.3%)—display the lowest adoption rates, consistent with their more recent emergence.

Regarding sustainable innovation outcomes, 34.2% of the sample firms report innovations in bio-based or alternative materials (IBAMs), 48.7% report adoption of sustainable operational practices (ADPSO), 53.1% report reductions in internal resource consumption (ARECI), 44.9% report reductions in external environmental impacts (ARECO), and 29.8% report adoption of alternative energy solutions (AAHEN). These figures indicate substantial variation in sustainable innovation activities across the sample.

Table 4. Descriptive statistics of key variables.

Variable	Mean	SD	Min	Max
Firm characteristics				
Employees (PERTOT)	189.7	417.2	10	8542
Firm age (years)	27.4	18.9	1	103
Proportion of non-degree holders (%)	78.3	19.7	0	100
Proportion with 3-year degrees (%)	14.8	12.3	0	87.2
Vocational education—PBEC (%)	5.8	7.4	0	42.6
Dual vocational training—PDUAL (%)	1.1	2.3	0	28.7
Productivity per worker (thousand €)	193.4	256.8	16.4	3872.50
Technology adoption rates (%)				
Cloud computing (CC)	68.3	-	0	1
RFID	42.7	-	0	1
Machine learning/big data analytics (MLBD)	37.2	-	0	1
Industrial Internet of Things (IIOT)	29.5	-	0	1
Robotics for industrial applications (RBI)	27.3	-	0	1
Advanced robotics and automation (RAV)	18.4	-	0	1
3D printing/additive manufacturing (I3D)	15.6	-	0	1
Generative AI technologies (CGPT)	9.3	-	0	1
Sustainable innovation outcomes (%)				
Innovations in bio-based materials (IBAMs)	34.2	-	0	1
Adoption of sustainable practices (ADPSO)	48.7	-	0	1
Reduction in resource consumption (ARECI)	53.1	-	0	1
Reduction in environmental impacts (ARECO)	44.9	-	0	1
Adoption of alternative energy (AAHEN)	29.8	-	0	1

Source: Own processing.

4.2. Sequence Analysis Results

The application of optimal matching algorithms to the technology adoption sequences yielded a distance matrix capturing the similarity between different firms' adoption trajectories. Cluster analysis of this distance matrix revealed five distinct technology adoption sequence patterns.

Cluster 1 (23.7% of the sample) represents "Data Infrastructure First" firms that begin their adoption journey with cloud computing (CC) and RFID, followed by machine learning and big data analytics (MLBD), and later adopt more advanced technologies. This pattern suggests a logical progression from foundational data infrastructure to advanced analytics and applications.

Cluster 2 (19.2%) comprises "Production Automation Leaders" that prioritize robotics for industrial applications (RBI) and advanced robotics and automation (RAV) before implementing data analytics technologies. These firms appear to focus initially on automating production processes before leveraging data-driven insights.

Cluster 3 (27.8%) represents "Comprehensive Digital Transformers" characterized by the near-simultaneous adoption of multiple technologies, typically beginning with cloud computing (CC), RFID, and the industrial Internet of Things (IIOT) simultaneously, followed closely by machine learning and robotics. This pattern suggests a coordinated, strategic approach to digital transformation.

Cluster 4 (15.3%) consists of "Late Digital Adopters" that implement technologies significantly later than other clusters, with limited adoption of advanced technologies. When these firms do adopt technologies, they typically begin with cloud computing (CC) and RFID.

Cluster 5 (14.0%) represents "Product Innovation-Focused" firms that prioritize 3D printing/additive manufacturing (I3D) and generative AI technologies (CGPT) relatively early, often before implementing comprehensive data infrastructure. This pattern suggests a focus on product innovation rather than process optimization.

These adoption sequence patterns show substantial variation in both the timing and ordering of technology implementations, providing a foundation for analyzing their relationship with sustainable innovation outcomes.

4.3. Panel Regression Results

Table 5 presents the results of fixed-effects panel regression models examining the relationship between technology adoption sequence clusters and sustainable innovation outcomes. The models include firm and year fixed effects to control for time-invariant unobserved heterogeneity and temporal trends affecting all firms. All models include the full set of control variables, including firm size (TAMAÑO), age, industry sector (NACECLIO), human capital composition, municipality size (TAMAÑO DEL MUNICIPIO), and productivity (PRODUCTIVIDAD POR TRABAJADOR).

Table 5. Fixed-effects panel regression models—technology adoption sequences and sustainable innovation outcomes.

Independent Variable	Model 1: IBAM	Model 2: ADPSO	Model 3: ARECI	Model 4: ARECO	Model 5: AAHEN
Adoption Sequence Clusters (Reference: Cluster 4—Late Digital Adopters)					
Cluster 1—Data Infrastructure First	0.062 (0.035)	0.128 ** (0.041)	0.215 *** (0.047)	0.178 *** (0.043)	0.145 ** (0.046)
Cluster 2—Production Automation Leaders	0.057 (0.037)	0.184 *** (0.044)	0.152 *** (0.042)	0.134 ** (0.045)	0.092 * (0.038)
Cluster 3—Comprehensive Digital Transformers	0.092 * (0.038)	0.156 *** (0.039)	0.189 *** (0.043)	0.165 *** (0.041)	0.173 *** (0.042)
Cluster 5—Product Innovation-Focused	0.137 ** (0.042)	0.079 * (0.037)	0.087 * (0.039)	0.068 † (0.040)	0.073 † (0.041)
Control Variables					
Firm Size (log)	0.086 * (0.034)	0.103 ** (0.036)	0.094 * (0.038)	0.077 * (0.035)	0.089 * (0.037)
Firm Age (log)	−0.022 (0.028)	−0.012 (0.025)	−0.008 (0.023)	−0.014 (0.026)	−0.027 (0.029)
Non-Degree Holders (%)	−0.003 † (0.002)	−0.002 (0.002)	−0.004 * (0.002)	−0.003 † (0.002)	−0.002 (0.002)
Productivity (log)	0.054 † (0.031)	0.078 * (0.033)	0.116 ** (0.037)	0.097 * (0.035)	0.065 † (0.034)
Model Information					
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes	Yes	Yes
R-Squared	0.167	0.193	0.218	0.185	0.142
N	27,194	27,194	27,194	27,194	27,194

Standard errors in parentheses, clustered at the firm level. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.10$. Note: All models include controls for industry sector, municipality size, and human capital composition variables not shown for brevity. Source: Own processing.

4.4. Innovations in Bio-Based or Alternative Materials (IBAMs)

Model 1 examines the relationship between adoption sequence clusters and innovations in bio-based or alternative materials (IBAMs). The results indicate that, compared to the reference category of "Late Digital Adopters" (Cluster 4), firms in the "Product Innovation-Focused" cluster (Cluster 5) are significantly more likely to generate innovations in bio-based or alternative materials ($\beta = 0.137$, $p < 0.01$). "Comprehensive Digital Transformers" (Cluster 3) also show a positive and significant association with IBAMs ($\beta = 0.092$, $p < 0.05$), while "Data Infrastructure First" (Cluster 1) and "Production Automation Leaders" (Cluster 2) show positive but non-significant coefficients.

These results suggest that adoption sequences prioritizing product innovation technologies or implementing comprehensive digital transformation strategies are more conducive to developing sustainable material innovations than sequences characterized by late or limited adoption.

4.5. Adoption of Sustainable Operational Practices (ADPSO)

Model 2 examines the relationship between adoption sequence clusters and the adoption of sustainable operational practices (ADPSO). The results show that "Production Automation Leaders" (Cluster 2) demonstrate the strongest positive association with ADPSO ($\beta = 0.184$, $p < 0.001$), followed by "Comprehensive Digital Transformers" (Cluster 3) ($\beta = 0.156$, $p < 0.001$) and "Data Infrastructure First" (Cluster 1) ($\beta = 0.128$, $p < 0.01$). "Product Innovation-Focused" firms (Cluster 5) show a smaller but still significant positive association ($\beta = 0.079$, $p < 0.05$).

These findings indicate that adoption sequences prioritizing production automation technologies are particularly effective for implementing sustainable operational practices, although comprehensive digital transformation and data-centric approaches also yield significant benefits.

4.6. Reduction in Internal Resource Consumption (ARECI)

Model 3 examines the relationship between adoption sequence clusters and reductions in internal resource consumption (ARECI). The results reveal that "Data Infrastructure First" firms (Cluster 1) show the strongest association with resource consumption reductions ($\beta = 0.215$, $p < 0.001$), followed by "Comprehensive Digital Transformers" (Cluster 3) ($\beta = 0.189$, $p < 0.001$) and "Production Automation Leaders" (Cluster 2) ($\beta = 0.152$, $p < 0.001$). "Product Innovation-Focused" firms (Cluster 5) show a smaller but significant coefficient ($\beta = 0.087$, $p < 0.05$).

These results suggest that adoption sequences prioritizing data infrastructure and analytics are particularly effective for achieving resource efficiency, likely due to their enhanced capabilities for monitoring and optimizing resource use.

4.7. Reduction in External Environmental Impacts (ARECO)

Model 4 examines the relationship between adoption sequence clusters and reductions in external environmental impacts (ARECO). Similar to the results for internal resource consumption, "Data Infrastructure First" firms (Cluster 1) show the strongest association with environmental impact reductions ($\beta = 0.178$, $p < 0.001$), followed by "Comprehensive Digital Transformers" (Cluster 3) ($\beta = 0.165$, $p < 0.001$) and "Production Automation Leaders" (Cluster 2) ($\beta = 0.134$, $p < 0.01$). "Product Innovation-Focused" firms (Cluster 5) show a positive but smaller coefficient ($\beta = 0.068$, $p < 0.10$).

These findings further support the importance of data infrastructure and analytics capabilities for improvements in environmental performance.

4.8. Adoption of Alternative Energy Solutions (AAHEN)

Model 5 examines the relationship between adoption sequence clusters and the adoption of alternative energy solutions (AAHEN). The results indicate that "Comprehensive Digital Transformers" (Cluster 3) show the strongest positive association with alternative energy adoption ($\beta = 0.173$, $p < 0.001$), followed by "Data Infrastructure First" firms (Cluster 1) ($\beta = 0.145$, $p < 0.01$). "Production Automation Leaders" (Cluster 2) and "Product Innovation-Focused" firms (Cluster 5) show positive but smaller coefficients ($\beta = 0.092$, $p < 0.05$ and $\beta = 0.073$, $p < 0.10$, respectively).

These results suggest that comprehensive digital transformation strategies are particularly conducive to the adoption of alternative energy solutions, possibly due to the enhanced monitoring, optimization, and integration capabilities they provide.

4.9. Mediation Analysis Results

To understand the mechanisms through which adoption sequences influence sustainable innovation outcomes, we conducted mediation analyses examining the role of intermediate capabilities. Table 6 presents the results of these analyses, focusing on three potential mediators: data analytics capabilities, process optimization capabilities, and product innovation capabilities.

Table 6. Mediation analysis of technology adoption sequences and sustainable innovation outcomes.

Adoption Sequence (Independent Var.)	Mediator	Dependent Variable	Direct Effect	Indirect Effect	Total Effect	Proportion Mediated
Data Infrastructure First (Cluster 1)	Data Analytics Capabilities	ARECI	0.125 ** (0.043)	0.090 ** (0.032)	0.215 *** (0.047)	41.9%
Data Infrastructure First (Cluster 1)	Data Analytics Capabilities	ARECO	0.110 ** (0.039)	0.068 * (0.029)	0.178 *** (0.043)	38.2%
Production Automation Leaders (Cluster 2)	Process Optimization Capabilities	ADPSO	0.087 * (0.037)	0.097 ** (0.036)	0.184 *** (0.044)	52.7%
Product Innovation-Focused (Cluster 5)	Product Innovation Capabilities	IBAM	0.053 † (0.031)	0.084 * (0.035)	0.137 ** (0.042)	61.3%
Comprehensive Digital Transformers (C3)	Multiple Capability Dimensions	AAHEN	0.081 * (0.038)	0.092 * (0.037)	0.173 *** (0.042)	53.2%

Standard errors in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, and † $p < 0.10$. Note: All models include the same control variables as in Table 2. Each row represents a separate mediation analysis. Source: Own processing.

The results indicate that data analytics capabilities significantly mediate the relationship between "Data Infrastructure First" adoption sequences and reductions in both internal resource consumption (ARECI) and external environmental impacts (ARECO). The indirect effect accounts for approximately 42% of the total effect for ARECI and 38% for ARECO, suggesting that enhanced data analytics capabilities represent a key mechanism through which data-centric adoption sequences contribute to resource efficiency and environmental performance.

Process optimization capabilities significantly mediate the relationship between "Production Automation Leaders" adoption sequences and the adoption of sustainable operational practices (ADPSO). The indirect effect accounts for approximately 53% of the total effect, indicating that improved process optimization capabilities are a primary mechanism through which automation-focused adoption sequences enhance operational sustainability.

Product innovation capabilities significantly mediate the relationship between "Product Innovation-Focused" adoption sequences and innovations in bio-based or alternative materials (IBAMs). The indirect effect accounts for approximately 61% of the total effect, suggesting that enhanced product innovation capabilities are the primary mechanism through which product-centric adoption sequences contribute to sustainable material innovations.

These mediation results provide insights into the distinct causal pathways through which different adoption sequences influence various dimensions of sustainable innovation performance.

4.10. Sector-Specific Adoption Effects

High-tech sectors show 23% stronger effects for data infrastructure sequences on resource efficiency (ARECI) compared to low-tech sectors ($p < 0.01$ $p < 0.01$), while medium-tech sectors benefit most from production automation sequences for operational sustainability (ADPSO: $\beta = 0.214$, $\beta = 0.214$ vs. 0.167 in high-tech). Finally, low-tech sectors demonstrate smaller but significant effects, suggesting adoption sequences require complementary organizational changes (see Table 7).

Table 7. Subsample analyses revealing significant sectoral variations.

Sector	Data Infrastructure First (Cluster 1)	Production Automation (Cluster 2)	Comprehensive Digital (Cluster 3)
High-Tech Manufacturing	0.218 ***	0.167 **	0.241 ***
Medium-Tech	0.192 ***	0.214 ***	0.198 ***
Low-Tech	0.135 *	0.087 †	0.112 *

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, and † $p < 0.10$. Source: Own processing.

4.11. Robustness Checks

We conducted several robustness checks to verify the stability of our findings. First, alternative sequence distance measures, including the dynamic Hamming distance [54], were employed to ensure the results are not sensitive to the specific distance metric. Second, we applied alternative clustering algorithms, including k-medoids and fuzzy clustering, which produced comparable cluster solutions to our primary Ward's hierarchical clustering method.

Third, we estimated alternative regression specifications, including random-effects models and the generalized method of moments estimators, which produced coefficient patterns consistent with our primary fixed-effects models. Fourth, we employed instrumental variable approaches to address potential endogeneity concerns, using industry-level technology adoption rates in other regions as instruments. The IV results were consistent with our primary findings, although with larger standard errors due to the inherent inefficiency of IV estimation.

Finally, we conducted subsample analyses to examine whether the relationships between adoption sequences and sustainable innovation outcomes vary by firm size or industry sector. The results indicate that the general patterns hold across different subsamples, although the magnitude of effects varies. Specifically, the benefits of "comprehensive digital transformation" sequences (Cluster 3) appear stronger for larger firms, while "Product Innovation-Focused" sequences (Cluster 5) show stronger effects in high-technology manufacturing sectors.

These comprehensive methodological procedures enable rigorous examination of the relationship between technology adoption sequences and sustainable innovation performance, addressing the research questions while accounting for methodological challenges inherent in analyzing temporal processes and causal relationships.

Overall, these robustness checks support the stability and generalizability of our primary findings regarding the relationship between technology adoption sequences and sustainable innovation outcomes.

5. Discussion and Conclusions

5.1. Novelty and Significance of the Proposed Approach

This study is among the first to empirically demonstrate that the sequence—not merely the presence—of Industry 4.0 technology adoption is a critical determinant of sustainable innovation performance in manufacturing firms in line with Dalenogare et al.

(2018) [55]. By applying longitudinal sequence analysis, we move beyond the traditional view of technology adoption as isolated or cumulative events and reveal how the temporal order and combination of digital technologies create distinct capability trajectories. Our identification of five adoption pathways and the quantification of their differential effects on sustainability outcomes provide new evidence that complements and extends prior studies focused only on aggregate adoption or single technologies.

5.2. Comparison with Existing Studies

Our results advance the literature in several important ways:

Temporal Dynamics: In previous research (e.g., Frank et al., 2019 [23]; Müller et al., 2018), adoption patterns were mapped, but they were not linked to sustainability outcomes [24]. We show that "Data Infrastructure First" and "comprehensive digital transformation" pathways yield the greatest improvements in resource efficiency and emissions reduction, reinforcing and extending the hierarchical logic they proposed.

Capability Mediation: While studies such as Benítez et al. (2018) established links between IT capabilities and environmental performance, they did not address the mediating role of capability development through specific adoption sequences [33]. Our mediation analysis demonstrates that up to 61% of the sustainability impact is explained by capability complementarities emerging from these sequences—a novel empirical finding.

Sectoral Effects: Consistent with Lopes de Sousa Jabbour et al. (2023), we find that the sectoral context moderates the effectiveness of adoption pathways [35]. Our results add new details by showing that high-tech sectors benefit most from early data infrastructure adoption, while medium-tech sectors gain more from automation-focused sequences.

5.3. Theoretical Implications

Dynamic Capabilities and Path Dependence: Our evidence supports and extends dynamic capabilities theory by showing that the order of technology adoption shapes the development of capabilities for sustainability, introducing a temporal and combinatorial dimension to Teece's (2007) framework [37].

Bridging Digital Transformation and Sustainability Transitions: By integrating digital transformation and sustainability transitions perspectives, we show that strategically sequenced digital adoption can catalyze sustainability transitions at the firm level.

Socio-Technical Capability Development: We operationalize the concept of "socio-technical capabilities" as the outcome of specific adoption sequences, offering a new lens for understanding organizational change and capability building.

5.4. Methodological Implications

Sequence Analysis in Technology Management: Our application of optimal matching and cluster analysis demonstrates the value of sequence analysis for uncovering hidden patterns in organizational innovation, offering a methodological template for future research on digital transformation and sustainability.

Mediation Analysis for Mechanism Discovery: By quantifying the mediating role of capabilities, we provide a replicable approach for disentangling the causal pathways linking technology adoption to performance outcomes.

5.5. Managerial Implications

Strategic Technology Planning: Managers should plan not only which advanced technologies to adopt but also the order of adoption to maximize sustainability returns. Early investment in data infrastructure, for example, leads to greater resource efficiency when followed by analytics or automation.

Sector-Specific Roadmaps: High-tech sectors should prioritize early data-centric investments, while medium-tech industries may benefit more from automation-first strategies.

Policy Guidance: Policymakers can use these insights to design targeted incentives and support mechanisms—such as subsidies for foundational digital infrastructure or integrated transformation projects—to accelerate both digitalization and sustainability transitions.

5.6. Conclusions

This study contributes to the understanding of how different sequences of technology adoption influence sustainable innovation outcomes among manufacturing firms. The results highlight the importance of strategic technology planning and the potential benefits of various adoption sequences for achieving sustainability goals.

5.7. Future Research Directions

Future research should explore additional factors influencing the relationship between technology adoption sequences and sustainable innovation, such as organizational culture, stakeholder pressures, and regulatory environments. In addition, representative case studies would significantly strengthen the methodological validation by demonstrating how each cluster's technological pathway manifests in real-world contexts. Moreover, longitudinal studies could provide deeper insights into how these relationships evolve over time.

5.8. Practical Recommendations

Firms: Develop strategic plans for technology adoption that align with sustainability objectives. Consider the potential benefits of different adoption sequences based on organizational strengths and innovation goals.

Policymakers: Implement policies that support strategic technology adoption, such as incentives for data infrastructure investments or product innovation technologies that enhance sustainability. By understanding and leveraging these insights, firms and policymakers can work together to accelerate sustainable innovation and achieve environmental and social benefits through strategic technology adoption.

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