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From Infrastructure to Productivity: A Partial Least Squares Structural Equation Modelling Analysis of Cloud and Artificial Intelligence Adoption in Germany

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Abstract

Purpose

This study aims to investigate whether digital infrastructure and the adoption of frontier digital technologies catalyze innovation and productivity on a national scale.

Research method

This exploratory study develops and tests a theory-driven model linking digital infrastructure, cloud adoption, and emerging technology intensity to innovation output and, ultimately, productivity. Using secondary indicators from the United Nations (UN), UN-affiliated sources, and the Organisation for Economic Co-operation and Development (OECD), a country-level dataset is assembled for Germany covering the years 2013-2024. A partial least squares structural equation model is then estimated using the R programming language.

Findings

The paper presents an integrated measurement and structural specification for macro-level digital transformation, providing transparent construct-to-indicator mappings that are suitable for replication using public data, as well as policy-relevant assessments of institutional contexts.

Limitations

The study relied on secondary data sources from a single country, Germany, which limited the number of observations used.

Implications

The results framework is intended to offer guidance to both academic analyses and evidence-based digital policy design.

Originality/value

The study makes three main contributions. First, it develops a unified empirical framework linking digital infrastructure, technology adoption, innovation, and productivity. Second, it leverages internationally comparable data from UN and OECD sources to move beyond sectoral studies. Third, it provides policy-relevant insights by testing whether cloud adoption fundamentally improves productivity; emerging technologies strongly drive innovation, with institutional readiness shaping the extent of these effects.

Categories: Innovation Economics, Social Innovation, Social systems (economies, governments, industry)
Keywords: ai, cloud computing, digital infrastructure, egdi, innovation, oecd, productivity, pls-sem, un
JEL Classifications: O50

Introduction

The digital transformation of economies is increasingly driven by frontier technologies such as cloud computing and artificial intelligence (AI), which hold promise for strengthening innovation capacity and enhancing productivity. Their successful adoption at the country level, as highlighted by various international institutional bodies, depends on enabling conditions such as digital infrastructure, institutional readiness, and human capital development (Dutta and Lanvin, 2024) (OECD, 2022). Policymakers and practitioners face the challenge of understanding how these factors interact to influence national competitiveness. Yet much of the existing research has focused primarily on individual drivers, such as infrastructure, research and development spending, or innovation outcomes, often resulting in fragmented evidence. Prior studies have not provided unified evidence connecting the central factors of digital infrastructure, cloud adoption, and emerging technology intensity to innovation output and productivity in a single study, leaving a critical gap.

Germany, ranked ninth globally in the 2024 Networked Readiness Index (Dutta and Lanvin, 2024), provides a relevant case for examining these setbacks, given its strong information and communication technology performance and policy emphasis on data-driven transformation strategies, highlighted by international organizations such as the Organisation for Economic Co-operation and Development (OECD) and International Telecommunication Union (ITU)-World Bank (ITU, 2023).

Review of literature

Digital infrastructure is seen as central to and a significant enabler of digital transformation. It is argued that a strong digital infrastructure is a prerequisite for digital transformation (ITU, 2023) (Dutta and Lanvin, 2024). These are considered the foundational resources required to enable cloud, AI, and other frontier technology adoption. Digital infrastructure often encompasses broadband networks, mobile connectivity, and affordable Internet access, all of which determine how well firms and citizens can adopt frontier technologies. The higher the quality of these factors, the greater the propensity to attain higher productivity levels in an economy (United Nations Conference on Trade and Development, 2023). A study by (Ofori et al., 2025) presented a number of emerging technologies such as AI, blockchain, drones, nanotechnology, biotechnology, and robotics, which they highlighted as significant technological innovations to industrial productivity and economic growth. Studies have already shown that countries with higher broadband penetration, for example, tend to adopt cloud computing and other digital technologies more rapidly (OECD, 2022) (United Nations, 2024). In the view of (Yang and Zhang, 2025), in the era of the digital economy, China's investment in broadband infrastructure and information infrastructure serves as a strategic resource driving high-quality economic development.

Whereas foundational digital infrastructure enables the adoption of frontier technologies, one of the most widely used of these emerging technologies is cloud computing. It was asserted by (Golightly et al., 2022) that cloud computing has shifted IT provisioning from capital-intensive models to flexible, service-based approaches, reducing costs, enhancing scalability, enabling faster deployment, and serving as a major driver of innovation. They note that firms adopting cloud services often experience improved agility in product development and faster market entry. A study by (Duso and Schiersch, 2022) investigated whether cloud computing allows firms to replace inflexible IT investments with flexible, usage-based spending and whether it potentially boosts productivity. They sampled German firms from 2014 to 2016 and found that cloud usage increases productivity, particularly for large firms, regardless of sector. Similarly, (Gaglio et al., 2022) examined the effects of digital transformation on innovation and productivity using firm-level evidence from South Africa. At the macro level, higher cloud adoption rates have been associated with improved productivity indicators (Katz and Jung, 2024) (Karamujic, 2025). However, the literature on the relationship between cloud adoption and innovation output is mixed. Some studies highlight productivity gains primarily in digitally mature firms, suggesting that contextual factors may moderate outcomes, which underscores the need to investigate the pathway from cloud adoption to innovation and productivity within broader national frameworks, such as Germany's.

Institutional bodies such as the United Nations Conference on Trade and Development have noted that emerging technologies such as AI, the Internet of Things, and robotics represent frontier innovations capable of reshaping entire industries and nations (United Nations Conference on Trade and Development, 2023). AI adoption has been generally linked to increased innovative output. Recent studies indicate that countries with higher AI intensity report more patent activity and greater innovation commercialization. As a result, technologies such as AI serve as benchmarks for a country's digital competitiveness, making them vital indicators of emerging technology intensity in empirical models. A study by (Krzywdzinski et al., 2025) observed that AI has the potential to deliver higher productivity gains, automate a broad range of tasks, and enable new forms of innovation and business models. Similarly, (Li et al., 2024) concluded that AI has great potential to support strategic emerging enterprises in achieving disruptive technological innovation and enabling the development of new quality productivity. Other works such as that by (Cockburn et al., 2018) studied the impact of AI on innovation. These studies point to a possible connection between intensified emerging technology activity in a country and higher national innovation output.

The relationship between innovation output and productivity, in the view of (Romer, 1994), is central to endogenous growth theory. Authors such as (Schumpeter, 2021), (Solow, 1956), and (Romer, 1994) have argued that innovation lies at the heart of a sustainable, inclusive, and prosperous society, emphasizing its remarkable contribution to national productivity, economic growth, and development. Contemporary empirical work suggests that countries with strong innovation output tend to experience sustained productivity growth. It is important to note, however, that the translation from innovation to productivity is not automatic. It has been argued by (Biasi et al., 2021) and (Mazorodze, 2025) that it requires absorptive capacity, human capital, and market openness. Several studies, including those by (Moser, 2013), (Hall, 2024), and (Taalbi, 2025), have attempted to establish a link between common innovation proxies such as patents, with mixed findings. It is argued that patents, high-tech products, and research and development outcomes do not only represent new knowledge but spill over into broader economic efficiency. Whether innovation remains the primary conduit through which digital adoption translates into productivity gains at national level remains an important question, which this present study seeks to address.

The United Nations' (UN) e-government development index (EGDI), which captures and reports on country-level institutional readiness, has emerged as a critical factor in digital transformation (United Nations, 2024). According to the index, a high EGDI score typically signals advanced digital services, strong telecommunications infrastructure, and an educated population, all of which are argued to potentially lead to effective use of cloud and emerging technologies. Studies have shown that supportive policy environments amplify the benefits of digital adoption, especially for innovation (Gkoutis et al., 2025) (Mettler et al., 2024) (Vu et al., 2024). This positions EGDI as a potential moderator of the cloud-to-innovation relationship, suggesting that countries like Germany, with more advanced e-government support, are better able to adopt cloud services and consequently achieve greater innovation outcomes.

Education and trade openness are consistently highlighted in the literature as key enablers of innovation and productivity. (Biasi et al., 2021) observed that higher levels of education are associated with an improved absorptive capacity of the workforce, which makes it easier to adopt new technologies and engage in innovative activities. Education has long been regarded as an important determinant of economic well-being (Hanushek and Wößmann, 2010). (Valero, 2021) summarized the literature linking education to economic growth and emphasized a strong relationship between the two. Similarly, (Musibau et al., 2024) investigated the relationship between education quality and economic growth across 37 OECD countries and found that a 1% increase in educational quality contributes to an annual economic growth rate of approximately 3%, highlighting the importance of education and justifying its inclusion in this study. Similarly, (Mazorodze, 2025) also asserts that trade openness exposes domestic firms to global competitions and knowledge flows, which stimulate technology transfer and innovation diffusion. Trade openness has generally been seen as a promoter of economic growth by boosting innovation and productivity through specialization, access to larger markets, and technology transfer. Several studies have focused on this relationship (Monyela and Saba, 2024) (Esaku, 2021) (Aggarwal and Karwasra, 2024). However, a few studies do note that the impact of trade openness is not always straightforward and that domestic policies, infrastructure, and other factors could be at play, necessitating further research, including its inclusion in this study.

This study therefore aims to address the research gap by applying partial least squares structural equation modelling (PLS-SEM) to secondary OECD and UN data. The objective of the study is to test a model that integrates digital infrastructure, cloud adoption, and emerging technology intensity as key drivers of innovation and productivity, while also examining the moderating role of institutional readiness and the control effects of education and trade openness in a single-country exploratory study. The following hypotheses were thus formulated to test the relationship between digital infrastructure, emerging technology adoption, innovation output, and productivity in Germany.

· H_1: INFRA - CLOUD - Higher digital infrastructure quality leads to greater cloud adoption by businesses in Germany.

· H_2: INFRA - EMERG - Better infrastructure also supports the development of emerging technologies (i.e. more AI-related activity).

· H_3: CLOUD - INNOV - Greater cloud adoption enables more innovation output (cloud services bolster research and development and innovation processes).

· H_4: EMERG - INNOV - Intensified emerging tech activity (such as AI development) drives higher innovation output.

· H_5: INNOV - PROD - Stronger innovation output translates into higher productivity at the national level.

· H_6: CLOUD - PROD (Direct) - Cloud adoption has a positive direct effect on productivity (beyond its direct effect via innovation).

· H_7: CLOUD - PROD (Indirect via INNOV) - Cloud adoption also improves productivity indirectly by first boosting innovation output, which in turn raises productivity (a mediated effect though INNOV).

· H_8: Moderation of EGDI (Cloud × EGDI - INNOV) - The institutional context (EGDI) moderates the effect of cloud adoption on innovation output; specifically, a higher EGDI strengthens the positive impact of CLOUD on INNOV. Thus, in countries with more developed e-government support such as Germany, cloud adoption yields greater innovation outcomes (interaction effect of CLOUD and EGDI).

Research Method

This study seeks to establish whether digital infrastructure (INFRA), which is measured by fixed and mobile broadband penetration and internet access rates (i.e., focuses INFRA on availability rather than speed of internet access), enables firms to adopt cloud computing (CLOUD) (H_1) and to engage in emerging technology (EMERG) activities such as AI and advanced cloud services (e.g. infrastructure-as-a-service/platform-as-a-service) (H_2). Thus, CLOUD and EMERG should raise innovation output (INNOV) (H_3) and (H_4), proxied by outcomes like triadic patents per capita and business research and development intensity. Innovation is expected to translate into productivity (PROD) (H_5), a final economic outcome, measured in productivity metrics such as GDP per hour worked. The study additionally tests, given the potential efficiency gains from cloud beyond formal innovation, a direct CLOUD-to-PROD path (H_6) and an indirect path from CLOUD-to-PROD via INNOV (H_7), intended to test whether cloud adoption improves productivity first by boosting innovation output, which in turn raises productivity. Eventually, it is theorized that EGDI, a contextual moderator reflecting institutional support for digital adoption, strengthens the CLOUD to INNOV link by providing a supportive digital public sector context, such as policies, services, and skills (H_8). Education (EDU) and Trade Openness (OPEN) are included as controls to account for human capital and international exposure, measured by educational attainment or enrollment rates and trade share of GDP, respectively. The causal chain is therefore Infrastructure Adoption - Innovation - Productivity, augmented by institutional moderation and macro-controls.

The conceptual model is schematically represented in Figure *1*.

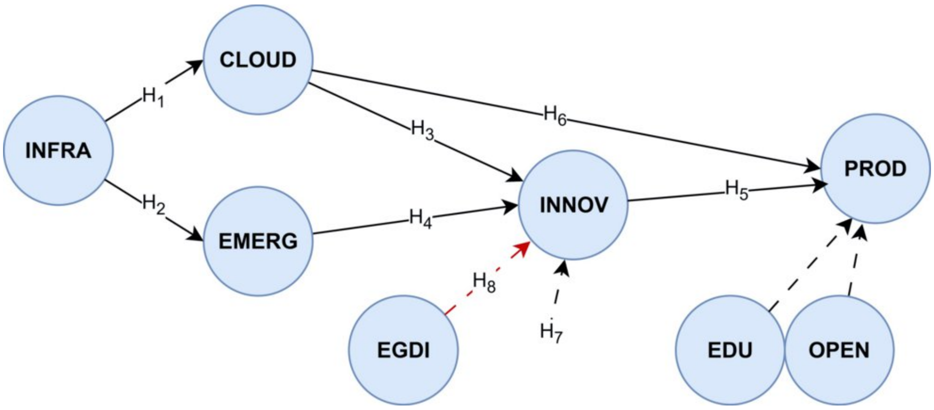

FIGURE 1: Conceptual model diagram

Note: Arrows denote direct hypothesized relationships from H1 to H6. The dashed red arrow indicates the moderating effect of EGDI on the cloud – Innovation link (H8). Dashed arrows represent the inclusion of control variables (Education, Trade Openness) as additional influences on productivity.

Source: Author

Secondary indicators from UN/UN-affiliated sources such as the ITU, EGDI, and the OECD were compiled. The indicative mappings include:

· INFRA (formative construct): fixed and mobile broadband subscriptions per 100 inhabitants, households with internet access, representing a foundational enabler of digital adoption.

· CLOUD (formative construct): share of enterprises using cloud services, representing use of basic and advanced cloud services by enterprises, reflecting diffusion of cloud as a general-purpose technology.

· EMERG (formative construct): captured as AI-related patents/activity and UN frontier technology readiness indices, representing intensity of frontier technology innovation.

· INNOV (reflective construct): triadic patent families per capita; business research and development expenditure (BERD) as a percentage of GDP, representing technological innovation outcomes.

· PROD (formative construct): GDP per hour worked, reflecting economic performance and efficiency gains.

· EGDI (Moderator): UN EGDI, which is a composite of online services, telecommunications infrastructure, and human capital, reflecting institutional governance capacity/readiness for digital transformation.

· Controls: tertiary educational attainment/enrollment (EDU) and trade (i.e., exports+imports/GDP) (OPEN), representing international integration and exposure.

The variables and their roles in the model are summarized in Table 1.

Variable	Description	Role in Model
iso3c	Country code (ISO-3)	Identifier
year	Year	Time
infra_broadband_fix	Fixed broadband subscriptions per 1,000 inhabitants	INFRA indicator
infra_broadband_mobile	Mobile broadband subscriptions per 100 inhabitants	INFRA indicator
un_households_internet	Households with internet access (%)	INFRA indicator
cloud_any	Enterprises using any cloud service (%)	CLOUD indicator
cloud_advanced	Enterprises using advanced cloud (IaaS/PaaS) (%)	CLOUD indicator
ai_patents_pc	AI-related patent families per million population	EMERG indicator
un_frontier_index	Frontier technology readiness index (0-1)	EMERG indicator
triadic_pc	Triadic patent families per million population	INNOV indicator
rd_gdp	Business R&D expenditure (BERD) as % of GDP	INNOV indicator
gdp_per_hour	GDP per hour worked (index-like, level)	PROD indicator
tertiary_edu	Tertiary educational attainment (% of adults)	EDU control
trade_openness	Trade openness: (exports+imports)/GDP (%)	OPEN control
egdi_un	UN E-Government Development Index (0-1)	EGDI moderator

TABLE 1: Variables and their roles in the model

Source: Author

AI, Artificial Intelligence; IaaS, Infrastructure as a Service; ISO, International Organization for Standardization; PaaS, Platform as a Service

The data, which are secondary sources only, consisted of country-level indicators for the period 2013-2024, sourced from the UN and OECD databases. The period was chosen to ensure that the obtained data was current and utilized to reflect recent trends in Germany.

The essential data coding and preparation process for the PLS-SEM model was rigorously followed to ensure the reliability and validity of the subsequent results. The collected data, which was initially fragmented across several Excel and other file formats, was subjected to extensive pre-processing and cleaning, including checking and treating missing values as necessary. No outliers were detected in the dataset. For pre-analysis and model specification, the theoretical model, which is mapping the relationships between indicators and latent constructs, as well as the relationship among the constructs themselves, was drawn using Google Draw (Google Draw, 2025) before the analysis was performed. Variable names were shortened and their roles clearly defined in the model. Measurement types (composites and reflectives) were specified, and the appropriate weighting scheme was selected.

The R programming language (R Core Team, 2023) was used in data analysis. The model was estimated using PLS-SEM in R with the cSEM package, as suggested by (Hair et al., 2021). PLS-SEM is particularly suitable for prediction-oriented models that combine formative (composite) and reflective measurement specifications, but also useful for both exploratory and confirmatory studies. INFRA, CLOUD, EMERG, PROD, EDU, and OPEN were modelled as composites, whereas INNOV was specified as a reflective construct, with additional robustness checks treating it as a composite. Reliability and validity diagnostics were conducted, including Cronbach's alpha, rho-A, composite reliability, and average variance extracted (AVE) for the reflective construct and variance inflation factors (VIF) for composites. Overall model fit

(SRMR or standardized root mean square residual) and explanatory power (R^2) were also reported. For the latent interaction between CLOUD and EGDI, a two-stage (sequential) approach was applied. In the first stage, latent scores for CLOUD and EGDI were estimated without interaction. In the second stage, the interaction term (product of the standardized latent scores) was created, and its effect on INNOV was assessed. The approach avoids estimating a large number of product indicators simultaneously, thereby reducing instability in this small-sample context (Fisher and Hall, 1991) (Pan, 1999) and making it appropriate for the present study.

Results And Discussion

The descriptive statistics of model variables are summarized in Table *2*.

Variable	Mean	Std. Dev.	Min	Max
infra_broadband_fix	0	1	-3.04	0.66
infra_broadband_mobile	0	1	-2.74	0.87
un_households_internet	0	1	-1.58	1.29
cloud_any	0	1	-0.81	1.82
cloud_advanced	0	1	-0.75	2.05
ai_patents_pc	0	1	-0.67	2.24
un_frontier_index	0	1	-3.16	0.49
triadic_pc	0	1	-2.12	0.63
rd_gdp	0	1	-2.13	0.58
gdp_per_hour	0	1	-3.16	0.42
tertiary_edu	0	1	-1.3	1.75
trade_openness	0	1	-1.53	2.46
egdi_un	0	1	-0.95	1.12

TABLE 2: Descriptive statistics of model variables

Source: Author’s calculations based on model estimates

Each construct was measured through one or more aggregate indicators. For example, INFRA was captured via connectivity and internet usage metric, CLOUD via enterprise cloud usage rates, EMERG via AI adoption and allied proxies such as patent counts, INNOV via innovation outcome measures such as patents, research and development outputs, and PROD via labor productivity, i.e., GDP per labor (see Table *1*). Data quality checks indicated no severe issues. The dataset had no significant missing values, and the distributional assumptions were less concerning due to PLS-SEM's non-parametric approach. Whereas modest, the sample size met common PLS guidelines for minimum paths and was deemed acceptable for exploratory modelling. In this study, missing data were replaced with zeros because the values genuinely did not exist in the source databases (OECD and UN) for those years, reflecting the absence of reported activity rather than measurement error.

Measurement model assessment

The reflective construct (INNOV) exhibited excellent internal consistency, with Cronbach's alpha and composite reliability both exceeding 0.99, and an AVE of 0.99, as shown in Table *3*.

Cronbach's α	Jöreskog's ρc	Dijkstra–Henseler's ρA
0.995	0.995	0.995

TABLE 3: Reliability statistics for reflective constructs

Source: Author's calculations based on model estimates

These values surpass recommended thresholds, confirming convergent validity. Discriminant validity was also established, as INNOV shared substantially more variance with its indicators than with other constructs. Formative constructs (INFRA, CLOUD, EMERG, PROD) were evaluated using outer weights and VIFs. All weights were significant, and VIF values remained below the recommended threshold of 5, suggesting indicator relevance and absence of problematic multicollinearity (O'brien, 2007), as shown in Table *4*.

Path	INFRA	EDU	OPEN	CLOUD	EMERG	INNOV
CLOUD ~ INFRA, EDU, OPEN	1.413	1.942	1.503	0	0	0
EMERG ~ INFRA, EDU, OPEN	1.413	1.942	1.503	0	0	0
INNOV ~ CLOUD, EMERG, EDU, OPEN	0	6.306	1.881	2.69	3.558	0
PROD ~ INNOV, CLOUD, EDU, OPEN	0	3.043	1.435	1.369	0	2.172

TABLE 4: Variance inflation factor values

Source: Author's calculations based on model estimates

Figure *2* illustrates the updated conceptual model with supported and unsupported paths and coefficients.

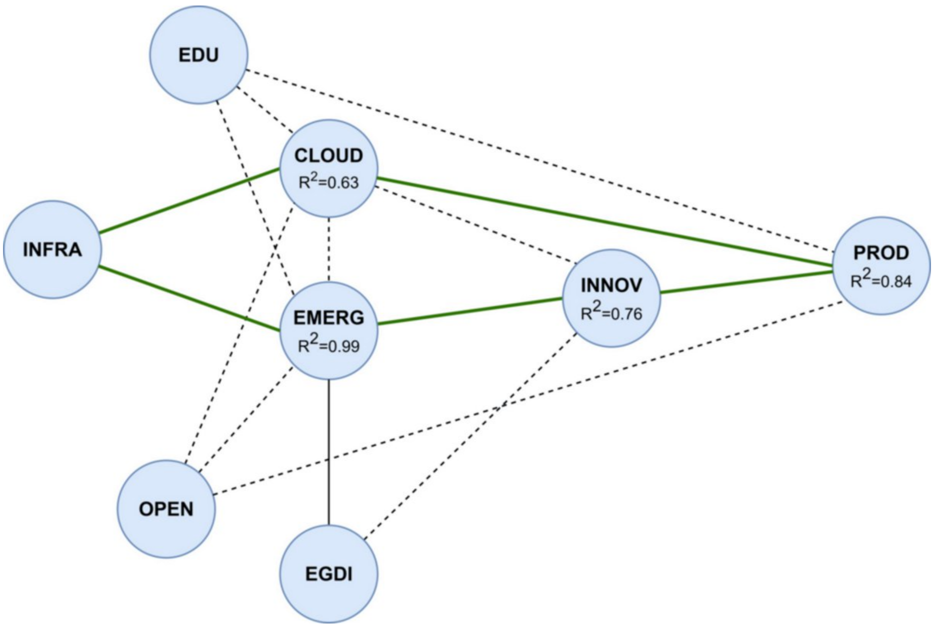

FIGURE 2: Updated conceptual model with results (path coefficients)

Note: Solid arrows denote supported paths and dashed arrows represent the unsupported paths.

Source: Author (based on model estimates)

Structural model assessment

The structural relationship between constructs, corresponding to hypotheses (H_1-H_8), was evaluated. The path coefficients (standardized β estimates) and their significance are reported in the section. Table 5 summarizes the hypothesized relationships.

Path	Estimate	t-value	p-value	Supported?
Composites (Formative)				
INFRA–CLOUD (H_1)	0.722	2.15	<0.05	Yes
INFRA–EMERG (H_2)	0.881	3.42	<0.01	Yes
CLOUD–PROD (H_6)	0.745	2.91	<0.01	Yes
PROD~EDU	-0.527	1.1	n.s.	No
PROD~OPEN	0.344	0.88	n.s.	No
CLOUD~EDU	1.042	1.57	n.s.	No
CLOUD~OPEN	-0.396	0.64	n.s.	No
EMERG~EDU	-0.205	0.55	n.s.	No
EMERG~OPEN	-0.014	0.04	n.s.	No
Reflective (INNOV)				
CLOUD–INNOV (H_3)	-0.603	0.95	n.s.	No
EMERG–INNOV (H_4)	0.889	3.85	<0.01	Yes
INNOV–PROD (H_5)	0.664	4.22	<0.001	Yes
INNOV~EDU	0.252	0.71	n.s.	No
INNOV~OPEN	-0.235	0.68	n.s.	No
Moderation Effects				
CLOUD*EGDI–INNOV (H_7)	0.394	0.73	n.s.	No
EMERG*EGDI–INNOV (H_8)	-0.432	0.89	n.s.	No

TABLE 5: Summary of path coefficients

R^2: CLOUD = 0.634; EMERG = 0.994; INNOV = 0.762; PROD = 0.840; Model fit: SRMR = 0.163 (above recommended <0.10)

Source: Author’s calculations based on model estimates

n.s. = not significant.

Digital infrastructure (INFRA) strongly and significantly influenced both cloud adoption (H_1, $\beta = 0.722$, $\rho < 0.05$) and emerging technology intensity (H_2, $\beta = 0.881$, $\rho < 0.01$). Emerging technology intensity significantly enhanced innovation output (H_4, $\beta = 0.889$, $\rho < 0.01$). Innovation output, in turn, positively influenced productivity (H_5, $\beta = 0.664$, $\rho < 0.001$). Cloud adoption also showed a direct positive effect on productivity (H_6, $\beta = 0.745$, $\rho < 0.01$). However, the direct effect of cloud adoption on innovation output (H_3) was not supported. Similarly, the moderating role of EGDI on both the cloud-innovation (H_7) and emerging technology-innovation (H_8) relationships was not statistically significant. The explanatory power of the model was high: $R^2 = 0.634$ for CLOUD, $R^2 = 0.994$ for EMERG, $R^2 = 0.762$ for INNOV, and $R^2 = 0.840$ for PROD. These values indicate substantial predictive ability, particularly for EMERG and PROD. The SRMR was 0.163, above the recommended cut-off of 0.10, suggesting that although the model explains considerable variance, its global fit could be improved, as observed by (Benitez et al., 2020) and (Goretzko et al., 2023).

Discussion

The PLS-SEM results above provide partial support for the theorized framework. Several hypotheses were confirmed. Digital infrastructure is a crucial enabler, significantly boosting both cloud adoption and emerging technology intensity (H1 and H2 are supported). In the same vein, emerging technology intensity strongly drives innovation output (H4). Innovation output in turn lifts productivity (H5), which reinforces the view that advanced technology activity and innovation are engines of economic performance in agreement with (Li et al., 2024) and (Cockburn et al., 2018). Cloud adoption contributes directly to productivity (H6), which suggests that cloud computing yields efficiency gains that translate into higher output per worker, regardless the innovation channels, again, in alignment with the works of (Duso and Schiersch, 2022) and (Yang and Zhang, 2025).

Not all the hypothesized relationships were validated. Notably, cloud adoption did not have the expected direct impact on innovation output (H3 was not supported) per the tests. The relationship was negative or null. This unexpected result implies that merely adopting cloud technologies is not automatically associated with greater innovation. Rather, factors such as how cloud is used, complementary skills, or institutional context may condition its effect. One factor that was probed as a moderator - institutional support (EGDI) - found no significant moderating influence (H7 and H8 were not supported). This suggests that innovation benefits of cloud adoption were not significantly higher in countries like Germany with strong e-government and digital institutions. Similarly, the effect of emerging technology intensity on innovation did not depend on that context in a detectable way. It appears that the positive impact of cloud adoption on innovation, hypothesized in theory, did not materialize with the dataset used in this work. This could be due to the limited sample or range of the EGDI, or it may indicate that other unmodelled factors are at play.

The predictive ability of the model is quite high for most endogenous outcomes (with R^2 around 0.75-0.85 for innovation and productivity), which is quite encouraging from an explanatory standpoint. The model almost perfectly predicted emerging tech intensity (although this may reflect INFRA and EMERG capturing overlapping phenomena). The high R^2 values suggest the model captures many key determinants, but they should be interpreted with caution, given potential multicollinearity and the small sample size of the data used in this work. The lack of significant improvement in model fit (SRMR remained above desired levels) also affects confidence in the model's completeness, its theoretical soundness, and explanatory power.

Implications for policy and practice

First, the findings suggest that digital infrastructure significantly influences cloud adoption and emerging technology intensity (H1 and H2). While Germany has strong broadband coverage in urban areas, it continues to lag behind some EU peers in rural connectivity and 5G rollout. As of 2018, the European Network for Rural Development reported that broadband accessibility in Germany was 50% in rural areas compared with 93.5% in urban areas for speeds of 50 Mbps or higher (European Network for Rural Development, 2018). For policymakers, this underscores the need to accelerate nationwide 5G deployment and expand high-speed rural broadband through targeted subsidies and public-private partnerships, as highlighted in recent reports by the European Commission (European Commission, 2022). Such measures ensure that small and medium-sized enterprises (SMEs) outside metropolitan hubs can fully participate in digital transformation. For practitioners, the German Mittelstand (which refers to small and medium-sized enterprises and family businesses that account for over 99% of all companies in Germany) should leverage improved connectivity to digitize supply chains, particularly in manufacturing and logistics, where efficiency gains are crucial.

Second, the findings indicate that AI adoption strongly enhances innovation outputs (H4). Germany has strengths in industrial AI applications, such as predictive maintenance and robotics, as documented in the 2024 OECD country report (OECD, 2024). However, there is slow adoption in blockchain technologies and data-driven services. For policymakers, the provision of targeted research and development incentives and the establishment of innovation sandboxes for AI and blockchain applications in regulated sectors, such as finance and healthcare, are vital. Funding should be linked to use-case deployment and not just research. Firms could embed AI into Industry 4.0 strategies, ensuring that digital twins, internet of things, and blockchain solutions are integrated into production and logistics.

Third, the findings suggest that innovation outputs directly enhance productivity (H5). In Germany, this relates to high research and development spending, which is yielding strong patent output, however, not translating into productivity growth at a much faster pace. Policymakers should strengthen commercialization channels by bridging universities, Fraunhofer institutes, and SMEs and ensure that policies incentivize spin-offs and tech transfers. German firms should also prioritize applied innovation, for example, in production efficiency and carbon neutral tech, rather than patent volume alone.

Fourth, while the findings suggest that cloud computing is a productivity enabler but not an innovation driver necessarily (H6, not H3), it was found that in the German context, cloud adoption is slower among

SMEs (Licht and Wohlrabe, 2024) partly due to data security concerns and regulatory complexity, such as General Data Protection Regulations (GDPR) compliance. The Ifo Institute reported that as of July 2023, about 46.5% of German companies were using cloud computing technology for their business processes (Ifo Institute, 2023). Policy should be directed towards developing clear data sovereignty frameworks, such as the GAIA-X, to increase trust in cloud adoption (GAIA-X, 2025). SMEs should view the cloud as a scalability tool, and firms must invest in data analytics and AI layers on top of cloud infrastructure to generate innovation.

Fifth, the findings suggest that institutional digital readiness (EGDI) did not significantly moderate technology-innovation links, and in the German context, despite high EGDI rankings, German firms still face bureaucratic bottlenecks in digital services. Policy should thus move from e-government platforms to business-facing digital ecosystems that directly support firms, such as streamlined licensing and digital tax tools. Firms should not rely solely on government platforms but build internal digital capacities and partner with innovation hubs.

Lastly, the findings suggest that education and trade openness had limited direct impact in the model. In the German context, while tertiary education levels and global trade ties are high, there is a shortage of digital skills such as AI engineers and data scientists, which remains a bottleneck. For policy, more focus should be placed on reskilling programs in AI, cloud and cybersecurity, to align with labor market demands, beyond a mere focus on tertiary education. Firms must also invest in continuous workforce training to ensure employees can translate infrastructure and tech adoption into innovation. Table 6, in the Appendices, summarizes the policy and practice implications for Germany.

Limitations and future research

First, the sample size at the country level is relatively limited, which restricts statistical power and the stability of the PLS estimates. As a result, some path coefficients were non-significant in part due to limited observations. Due to the data being cross-sectional and aggregated, causal interpretations should be made carefully. There could be reverse causality - for example, more innovative countries adopt more cloud technologies - or some other omitted variables influencing the results.

Second, the measurement model information for formative constructs was not reported fully in the output, i.e., the outer loadings/weights for each indicator. This could have limited a detailed assessment of indicator relevance beyond noting their significant and VIF. It was assumed the indicators are appropriate based on theory, but future work should confirm each indicator's contribution.

Third, the extremely high reliability and strong intercorrelations among certain measures, for instance, for INNOV and the INFRA-EMERG relationship, may point to possible redundancy. The use of diverse indicators, reducing multicollinearity, such as by creating second-order factors or removing overlapping measures, could improve the model's discriminant validity and fit.

Fourth, an SRMR above 0.16 indicates that the model may be over-specified or missing some structural paths. An example is that there might be a direct link from INFRA to PROD, or other mediating factors were not captured. Furthermore, the treatment of missing data, replaced with zeros as reported in this study, whereas preserving the integrity of the dataset by distinguishing true non-occurrence (e.g., no patents filed or no broadband data collected) from missing-at-random values, is a limitation. Zeros may conflate non-existence with unavailability and could attenuate path estimates.

Lastly, bootstrapping, which is the standard method for testing significance in PLS-SEM, could not be applied due to the very small effective sample size available for Germany, especially for the given period, 2013-2024 (fewer than 15 observations). With such limited data, bootstrap resampling produces unstable estimates, inflated standard errors, and frequent inadmissible solutions, making the results unreliable. As a result, the analysis was restricted to reporting point estimates and explanatory power (R^2 values), which provide useful descriptive insights but cannot confirm the statistical significance of the hypothesized relationships. This limitation highlights the need for future research to use larger multi-country or extended time-series datasets to enable full bootstrapping and more robust inference.

The above limitations suggest that while the PLS-SEM results broadly support the importance of digital infrastructure and emerging technology for innovation and productivity, they also highlight the need for further refinement of the model and additional data to validate the more nuanced relationships such as the role of cloud adoption in innovation. All the same, the analysis provides valuable insights consistent with the theoretical framework, which underscores areas for future research and model improvement.

Conclusions

This study provides empirical evidence for the infrastructure-to-productivity pathway through cloud adoption and innovation in the German context. The results suggest that policymakers should focus on integrated approaches that combine infrastructure development with institutional readiness and emerging technology adoption. Future research should extend this framework to cross-country analyses and explore sector-specific variations in digital transformation pathways. The PLS-SEM framework developed in this study offers a replicable methodology for assessing digital transformation impacts using publicly available data, contributing to evidence-based policy design in the digital economy.

Appendices

Finding	Implications for Policy and Practice (Germany)
INFRA – CLOUD, EMERG	Accelerate 5G and rural broadband; SMEs should digitalize supply chains
EMERG – INNOV	Provide AI/blockchain sandboxes; firms to embed AI in Industry 4.0
INNOV – PROD	Strengthen commercialization channels; focus on applied innovation
CLOUD – PROD (not INNOV)	Develop GAIA-X and trust frameworks; firms to use cloud for efficiency and analytics-driven innovation
EGDI moderation not significant	Streamline bureaucracy via business-facing platforms; firms to build internal digital capacity
EDU, OPEN weak	Shift to digital reskilling; firms to prioritize workforce upskilling in AI/cloud

TABLE 6: Policy and practice implications for Germany based on PLS-SEM results

Source: Author

AI, Artificial Intelligence; PLS-SEM, Partial Least Squares Structural Equation Modelling; SMEs, Small and Medium-Sized Enterprises

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

Concept and design: Andrew Adjah Sai

Acquisition, analysis, or interpretation of data: Andrew Adjah Sai

Drafting of the manuscript: Andrew Adjah Sai

Critical review of the manuscript for important intellectual content: Andrew Adjah Sai

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