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Digital Transformation and Human Capital in Europe's Twin Transition: Sectoral Pathways to Productivity and Greenhouse Gas Intensity

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Abstract

The twin transition combines digital transformation and the green transition and is a core pillar of the European agenda for the Digital Decade. This study examines how digital transformation and digital human capital relate to labor productivity and greenhouse gas (GHG) intensity across European industries. We compile a country–sector dataset covering 26 European Union Member States and ten NACE A*10 sectors for 2023 using harmonized Eurostat sources. We employ a path-analytic framework based on composite indicators to assess direct, indirect, and context-dependent associations among digital transformation, digital human capital, labor productivity, and environmental performance. The results indicate a positive association between digitalization and digital human capital. While digital skills are positively related to labor productivity, their mediating role between digitalization and labor productivity appears limited. The available evidence also suggests that artificial intelligence plays only a small moderating role in the relationships analysed. On the environmental side, higher levels of digitalization and digital skills are associated with a slight reduction in GHG intensity, although effects are modest and display sectoral heterogeneity. Overall, the findings provide disciplined empirical evidence that can inform discussions on policies and strategies aimed at fostering a competitive, digitally advanced, and lower-emissions economy in the European Union.

Keywords: digital transformation; digital human capital; artificial intelligence; twin transition; labor productivity; greenhouse gas intensity; European Union; sectoral heterogeneity

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1. Introduction

The European Union has placed digital transformation at the center of its economic and social strategy, promoting a sustainable and people-centered vision to empower both citizens and businesses. Thus, the Digital Decade constitutes the policy framework that sets the EU's vision and objectives for digital transformation through 2030 [1]. This approach is embedded in the twin transition, which integrates the simultaneous convergence of digitalization and the green transition and has become a key element of the European Union's strategy in recent years [2]. This dual transition seeks not only to advance digital technologies, but to do so in ways that contribute to environmental sustainability by supporting energy efficiency and emissions reductions [3]. European policies should promote integrated governance that can jointly deliver digital leadership and climate objectives, challenging the view that the digital and the green are separate agendas [4]. To strengthen

the Digital Decade's strategic framework, it is essential to maintain coherence across the rules, strategies, plans, and public actions designed and implemented by European governments and institutions to promote digitalization, environmental sustainability, and economic competitiveness, thereby avoiding contradictions and maximizing synergies [5].

Many firms acknowledge the disruptive impact of digital technologies; however, the successful implementation of digital transformation initiatives remains uneven, and organizational readiness gaps persist when addressing emerging challenges [6]. Moreover, even firms with strong sustainability performance continue to generate significant environmental impacts, and progress toward decarbonization targets remains limited [6,7]. Official statistics show that enterprise uptake of AI has increased in recent years, policy monitoring frameworks emphasize continued diffusion in the coming years [8,9] Nevertheless, despite these expectations, the completion of digital transformation and the capacity to operationalize it effectively still vary widely across firms [6].

The convergence between digital transformation and the green transition is not free from tensions and trade-offs [10]. While digitalization can improve productive efficiency and resource management, it also entails increased energy consumption associated with digital infrastructure, data centers, and information-intensive processes, whose environmental impacts vary significantly across sectors and productive contexts [11]. These impacts are not homogeneous: energy-intensive industrial activities, cloud-based advanced services, and digitally integrated logistics chains combine efficiency gains with environmental costs and organizational reconfiguration requirements in different ways. In addition, social implications arise regarding workforce skill requirements, the territorial redistribution of economic activity, and the risk of widening gaps between leading sectors and lagging regions. In this sense, digitalization does not in itself guarantee sustained environmental improvements and may even give rise to rebound effects that partially or fully offset efficiency gains, reinforcing the need to jointly analyze the economic, environmental, and social outcomes of digital transformation within the twin transition framework [12] as well as its role in national economies' adaptation strategies to global structural and post-industrial changes.

This study is motivated by the concern that digitalizing firms alone is not sufficient; adequately trained human capital is also required for digitalization to translate into gains in labor productivity [13,14]. The effective use of new technologies is strengthened by a skilled workforce, fostering not only competitiveness but also a more sustainable and environmentally responsible productive transformation [15,16]. The existing literature indicates that these linkages have largely been examined in a fragmented manner, leaving room for more integrative analytical approaches.

For clarity, we refer to digital transformation as DT, digital human capital as DHC, labor productivity as LP, greenhouse gas intensity as GHG intensity, and the national artificial intelligence environment as the AI context.

The twin transition can be understood as a systemic process in which DT, DHC, LP, and GHG intensity interact in an interdependent manner, generating complementarities, feedback effects, and potential nonlinearities within production systems [17]. The evidence suggests that the economic and environmental impacts of digitalization depend to a large extent on complementary intangible assets, organizational capabilities, and the institutional context in which digital technologies are embedded, rather than on isolated technological adoption [18]. Consequently, an integrated analytical approach is required to capture these mechanisms and to avoid partial or deterministic interpretations.

This research pursues three interrelated objectives. First, it examines the relationship between DT and LP in European sectors, focusing on the mediating role of DHC. Second, it evaluates whether DT and DHC contribute to reducing GHG intensity, thereby shedding light on their role within the twin transition framework. Third, it assesses the

moderating role of the AI context, understood as a technological environment that may amplify—though not guarantee—the translation of digitalization into human capital accumulation and economic outcomes. Existing evidence shows that the diffusion of AI-enabled automation has significant implications for labor-market outcomes, underscoring that technological change can affect economic performance through multiple channels [19]. Against this background, our integrated analysis provides a comprehensive examination of key challenges and opportunities related to competitiveness, sustainability, and resilience in European economies.

To this end, we provide a cross-sectional snapshot of the European Union for 2023, constructed from Eurostat statistical data for 26 countries (all Member States except Greece) and 10 broad economic sectors defined according to the NACE classification (A*10). This coverage enables us to analyze the relationships among DT, DHC, LP, and GHG intensity both at the aggregated country level and through sectoral analysis, offering an integrated and detailed view of the digitalization process and its implications for the European economic, social, and environmental context.

The 2023 data provide an essential starting point for three complementary reasons. First, they mark the transition from the Digital Economy and Society Index (DESI) to the new State of the Digital Decade (SDD) framework, establishing a new statistical series with indicators aligned with the 2030 targets and a methodology that is not fully comparable with previous years [20]. Second, the first SDD report, published in September 2023, includes Member State–specific strategic recommendations, thereby setting the baseline for national roadmaps and the annual monitoring of the Digital Decade [21]. Third, throughout that year, the diffusion and perceived impact of generative AI accelerated, marking a turning point in the pace and scope of business digitalization in the global context [22–24]. Therefore, the 2023 data reflect a different context from previous years, which justifies using them as a reference point for analyzing the future evolution of European digitalization.

This study introduces a statistical model applied to European sectoral data for 2023, incorporating DT, DHC, and GHG intensity. The approach makes two main contributions. First, it offers empirical, contextualized, and multidimensional evidence on how DT, channeled through DHC and influenced by the AI context, relates to LP and environmental outcomes within the framework of the twin transition. Second, it offers a parsimonious, replicable methodological approach suitable for sectoral analysis that can inform the development of competitive business strategies and policy debates while maintaining sustainability objectives.

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature and develops the hypotheses underpinning the proposed conceptual model. Section 3 explains the data sources, how variables are constructed, and the empirical strategy, along with the model specification. Section 4 presents the results. Section 5 discusses the main findings from a systems perspective, outlines policy and managerial implications, and highlights the study's limitations and directions for future research. Section 6 concludes.

2. Theoretical Background and Hypotheses

2.1. Digital Transformation, Digital Human Capital, and Labor Productivity

In this study, digital transformation is understood as a socio-technical process that reshapes firms' production and organizational practices through the diffusion and effective use of digital technologies, rather than as the mere adoption of isolated tools [25,26].

DT has become a process of change that influences the organization of production, work management, and value creation within firms. These changes extend beyond the mere adoption of digital technologies and shape economic outcomes and productivity

through the interplay of technology, organizational structures, and internal capabilities. From this perspective, DT can be seen as a socio-technical process whose implications arise from the articulation of multiple interrelated elements [27].

Recent reviews show that digital technologies do not generate uniform productivity effects; instead, their returns differ across various contexts. This heterogeneity has shifted analytical focus from the technology itself to the complementary factors that facilitate its effective use.

A central element in this transformation process is DHC [28], understood as the set of competencies, skills, and knowledge required to develop, implement, and use digital technologies effectively [27,29]. Several studies indicate that digitalization is associated with an increased demand for specialized competencies and a gradual reconfiguration of occupational profiles within organizations [30,31]. These dynamics strengthen the view that DHC is a crucial complementary asset for achieving the potential benefits of digitalization [32].

In this investigation, DHC is operationalized using harmonized Eurostat indicators that capture foundational and enabling digital skills, rather than advanced or frontier competencies. This choice reflects data availability and ensures cross-country and cross-sector comparability, while implying that the measure represents a proxy for broader digital capabilities.

Empirical evidence suggests that the relationship between DT and LP is not solely direct but is mediated by firms' ability to develop and mobilize DHC [33]. Firm-level studies show that investments in digital technologies yield higher productivity returns when paired with skilled workers, appropriate organizational practices, and continuous training strategies [34,35]. Similarly, cross-country comparisons indicate that economies with higher levels of digital skills and innovation tend to achieve greater productivity gains from digital transformation [36]. At the same time, the literature emphasizes significant variability in how DT affects productivity. Factors such as industry, firm size, and the institutional environment influence both the size and, in some cases, the direction of these effects, especially when DHC is limited [37,38].

Most existing studies examine these relationships in a limited way, which restricts a comprehensive understanding of how DT translates into productivity improvements. This gap motivates the need for analytical approaches that can examine DT, DHC, and LP simultaneously.

Hypothesis 1 (H1). *In European sectors, DT is positively linked to DHC, DHC is positively linked to LP, and DHC partially mediates the relationship between DT and LP.*

Formally, the indirect effect can be expressed as:

$$\text{Ind} = \alpha_1 \cdot \beta_2 > 0,$$

where α_1 represents the effect of DT on DHC and β_2 represents the effect of DHC on LP.

2.2. Twin Transition: Digital Transformation, Digital Human Capital, and Greenhouse Gas Intensity

The twin transition perspective highlights the possibility of reconciling gains in productivity and competitiveness with improvements in environmental indicators. Therefore, as organizations pursue DT, aligning it with sustainability has become a major challenge [11]. In this context, DT may help reduce GHG intensity by improving energy efficiency, optimizing processes, and utilizing monitoring and data analytics technologies [39,40]. However, these potential benefits are often reduced by structural factors such as output expansion, sectoral specialization, and changes in final demand [41,42]. At the same time, other stud-

ies warn that digital adoption might be insufficient or even harmful if it is not properly integrated into firms' environmental strategies [43,44], and that some of the benefits may be offset by rebound effects and the expansion of energy-intensive activities associated with digitalization. From an empirical perspective, the overall effect of digital transformation on emissions remains uncertain [10], although it generally improves over time as organizations develop capabilities, adopt cleaner technologies, and modify their production models [45].

Recent studies on Europe's twin green and digital transition further suggest that digitalization alone does not ensure sustained environmental improvements and that its effects rely on complementary clean technologies and suitable regulatory frameworks [10].

Hypothesis 2 (H2). *In the European productive structure, higher levels of DT and DHC are, on average, linked to lower GHG intensity, once other structural characteristics are controlled for, in line with the twin transition agenda.*

2.3. Artificial Intelligence as Contextual Moderator

From a theoretical perspective, AI can be understood as a form of technological enablement that supports and amplifies DT by increasing the demand for complementary digital skills and organizational capabilities. Recent research emphasizes that AI does not generate value in isolation but requires continuous learning, skill upgrading, and organizational adaptation to be effectively integrated into production and decision-making processes [46]. In this sense, AI ecosystems may strengthen the relationship between DT and DHC by fostering organizational learning and capability development, thereby facilitating the accumulation and effective deployment of digital competencies across sectors [47].

Empirical evidence shows that adopting advanced digital tools, including AI, is also associated with improvements in LP, especially when these technologies are effectively embedded into organizational processes and work management practices [14,48]. In this context, the increasing influence of digitalization and AI in the global economy is substantially reshaping work organization and human resource management by automating repetitive and low-value tasks such as documentation, programming, equipment inspection, and data collection [49]. Digitalization has also helped reduce transaction costs and foster new business models, which in turn influence how human resource functions are designed and managed within organizations [50].

A growing body of research agrees that AI-based automation does not eliminate the need for the human factor; instead, it redefines its role within organizations, maintaining the importance of skills, intuition, and cognitive abilities for business success in digital environments [51]. Nevertheless, although the literature on integrating AI into information systems and human resource management has expanded substantially, it remains highly fragmented and reports heterogeneous findings due to differences in theoretical approaches, levels of analysis, and empirical contexts [52,53]. This heterogeneity supports conceptualizing AI not just as a direct determinant of performance, but as a contextual moderator that shapes the strength and direction of the effects of digital transformation and digital human capital impact the economy outcomes.

Hypothesis 3 (H3). *The national AI context positively moderates the indirect effect of DT on LP through DHC.*

Building on the literature review, Figure 1 shows the conceptual model that guides the empirical analysis, summarizing the relationships among DT, DHC, LP, and GHG intensity, as well as the moderating role of the AI context. This framework forms the basis for the structural model outlined in Section 3.

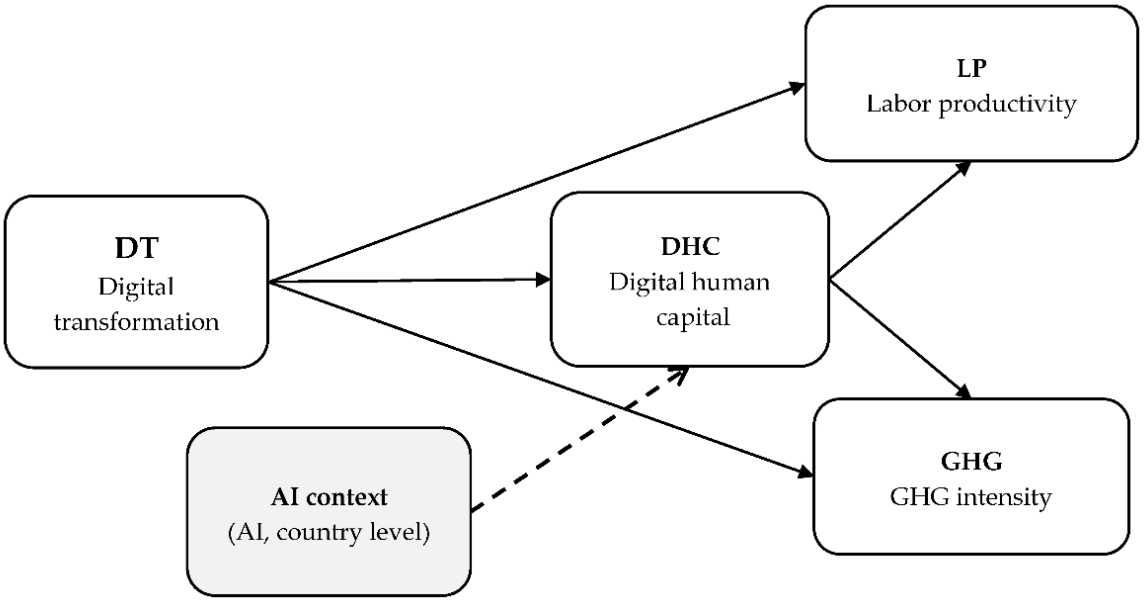

Figure 1. Structural model of DT, digital human capital, productivity, and GHG intensity.

3. Materials and Methods

3.1. Research Design and Analytical Framework

This study employs a quantitative, cross-sectional, comparative research design to analyze the structural relationships among DT, DHC, LP, and GHG intensity within the context of Europe's twin transition. We also consider the national AI landscape as a moderating variable that moderates the relationship between digital transformation and digital human capital. The empirical analysis focuses on 2023 and combines data at the country–sector level, thereby capturing both cross-country differences and sectoral heterogeneity within the European Union.

The analytical framework is based on research that conceptualizes digitalization as a systemic process, where economic and environmental effects rely on intermediate mechanisms, like human capital, and on technological and organizational contextual conditions [54,55].

Given the limited number of countries (EU-26) and the aggregated nature of the data, we intentionally avoid highly parameterized latent-variable SEM models. Instead, we use a path-analytic approach where composite indicators are treated as observed variables and estimated with regression-based methods [56,57]. This approach guarantees coherence between theoretical goals, data design, and statistical power, aligning with best practices for mediation analysis in small to moderate samples [58].

Figure 2 summarizes the empirical workflow used in this study, from data preparation and constructing composite indicators to specifying the structural model and testing robustness checks.

3.2. Sample and Data Sources

The unit of analysis is the country–sector pair, defined as the combination of 26 European Union Member States (EU-26) and ten NACE A*10 sectors, yielding a potential sample of 260 observations. Greece is excluded from the analysis due to the lack of fully comparable information for key indicators of business digitalization and sector-level GHG intensity.

All variables are derived from harmonized official statistics provided by Eurostat [59–66], ensuring comparability across countries and sectors. Data are obtained from the Digital Economy and Society, National Accounts, and Environmental Accounts domains.

The indicator measuring enterprises' adoption of artificial intelligence is only available at the national level; therefore, it is uniformly assigned to all sectors within each country, maintaining the country–sector structure of the dataset.

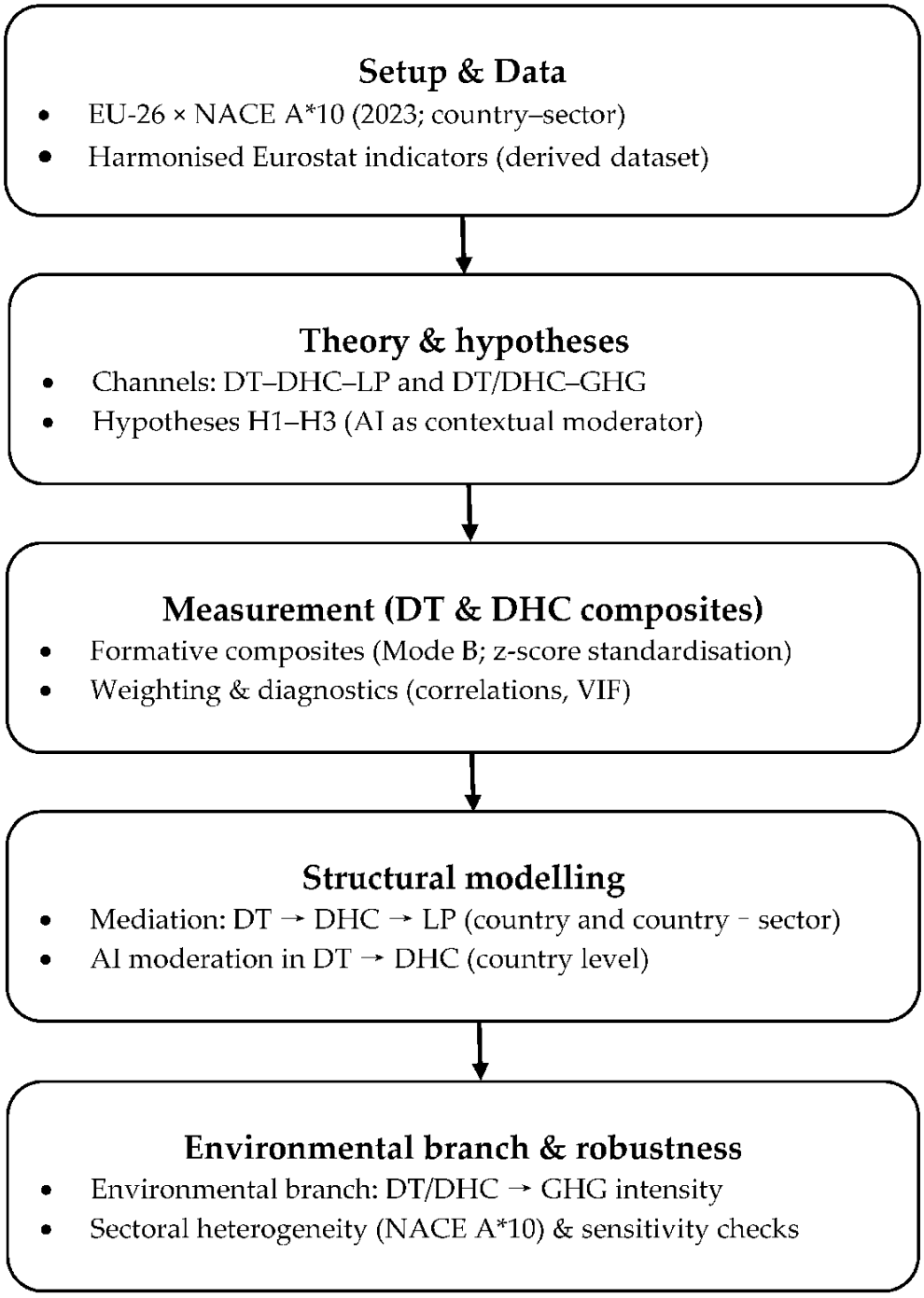

Figure 2. Empirical workflow for building digital indices and a strategy for structural estimation.

3.3. Construction of Variables and Composite Indicators

The six indicators were chosen based on four primary criteria. First, each indicator demonstrates a direct and well-established theoretical connection to the constructs of DT and DHC. Second, these indicators are derived from harmonized Eurostat datasets, ensuring consistent definitions and full comparability across EU countries and NACE sectors. Third, only indicators with complete or nearly complete coverage for the 2023 reference year were selected, which is vital for a cross-sectional sectoral analysis. Finally,

the set of indicators adopts a parsimonious approach, balancing analytical breadth with data quality and statistical robustness while avoiding redundancy and multicollinearity in the development of the composite indices.

3.3.1. Digital Transformation (DT)

DT is operationalized as a formative composite index measuring the level of business digitalization at the country–sector level. The index relies on three indicators: (i) the percentage of enterprises using cloud computing services; (ii) the percentage of enterprises performing big data analytics; and (iii) the percentage of enterprises conducting online sales (e-sales). Each indicator is standardized using z-scores, and the DT index is calculated as the unweighted mean of the standardized score values.

Conceptually, DT is treated as a formative construct, with indicators serving as contributing components that jointly define the level of digital transformation, rather than as reflective indicators of a single common latent trait. This specification is consistent with established guidelines for using composite indicators in structural models and in applied systems research [67].

3.3.2. Digital Human Capital (DHC)

DHC is constructed in a manner similar to a formative composite index that measures the availability of digital skills and competencies in the workforce. The index includes two indicators: (i) the share of information and communication technology (ICT) specialists in total employment; and (ii) the share of individuals with at least basic digital skills. The resulting DHC index captures complementary skill-related dimensions that support the effective use and adaptation of digital technologies. In line with the DT construct, DHC is conceptualized as a formative composite measured through observed indicators [68].

3.3.3. Outcome Variable

LP is defined as the ratio of gross value added to employment for each country–sector pair. It is calculated using Eurostat's national accounts by branch of activity for 2023, based on the nama_10_a10 (value added) and nama_10_a10_e (employment) tables. Because of the highly right-skewed distribution of productivity across countries and sectors, LP is transformed using the natural logarithm. This common practice in applied economics reduces skewness and heteroskedasticity and makes the interpretation of estimated coefficients easier [69].

GHG emission intensity is defined as greenhouse gas emissions per unit of value added, following Eurostat environmental accounting standards, and is widely employed to assess environmental efficiency at the sectoral level [39]. Data are sourced from Eurostat air emissions accounts by economic activity (NACE Rev.2) for 2023. This indicator reflects sector-level environmental efficiency and serves as the outcome variable in the environmental branch of the twin transition framework.

3.3.4. Artificial Intelligence as Contextual Variable

As a contextual variable, we include a country-level indicator of AI adoption that approximates the extent to which enterprises use AI technologies. This indicator is sourced from Eurostat's ISOC table on AI use in enterprises (isoc_eb_ain2) for 2023 and is measured as the percentage of enterprises with ten or more employees reporting the use of AI technologies. Because it is a single indicator, it is standardized using z-scores across the countries considered and is not aggregated into a composite index.

The resulting AI variable is assigned uniformly across all sectors within each country and serves as a national contextual attribute to assess whether national technological environments influence the DT–DHC relationship in structural models.

Table 1 summarizes the definitions, levels of aggregation, and measurement types of all variables included in the empirical analysis and serves as the basis for the structural model specification presented below.

Table 1. Definition of variables.

Variable	Level	Type	Definition
DT	Country–sector	Formative composite index	Mean of z-scores of cloud use, big data analytics, and e-sales
DHC	Country–sector	Formative composite index	Mean of z-scores of ICT specialists and basic digital skills
LP	Country–sector	Observed (log)	ln(gross value added/employment)
GHG intensity	Country–sector	Observed	GHG emissions per unit of value added
AI	Country	Standardized indicator	% of enterprises using AI technologies

Source: Own elaboration.

Additional details on the individual indicators used to construct the DT and DHC composites are provided in the Supplementary Material (Table S1).

3.4. Structural Model and Estimation Strategy

The empirical analysis is structured around a framework with two interconnected branches. In the economic branch, DT is related to LP both directly and indirectly through DHC, which enables us to decompose the total association between DT and LP into direct and indirect effects. In the environmental branch, DT and DHC are related to GHG intensity. To examine whether DT leads to DHC similarly across countries, the model considers the level of AI in each national context.

Because the constructs are proxied by observed composite indices, the empirical framework is implemented as a path-analytic system estimated via regression. Let c denote countries and s sectors. The structural model is formalized as the following system of equations:

$$DHC_{cs} = \alpha_0 + \alpha_1 DT_{cs} + \alpha_2 IA_c + \alpha_3 (DT_{cs} \times IA_c) + \varepsilon_{cs} \quad (1)$$

$$LP_{cs} = \beta_0 + \beta_1 DT_{cs} + \beta_2 DHC_{cs} + u_{cs} \quad (2)$$

$$GHG_{cs} = \gamma_0 + \gamma_1 DT_{cs} + \gamma_2 DHC_{cs} + v_{cs} \quad (3)$$

In this system, α_1 captures the effect of DT on DHC; β_1 and γ_1, represent the direct effects of DT on LP and GHG intensity, respectively; and β_2 and γ_2, capture the contribution of DHC to the economic and environmental outcomes. All variables are standardized so that coefficients can be interpreted in standard deviation units. The terms ε_{cs}, u_{cs} and v_{cs} denote equation-specific error terms.

The indirect effect of DT on labor productivity via DHC is defined as:

$$\text{Indirect effect}_{DT \to LP} = \alpha_1 \times \beta_2 \quad (4)$$

While the total effect of DT on LP is given by the sum of the direct and indirect components:

$$\text{Total effect}_{DT \to LP} = \beta_1 + (\alpha_1 \times \beta_2) \quad (5)$$

When moderation by AI is considered, the conditional indirect effect is:

$$\text{Indirect effect}_{DT \to LP}(IA) = (\alpha_1 + \alpha_3 IA_c) \times \beta_2 \quad (6)$$

Although this framework aligns conceptually with the logic of structural equation models, its implementation using observed composite variables and a nearly saturated system makes global SEM fit indices for latent-variable models (e.g., CFI or RMSEA) uninformative. Therefore, model evaluation emphasizes the coherence of the estimated paths, effect sizes, and confidence intervals for direct and indirect effects, in line with methodological recommendations for saturated structural models and mediation analysis [58,70].

All structural relationships are estimated using ordinary least squares (OLS). Statistical inference relies on bootstrap resampling, which does not require distributional assumptions and is especially useful for mediation analysis and small samples [71].

3.5. Robustness Checks

To assess the stability of the empirical findings and ensure that the results are not driven by specific modeling or measurement choices, we perform a series of robustness checks. First, we consider alternative constructions of the DT and DHC composite indices, including variations in indicator selection and aggregation methods, to confirm that the estimated relationships are consistent across different index specifications. Second, we conduct leave-one-out (jackknife) analyses at the country level to examine whether any single national context has an undue influence on the results estimates.

Third, we explore alternative transformations of the outcome variables to assess robustness against different scaling choices and distributional features. Finally, we estimate the structural models both at the country level and using the full country–sector dataset, which allows us to evaluate whether the main patterns hold across various levels of aggregation. Overall, these checks provide additional confidence that the estimated relationships reflect systematic patterns rather than artifacts of measurement, sample composition, or modeling choices.

For conciseness, detailed outputs from these robustness exercises are not reported here and are available in the replication repository.

3.6. Software and Reproducibility

All analyses were performed in R (version 4.5.2) using a reproducible workflow implemented in R Markdown. Data preparation and harmonization, model estimation, and the creation of tables and figures were performed using standard packages in the R ecosystem. Consistent with Systems' focus on transparency and reproducibility, the derived dataset and replication materials (including code and documentation) will be made available in an open-access repository, which will be cited in the Data Availability Statement.

4. Results

To improve interpretability, results are reported at two complementary levels of aggregation. First, we describe patterns in the full country–sector dataset (EU-26 × NACE A*10, 2023), which is the unit of analysis of the study. Second, we test the baseline mediation and moderation hypotheses at the country level (EU-26, 2023) to keep the structural models parsimonious, given the limited number of countries and because the AI context is measured at the national level. Finally, we return to the country–sector dataset to assess sectoral heterogeneity and robustness.

4.1. Descriptive Overview (Country–Sector Level)

Table 2 presents descriptive statistics for the main study variables at the country–sector level (EU-26 × NACE A*10, 2023). The DT and DHC composite indices show substantial variation across observations, with standard deviations near one, indicating notable heterogeneity in business digitalization and digital capabilities across European countries and sectors. LP and GHG intensity display broader dispersion than the digital vari-

ables. For LP, the distribution is right-skewed, with relatively high values in a subset of country–sector pairs.

Table 2. Descriptive statistics for key variables at country–sector level (EU-26 × NACE A*10, 2023).

Variable	N	Mean	SD	Min	Max	NA (%)
z_cloud	260	−0.01	1.00	−1.79	2.11	0.00
z_bigdata	260	−0.00	1.00	−1.36	2.61	0.00
z_esales	260	−0.00	0.98	−1.76	2.18	0.00
DT_index	260	0.00	0.80	−1.49	1.58	0.00
z_ict_spec	260	−0.00	1.00	−1.86	2.51	0.00
z_skills_AB	260	0.01	1.00	−1.96	1.82	0.00
HC_index	260	0.00	0.74	−1.26	1.47	0.00
z_ai_ctry	260	−0.01	1.00	−1.52	2.58	0.00
z_labprod	260	−0.04	0.96	−0.56	7.09	0.00
z_lnghg_pos	231	0.74	0.60	−0.65	2.40	11.15

Source: Own elaboration.

Coverage is complete for DT, DHC, LP, and the AI context indicator, while GHG intensity data are available for 231 observations (i.e., a non-negligible share of missing values at the country–sector level).

Figure 3 summarizes the bivariate association structure using a Pearson correlation heatmap. The DT–DHC correlation is distinctly positive, while correlations involving LP, GHG intensity, and the AI context are more heterogeneous in sign and strength. Figure 4 complements this by plotting DT against DHC across country–sector observations, revealing a clearly positive relationship with notable dispersion around the fitted trend, consistent with substantial cross-country and cross-sector heterogeneity.



Figure 3. Pearson correlation heatmap for DT, DHC, LP, GHG intensity and AI context (EU-26 × NACE A*10, 2023).

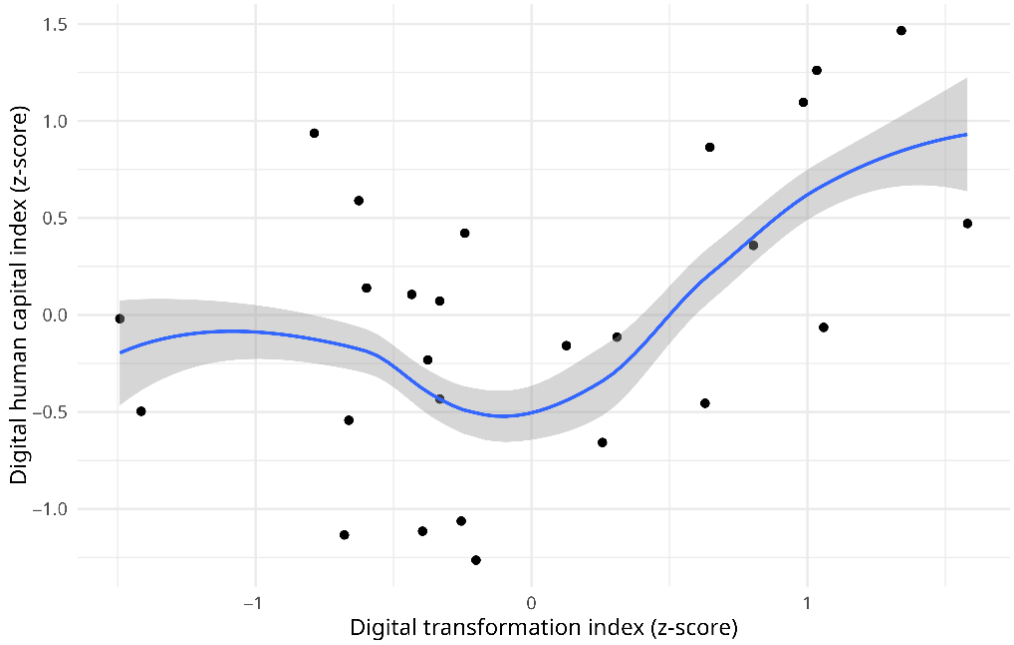

Figure 4. Scatter plot of digital transformation (DT) and digital human capital (DHC) at country–sector level (DT_index vs. HC_index, EU-26 × NACE A*10, 2023).

4.2. H1—Digital Transformation, Digital Human Capital, and Labor Productivity (Country-Level Mediation)

At the country level, the mediation model outlined in Equations (5) and (6) shows a positive relationship between DT and DHC. The standardized path from DT to DHC is 0.42 (95% bootstrap CI: 0.13–0.74), with an R^2 of about 0.23, indicating that a non-trivial share of cross-country variation in DHC aligns with differences in DT.

In the LP equation, the direct effects of DT and DHC are relatively small and uncertain statistically (0.06 and 0.10, respectively), as their bootstrap confidence intervals include zero. The estimated indirect effect of DT on LP via DHC is 0.04, while the total effect of DT on LP reaches 0.10 (95% bootstrap CI: 0.02–0.20). Overall, the model explains about 20% of the observed variation in LP.

Taken together, these results broadly support H1: DT is positively linked with LP at the country level, while DHC acts as a mediating pathway with limited impact in this sample and time period. Table 3 shows the direct, indirect, and total effects, and Figure 5 offers a visual representation of the mediation structure. The robustness checks (detailed in Section 3.5) reproduce the same sign pattern and order of magnitude, with expected variations in the confidence interval widths.

Table 3. Bootstrap mediation estimates for DT, DHC, and LP at the country level (EU-26, 2023).

Effect	Estimate	SD (Bootstrap)	CI 2.5%	CI 97.5%
a: effect of DT on HC	0.42	0.16	0.13	0.74
b: effect of HC on LP	0.10	0.07	−0.04	0.23
c′: direct effect of DT on LP	0.06	0.05	−0.03	0.18
Indirect effect (DT via HC)	0.04	0.03	−0.02	0.11
Total effect (DT on LP)	0.10	0.05	0.02	0.20

Source: Own elaboration. Note: Estimates are based on country-level data (EU-26, 2023). Effects are standardized; SD and confidence intervals are obtained from bootstrap resampling.

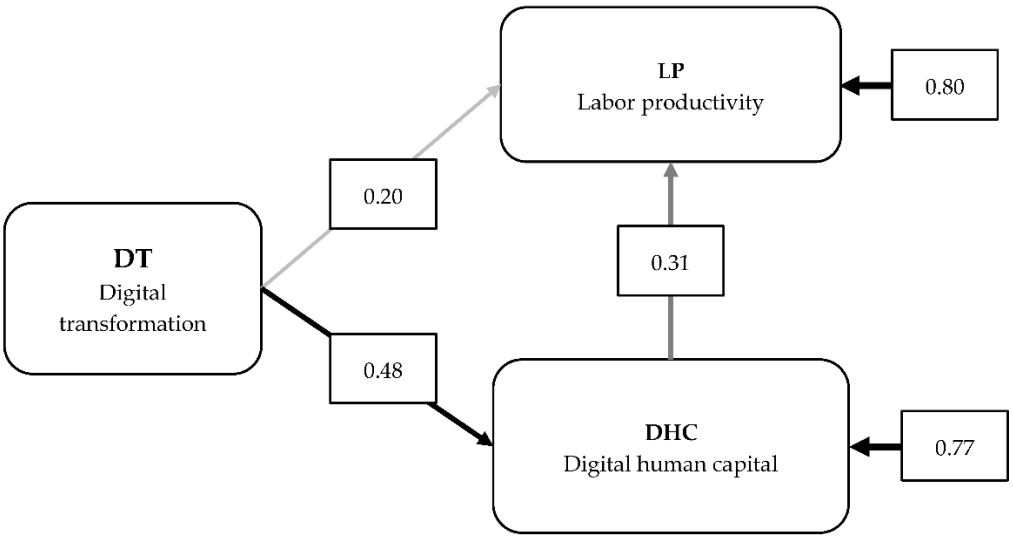

Figure 5. Structural mediation model between DT, DHC, and LP at the country level (EU-26, 2023).

4.3. Environmental Branch: DT, HC, and GHG Intensity (Country)

The environmental branch extends the mediation framework by including GHG intensity as an additional dependent variable. In this model, GHG intensity is expressed as a function of DT and DHC, while maintaining the positive DT–DHC relationship documented in Section 4.2.

As shown in Table 4, the direct effects of DT and DHC on GHG intensity are negative but small in magnitude ($\gamma_1 \approx -0.03$ and $\gamma_2 \approx -0.04$), with bootstrap confidence intervals that include zero. The indirect effect of DT on GHG intensity through DHC is approximately -0.02, while the total effect is around -0.05, with the upper bound of the confidence interval close to zero. Overall, these estimates suggest a modest negative correlation between digitalization indicators and GHG intensity at the country level, although statistical uncertainty persists substantially.

Table 4. Environmental mediation results: OLS effects of DT and DHC on GHG intensity at the country level (EU-26, 2023).

Effect	Estimate	SD (Bootstrap)	CI 2.5%	CI 97.5%
DT → DHC (α_1)	0.42	0.16	0.13	0.74
DHC → GHG intensity (γ_2)	−0.04	0.03	−0.09	0.02
Direct DT → GHG intensity (γ_1)	−0.03	0.03	−0.09	0.03
Indirect DT → DHC via ($\alpha_1 \cdot \gamma_2$)	−0.02	0.01	−0.05	0.01
Total DT → GHG ($\gamma_1 + \alpha_1 \cdot \gamma_2$)	−0.05	0.02	−0.09	0.00

Source: Own elaboration.

The extended structural model that simultaneously includes LP and GHG intensity shows the same broad pattern: positive links between DT and DHC (and, within the productivity branch, between DHC and LP), along with small negative associations of DT and DHC with GHG intensity. Because the environmental part of the model is nearly saturated, the focus is mainly on the consistency of signs and the size of effects rather than on overall fit indices.

Figure 6 provides a visual summary of both the productivity and environmental branches. It presents standardized SEM path coefficients for the joint system, whereas Table 4 reports OLS mediation estimates with bootstrap uncertainty for the environmental branch. Accordingly, the coefficients should be consistent in sign and broadly comparable in magnitude, but they are not expected to coincide exactly.

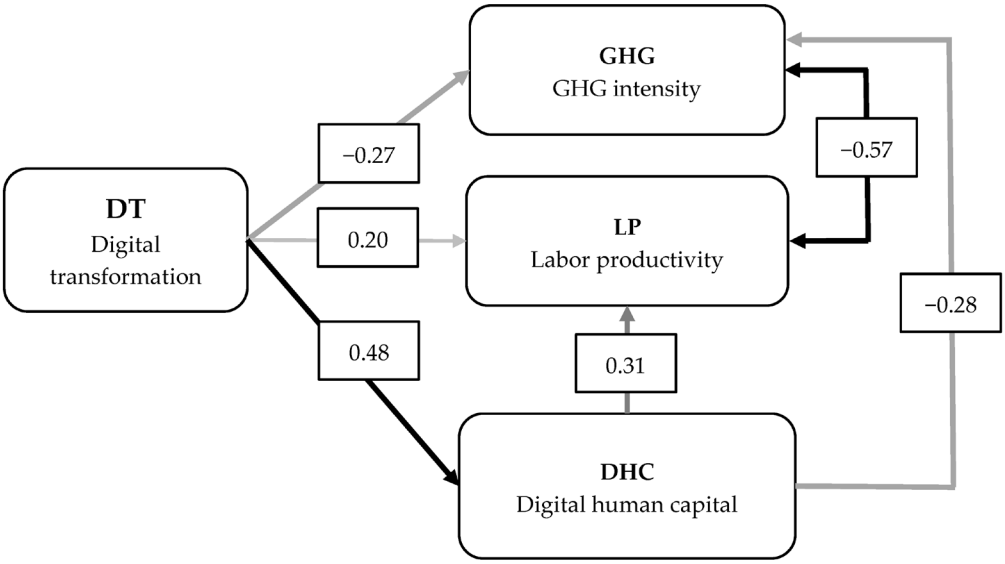

Figure 6. Structural model linking digital transformation, digital human capital, labor productivity, and GHG intensity at the country level (EU-26, 2023).

4.4. AI Moderation: Digital Transformation, AI Context, and Digital Human Capital (Country Level)

The analysis of H3 builds on the moderated mediation framework introduced in Section 2.3, in which DHC is modeled as a function of DT, the national AI context, and their interaction. DT and AI are entered as mean-centered variables, and standard collinearity diagnostics indicate no material concerns (VIF < 3). The standardized interaction term (DT × AI) is positive but small (≈0.07), suggesting that, in countries with higher AI adoption, the DT–DHC association is slightly stronger.

To aid interpretation, Table 5 reports simple slopes for the effect of DT on DHC at low, mean, and high levels of the AI context (−1, 0, and +1 SD). Point estimates increase from about 0.19 in low-AI contexts to roughly 0.34 in high-AI contexts. However, bootstrap confidence intervals are wide and include zero in all cases, indicating substantial uncertainty around these conditional effects estimates.

Table 5. Simple slopes of DT on DHC at different levels of the AI context (country level, EU-26, 2023).

AI Context Level	β_{DT-DHC}	SD (β_{DT-DHC})	CI 2.5%	CI 97.5%
low (AI = −1 SD)	0.19	0.35	−0.58	0.80
mean (AI = 0)	0.26	0.27	−0.24	0.79
high (AI = +1 SD)	0.34	0.34	−0.21	1.13

Source: Own elaboration.

Point estimates increase from about 0.19 in low-AI contexts to around 0.34 in high-AI contexts, suggesting that the DT–DHC relationship is somewhat stronger in countries with more developed AI ecosystems. However, the bootstrap confidence intervals are broad and include zero in all cases, indicating considerable uncertainty in these conditional estimates. Figure 7 illustrates this pattern, showing positive slopes across all AI levels, with a slightly steeper slope when the AI context is high.

When these conditional effects of DT on DHC estimates are combined with the LP equation from the mediation model, the resulting AI-conditional indirect effects of DT on LP via DHC are small (around 0.02–0.03). Although point estimates are somewhat higher in contexts with more AI, the confidence intervals also include zero, indicating that the additional impact of AI context on the indirect productivity pathway is limited in this sample.

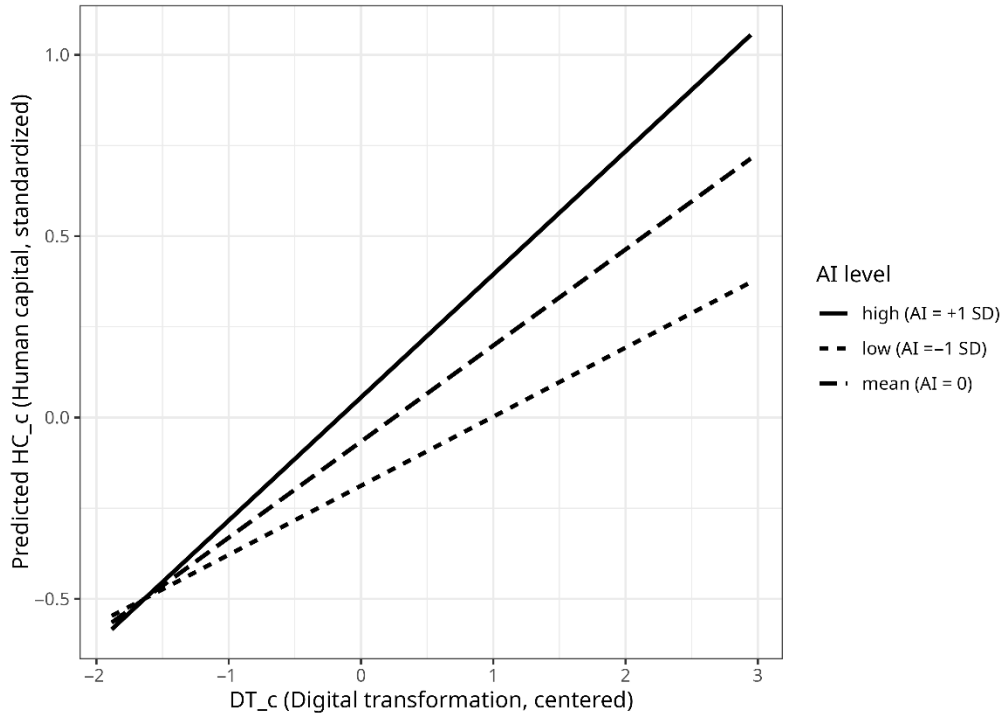

Figure 7. Interaction between DT and AI context in explaining DHC at the country level (EU-26, 2023).

Overall, the evidence provides only qualified support for H3: the translation of DT into DHC appears slightly stronger in countries with more developed AI environments, but the small interaction term, the modest magnitude of the conditional indirect effects, and the wide uncertainty intervals recommend interpreting this pattern as weak complementarity rather than strong moderation.

4.5. Sectoral Heterogeneity (Country–Sector Extension)

Extending the mediation framework to the country–sector level (EU-26 × NACE A*10, 2023) yields average coefficients that are broadly consistent with those at the country level. In the pooled country–sector model, the indirect link between digital transformation and labor productivity via digital human capital remains positive and small (average indirect effect ≈ 0.05), and the total effect is approximately 0.10, despite broad bootstrap confidence intervals. This pattern suggests that the overall evidence is not solely influenced by differences between countries but also emerges when analyzing within-country sectoral data variation.

To examine sectoral heterogeneity more explicitly, we allow the effect of DHC on the LP path in the mediation framework to vary across NACE A*10 sectors. Table 6 reports sector-specific estimates for the association between DHC and LP, the implied indirect component of DT on LP through DHC, and the explained variance in LP. Larger sector-specific coefficients are observed in Information and Communication (J), Financial and Insurance Activities (K), Industry (B–E), and especially Real Estate Activities (L), where the implied indirect component is close to 0.20. In contrast, primary activities, public services, and several market-service sectors display small or very limited indirect components, even where digitalization and digital skills are not negligible.

Figure 8 ranks sectors by the estimated sensitivity of labor productivity to digital human capital, highlighting substantial cross-sector heterogeneity and qualifying the country-level aggregate interpretation.

Table 6. Sectoral mediation: effect of DHC on LP and indirect effect of DT via DHC (EU-26 × NACE A*10, 2023).

Sector (NACE A*10)	N	$\beta_{2,s}$ (*DHC*→*LP*)	$\alpha_1\beta_{2,s}$ (*Indirect DT*−*DHC*)	R^2 (*LP*)
A	26	0.02	0.01	0.23
B–E	26	0.13	0.06	0.28
F	26	0.03	0.01	0.34
G–I	26	0.03	0.01	0.27
J	26	0.28	0.13	0.22
K	26	0.13	0.06	0.28
L	26	0.45	0.21	0.06
M–N	26	0.05	0.02	0.23
O–Q	26	0.03	0.01	0.12
R–U	26	0.03	0.01	0.34

Source: Own elaboration.

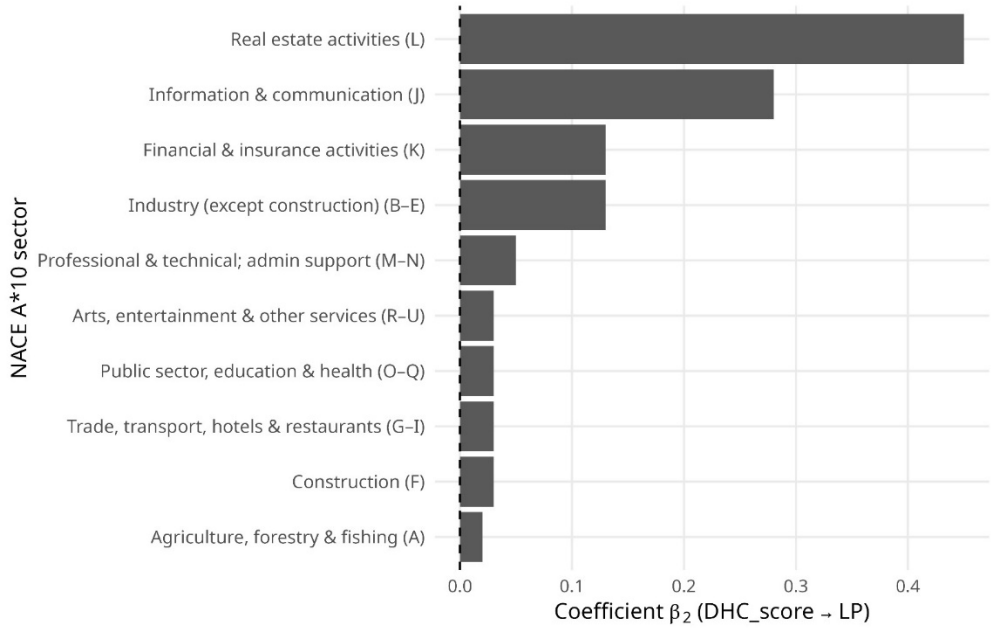

Figure 8. Sectoral sensitivity of LP to DHC in the EU-26 (NACE A*10, 2023).

5. Discussion

Beyond a strictly linear specification, the model incorporates several elements designed to capture heterogeneity in DT outcomes. In the economic branch, the inclusion of the DT × AI interaction term in the HC equation implies that the marginal effect of DT on DHC depends on each country's AI context, so that the DT→HC slope is steeper in more AI-intensive environments and weaker in countries with lower AI development. In addition, estimating the mediation paths DT→HC→LP and DT/HC→GHG at the country–sector level allows us to examine how the relationship between digitalization, productivity, and emissions intensity varies across NACE A*10 aggregates rather than only in terms of an average national effect. In this way, the combination of mediation, AI-based moderation, and sectoral heterogeneity introduces substantive flexibility into the interpretation of results without resorting to more complex nonlinear specifications that would be difficult to identify with the available sample size.

5.1. Synthesis of Main Findings in the Twin Transition Context

The empirical evidence indicates that DT consistently correlates with somewhat higher DHC and, through this pathway, is associated with modest differences in LP. At the country level, the DT–DHC relationship is positive and moderate in magnitude, whereas the link to productivity via the mediation pathway is limited, as the estimated indirect effects are small and accompanied by considerable uncertainty. This pattern aligns with prior research emphasizing that digitalization generally does not result in large, automatic productivity improvements but instead works through complementarities with human capital and work organization [33,72,73]. Overall, the findings are broadly consistent with H1, as the DT–LP association seems to be mediated by DHC, though of limited strength in this cross-sectional snapshot.

At the same time, the overall variance in LP explained by the model is modest, consistent with the cross-sectional nature of the analysis and the pronounced structural heterogeneity in productivity across countries and sectors. Previous studies show that productivity differences are substantial and persistent, and they are unlikely to be fully captured by a small set of explanatory variables [74–76].

Regarding H3, the results indicate that the national AI environment may slightly influence how much DT translates into DHC, as the DT–DHC relationship tends to be somewhat stronger in countries with more advanced AI ecosystems. However, the statistical evidence is limited and should be interpreted with caution. This perspective aligns with views that view AI as a general-purpose technology whose productive effects largely depend on available human capital and organizational complementarities rather than automatic direct effects [18,19].

The environmental branch offers a cautious interpretation of the twin transition. Both in the country-level estimates and the extended structural model, the relationships of DT and DHC with GHG intensity are usually negative but tend to be small and are estimated with considerable uncertainty. In this way, higher DT and DHC levels are compatible with slightly reduced emissions intensity, providing only qualified support for H2 and not strong evidence to infer decarbonization trajectories from a single year cross-section.

This evidence aligns with the twin transition literature, highlighting the ambivalent environmental role of digitalization. Efficiency gains may be offset by rebound effects and by pronounced sectoral heterogeneity, so the net balance depends on the technological and productive context [12,77]. The sectoral analysis strengthens this interpretation by showing that the strongest links are usually found in knowledge-intensive sectors and advanced services [78].

5.2. Policy and Managerial Implications

From a public policy perspective, the results indicate that DT strategies focused solely on technology adoption are likely to produce limited improvements in productivity and sustainability. For European governments and institutions, investing in digital infrastructure and services is probably more effective when complemented by initiatives that improve digital skills through training, reskilling, and attracting talent [73,79], especially in sectors where the estimated DHC–LP association is stronger (e.g., Information and communication; Financial and insurance activities; Industry; and other knowledge-intensive fields).

More generally, the observed sectoral heterogeneity and the role of national technological environments indicate that digitalization policies could benefit from being tailored to specific productive and technological conditions in each sector, rather than using uniform approaches, and from promoting enabling contexts that support the effective adoption of advanced technologies [80].

Beyond their aggregate productivity and environmental implications, the patterns documented in this paper have clear distributional overtones. Differences in DT and HC across countries and sectors can be seen as an upstream layer of the digital divide, as persistent gaps in digital capabilities and skills tend to translate into more fragile productivity trajectories and fewer options for reducing GHG intensity at the sectoral and territorial levels [81,82]. If the twin transition progresses based on these asymmetries, its benefits may accrue disproportionately to already advantaged segments of the workforce and regions. At the same time, adjustment costs are concentrated in sectors and local labour markets characterized by weaker digital human capital and greater exposure to carbon-intensive activities [83]. From this perspective, a just transition framework calls for combining the sector-sensitive instruments discussed above with explicitly inclusive measures—such as targeted upskilling and reskilling for workers in lagging sectors, support for regions with high concentrations of vulnerable industries, and social dialogue mechanisms to accompany restructuring—so that the joint deployment of DT and HC contributes not only to higher productivity and lower emissions, but also to a more even distribution of opportunities within European production systems.

The sectoral patterns documented in this paper suggest a differentiated policy mix rather than a uniform digital or skills agenda. In knowledge-intensive services such as information and communication or professional, scientific and technical activities—where both DT and HC levels are comparatively high—policy efforts could focus on deepening advanced capabilities and strengthening complementarities with AI, for example by supporting continuous reskilling in data-intensive occupations, fostering firm–university partnerships for AI experimentation, and reducing regulatory uncertainty around the deployment of new digital tools [84]. In medium- and low-technology manufacturing and in parts of market services, our estimates indicate that shortfalls in DHC still limit the productivity payoff of existing and potential DT investments; here, a plausible priority is to combine support for the adoption of basic and intermediate digital tools with sector-specific vocational education and on-the-job training programmes co-designed with social partners. In sectors with high carbon emissions, where DT and HC profiles interact with high GHG intensity, the dual transition perspective aims to link digital support instruments (innovation grants, R&D investment, and subsidies or tax credits to implement DT) with verifiable improvements in process efficiency and emissions performance, in line with recent evidence on the alignment of incentives for digital and green innovation [85] Overall, the evidence underscores that exploiting the joint productivity and decarbonization potential of DT and HC requires sector-sensitive instruments targeted at the specific combinations of digital capabilities and environmental pressures observed across European production systems.

This sector-sensitive perspective is further reinforced by Figure 8. In particular, although it may seem counterintuitive that real estate activities (NACE L) display the highest estimated sensitivity of labor productivity to digital human capital, this pattern is consistent with the sector's strong dependence on information processing and coordination. Real estate productivity is heavily shaped by search, valuation, matching, contracting, and portfolio/asset management—domains where digitally skilled labor can rapidly reduce transaction costs and cycle times through analytics, automation of documentation, and platform-based intermediation. Moreover, the complementarity between digital skills and intangible assets (data, networks, customer relationships, and organizational routines) can be especially pronounced in real estate, yielding disproportionately large productivity gains relative to sectors where output is more tightly constrained by physical processes and capital deepening [45,54].

A measurement/composition channel may also contribute: value added in real estate can scale with a relatively stable workforce when digital capabilities enable professionals

to manage more transactions or assets per worker, amplifying observed labor-productivity responses. Taken together, this ranking supports interpreting country-level coefficients as structure-weighted averages rather than homogeneous economy-wide effects; in practice, aggregate relationships may be driven by a subset of sectors—such as real estate—where digital skills directly relax information frictions and organizational bottlenecks.

From a managerial perspective, the joint patterns of digital transformation (DT) and human capital (HC) can be interpreted through the lens of dynamic capabilities. The DT index approximates the stock of digital assets and infrastructures available in a given country–sector. In contrast, the HC index reflects the underlying pool of digital skills and learning capacity. Our results indicate that these two dimensions are most effective when combined, as part of an organisational capability to reconfigure processes and decision routines rather than as isolated inputs [86]. In sectors where both DT and HC are relatively strong, firms are better positioned to leverage data, analytics, and digital tools to redesign workflows, optimize resource use, and support eco-innovative practices. This interpretation is consistent with evidence showing that digital capabilities and digitally enabled collaboration can enhance green innovation performance [87].

For managers operating in lagging sectors, the findings suggest that investments in digital technologies and skills should be explicitly linked to the development of organisational routines that (i) connect digital and environmental objectives within the firm, (ii) foster cross-functional teams capable of translating digital information into concrete process changes, and (iii) deploy digital tools to monitor emissions and resource use along the value chain. This approach aligns with recent empirical evidence indicating that digital governance structures and digital infrastructures can enable more accurate monitoring and management of carbon emissions [88]. In this sense, DT and HC can be viewed as the foundational elements of "green digital capabilities" that allow organisations to translate the twin transition into tangible productivity and environmental gains, rather than treating digital and green initiatives as disconnected projects.

More broadly, the strategy and management literature emphasizes that the benefits of digitalization largely depend on firms' ability to combine digital technologies with appropriate competencies, managerial practices, and organisational redesign [89,90]. In line with this perspective, the small negative associations observed between DT, DHC, and GHG intensity suggest that digitalization and skill upgrading may contribute to efficiency and decarbonization objectives but are unlikely to do so automatically—particularly in energy- and material-intensive activities. This reinforces the need for firms to explicitly embed efficiency and sustainability goals into DT initiatives, aligning technology choices, workforce development, and organisational structures with both environmental and productivity objectives, in accordance with the twin transition agenda and sustainability-oriented strategy approaches. Finally, the AI context can be interpreted as an enabling condition that may amplify—rather than substitute for—investments in DT and HC within firms [91].

5.3. Limitations and Directions for Future Research

First, the design depends on a single cross-sectional snapshot (2023), which limits the analysis of dynamics, the separation of level and change effects, and the ability to make strong causal claims. Therefore, the results should be understood as structured associations among DT, DHC, LP, and GHG intensity at a specific point in Europe's twin transition. the separation of level and change effects, and the ability to make strong causal claims. Therefore, the results should be understood as structured associations among DT, DHC, LP, and GHG intensity at a specific point in Europe's twin transition. Second, the core constructs are measured using proxies and count of AI technologies; Dc-to-intermediate digital skills; and LP and GHG intensity are derived from sectoral aggregates. While these

measures capture relevant aspects, using proxies and sectoral averages may hide significant within-sector heterogeneity among firms and does not allow for direct observation of organizational capabilities or more advanced digital competencies.

Additionally, the country-level sample size limits statistical power, especially for models with interaction terms and for the environmental branch of the path-analytic system, which is nearly saturated and thus provides limited information from global fit statistics. The EU-26 × NACE A*10 extension increases the number of observations but still relies on aggregates that c DT and DHC composite indices depend on choices regarding indicator selection, standardization, and weighting, which, although documented and tested in robustness exercises, remain partly conventional.

At the country level, we adopt a deliberately parsimonious structural specification due to the limited sample size (EU-26) and the strong collinearity among potential macroeconomic controls. In preliminary versions of the model, we explored specifications that included additional indicators of economic structure and level of development (e.g., measures of income and educational attainment), which capture some of the structural differences highlighted in the literature. These robustness checks did not change the sign or the statistical relevance of the main effects of DT and HC on productivity. However, they increased multicollinearity and reduced the precision of the estimates. Accordingly, the final specification retains a limited set of country-level variables—including the AI context index as a summary measure of the digital and innovation environment—and focuses the heterogeneity analysis on the sectoral dimension. We nevertheless recognize that this strategy does not fully eliminate the risk of omitted variable bias.

These limitations suggest several directions for future research. Expanding the dataset into a panel would allow for a dynamic evaluation of the twin transition. Additionally, incorporating more detailed information—covering both sectoral and firm levels—could help identify specific configurations of digital technologies, skills, and business models associated with more favorable productivity and emissions patterns. Complementarily, adding institutional and governance factors, such as regulatory quality, innovation-policy strength, or national AI strategies, could clarify the contexts where digitalization and the enhancement of digital human capital are more likely to serve as effective tools for an inclusive and sustainable twin transition.

In this sense, the approach adopted here—focused on 2023 and based on a carefully curated dataset—should be viewed as a first step toward a genuinely dynamic analysis within the European Digital Decade framework, which will require longer and more fully harmonized time series in future releases of official indicators.

6. Conclusions

From a quantitative perspective, the results show that the composite indices of DT and DHC capture substantial variation across countries and sectors, with differences of several standard deviations in the DT_index and HC_index at the EU-26 × A*10 level. In this context, the standardized coefficients of the model indicate that increases in DT and, in particular, in DHC are associated with appreciable improvements in apparent labor productivity. At the same time, the sign and magnitude of the effects on GHG intensity depend on sector-specific combinations of digital technologies and skill profiles. These estimates provide a clear empirical basis for assessing the economic relevance of gaps in digitalization and digital capabilities within the twin transition framework.

In addition, the indicators employed—composite indices of DT and DHC, harmonized measures of productivity and emissions intensity, and a country-level AI context index—offer a replicable starting point for future research on digitalization, productivity, and sustainable development. Their construction from official Eurostat statistics and their

integration into mediation and moderation models allow the analysis to be extended toward dynamic approaches, threshold analyses, or temporal comparisons, as well as to explore in greater detail the role of specific sectoral policies. In this way, the set of indicators and quantitative results presented in this study provides not only empirical evidence on the current situation but also operational tools for further examining the economic and environmental effects of digital transformation in Europe.

This study advances the debate on the twin transition by providing an integrated, sector-specific empirical analysis of the connections between DT, DHC, LP, and GHG intensity in the EU. In all specifications, DT consistently correlates with higher DHC, and the DT–DHC–LP pathway appears as the main empirical link connecting digitalization to productivity. However, estimated indirect effects are small, suggesting that digitalization alone is unlikely to produce significant productivity gains without additional investments in capabilities and organizational change. An important finding is the significant sectoral variation. The strongest DT–DHC–LP relationships are observed in knowledge-intensive and advanced service sectors, whereas in other industries these links are weaker or less consistent. This heterogeneity emphasizes the need to consider productive structure when evaluating the economic impact of digitalization.

From an environmental perspective, the results support a cautious interpretation of the twin transition. Both DT and DHC are linked to small reductions in GHG intensity, but these effects are modest and estimated with substantial uncertainty. The evidence, therefore, indicates that digitalization can help achieve efficiency and decarbonization goals, but it should not be seen as a sole driver of environmental change. In this context, the national technological environment, including AI adoption, seems to influence the extent to which DT translates into human capabilities, although the available evidence indicates small effect sizes.

Beyond the substantive findings, the paper offers an empirical and methodological contribution by establishing a quantitative baseline for tracking the European Digital Decade. Specifically, it provides a transparent set of indicators and a repeatable analytical framework for jointly analyzing economic and environmental outcomes of digitalization in a comparative, sector-aware way.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/systems14030227/s1, Table S1: Indicators used in the construction of DT and DHC composites.

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Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

DT	Digital transformation
DHC	Digital human capital
LP	Labor productivity
GHG intensity	Greenhouse gas intensity
AI context	National artificial intelligence environment

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