

Beyond Adoption: A Complementarity Threshold in the Digitalization–Innovation Nexus in the Brazilian Industry

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Abstract

This article examines whether the innovation effects of digitalization in industrial firms arise from the adoption of isolated digital technologies or from the integrated use of complementary technology portfolios. Using firm-level microdata for 1,435 Brazilian industrial firms with 100 or more employees, built from two 2022 databases of the Brazilian statistical office (IBGE), the innovation and digital technologies survey (PINTEC Semestral) and industrial performance survey (PIA- Enterprise), the analysis estimates the probability of product innovation, process innovation, and their joint occurrence as a function of both partial and comprehensive digital adoption. Two indicators are central to the empirical strategy: one captures the use of at least one advanced digital technology, while the other identifies firms that simultaneously adopt six technologies - Big Data, Cloud Computing, Artificial Intelligence, Internet of Things, Additive Manufacturing and Robotics. The results show a threshold pattern. The adoption of isolated technologies does not consistently increase innovation probability in baseline models, whereas the full digital portfolio is positively associated with product and/or process innovation and with the joint introduction of both. Instrumental-variable estimates further indicate that endogeneity is concentrated in partial adoption, while full digital portfolios behave as a more stable strategic commitment. These findings suggest that the innovative payoffs of digital transformation depend on complementarities between technologies and on their articulation with firms' broader innovation capabilities. The article contributes to the literature on digital transformation and innovation in emerging economies and offers policy implications for industrial strategies that prioritize systemic digital upgrading over piecemeal technological adoption.

JEL: O30; O54; C25.

1. Introduction

Digital technologies are increasingly recognized as important enablers of innovation, productivity and organizational change across firms in both advanced and emerging economies (Luo, 2023; Zhou et al., 2023; Chen et al., 2024). Yet an important question remains insufficiently answered: do firms benefit innovatively from adopting individual digital technologies, or do such gains depend on the coordinated use of complementary technologies as part of a broader digital transformation strategy?

This question is especially relevant in emerging economies, where structural heterogeneity, capability gaps and uneven access to digital infrastructure may limit the returns to isolated technological adoption. In this context, Brazil offers a valuable setting for analysis. Its industrial structure combines technologically advanced segments with large groups of firms facing persistent productivity and innovation constraints, making it possible to examine whether digitalization generates linear gains or whether innovation effects emerge only after a threshold of technological breadth is reached.

This article investigates the relationship between digital technology adoption and innovation performance in Brazilian industrial firms. More specifically, it estimates the probability that firms introduce product innovation, process innovation, or both, as a function of adopting specific advanced digital technologies and, crucially, as a function of adopting them in combination. The analysis focuses on six technologies covered by the 2022 survey: Big Data, Cloud Computing, Artificial Intelligence, Internet of Things, Additive Manufacturing and Robotics.

The article advances three main propositions. P1: the innovation effects of digitalization are stronger when firms adopt broad and complementary portfolios of digital technologies than when they adopt isolated technologies. P2: the innovation effects of digitalization are more visible in combined product-and-process innovation than in narrowly defined innovation outcomes. P3: partial digital adoption is more likely to be endogenous to firms' pre-existing innovation behaviour, whereas comprehensive digital portfolios reflect a more structured transformation strategy.

Empirically, the study combines two PINTEC Semestral 2022 survey rounds—one on innovation and one on advanced digital technologies—with selected information from the industrial performance survey PIA-Enterprise, generating a firm-level database of 1,435 industrial firms with 100 or more employees. The empirical strategy proceeds in two steps. First, descriptive evidence is used to characterize the innovation and digitalization profiles of firms. Second, probabilistic models (probit) and instrumental-variable probabilistic models (ivprobit) are estimated to test the relationship between innovation and digitalization while assessing possible endogeneity.

The findings show that adopting the full set of six digital technologies is positively associated with the probability of product and/or process innovation and with the joint occurrence of product and process innovation. By contrast, the adoption of at least one digital technology does not generate significant innovation effects in the baseline models. Instrumental-variable estimates reveal an additional asymmetry: endogeneity appears in the model for partial adoption, but not in those for full digital portfolios. Together, these results suggest that the innovative value of digitalization lies less in isolated tools than in systemic and complementary adoption.

This article contributes to the literature in three ways. First, it provides evidence that digital transformation should be understood as a complementary system rather than as the sum of independent technologies. Second, it expands the evidence base on digitalization and

innovation in emerging economies by using original Brazilian firm-level data. Third, it derives implications for industrial and innovation policy, indicating that support for fragmented digital adoption may be less effective than policies aimed at integrated digital transformation.

The remainder of the article is organized as follows. Section 2 develops the conceptual argument and reviews the empirical literature. Section 3 presents the database, variables and estimation strategy. Section 4 reports the descriptive and econometric results. Section 5 presents the econometric analysis. Section 6 discusses the main implications of the findings. Section 7 concludes.

2. Digital transformation, complementarities and innovation performance

Among studies examining the effects of digital technologies on firms' innovative performance, two main groups of technologies can be distinguished according to their role in the innovation process (Li et al., 2023). The first group comprises physical technologies directly related to production and innovation development, whereas the second encompasses intangible, data-based technologies that cut across business functions and indirectly support innovation. These technologies exhibit strong complementarities because their adoption typically involves complex systems that integrate interdependent tangible and intangible components. The mere adoption of digital technologies does not automatically enhance innovation, which makes the presumed linear and unequivocal link between digital transformation and innovative performance contentious (Usai et al., 2021).

Digital transformation can influence multiple stages of the innovation process in complex and causally ambiguous ways, given the diversity of enabling technologies and their heterogeneous effects on product, process, and service performance. A central theoretical tension follows: if digital technologies are general-purpose technologies characterized by strong complementarities, their innovation-enabling potential should increase non-linearly with the breadth of adoption, yet most empirical studies either treat digitalization as a binary state or focus narrowly on a single technology. This article addresses this tension by testing whether innovation gains from digitalization are concentrated among firms that deploy broad technological portfolios rather than those adopting a single technology.

Digitalization unfolds through multiple channels and is frequently associated with improvements in business performance, including cost reductions, new revenue opportunities, productivity gains, and new business models (Jung & Gómez-Bengoechea, 2022; Luo, 2023). These outcomes, however, rest on underlying processes of change and innovation. Digitalization may affect both the breadth and speed of innovation, reinforcing firms' capacity to modernize processes and to develop new products and services. In analysing these impacts, Blichfeldt and Faullant (2021) distinguish between breadth and depth of digital technology adoption: breadth captures whether a technology is adopted, while depth reflects the extent to which its potential is exploited, supporting the generation of more sophisticated knowledge and shaping subsequent innovation trajectories. This distinction is particularly relevant for Brazil, where industrial heterogeneity raises the question of whether the marginal innovation effect of additional technologies is uniform across firms.

Digital transformation enables organizations to leverage the pervasive connectivity of people, data, information, and knowledge, fostering process modularization and enabling more flexible and efficient production and supply-chain operations (Nwankpa & Roumani, 2016). Liu et al. (2023) instead emphasize that innovation drives organizational transformation through two key properties of digital technologies: convergence and generativity. Convergence refers to open technological architectures that aggregate information from multiple sources and facilitate the participation of multiple actors, recombining previously separate products, services, and even industries (Yoo et al., 2012). Generativity denotes the capacity to produce unprompted change driven by large, varied, and uncoordinated audiences and underpins the role of digital technologies as enablers of new products, processes, and services (Zittrain, 2006; Kohli & Melville, 2019). Many digital technologies depend on the reprogramming and homogenization of data. This creates conditions of open and flexible accessibility, where "accessibility" (affordance) captures their combinatorial and distributed nature and the possibility that organizations can purposefully exploit their potential (Yoo et al., 2012). Against this background, a key question for Brazil is whether the generative and combinatorial properties of digital technologies suppress innovation—as some critics suggest—or, when deployed as an integrated portfolio, generate innovation-enhancing synergies.

Zhou et al. (2023) distinguish two main strands in the literature on digital technology adoption and firms' innovative performance. One focuses on specific technologies and their effects on innovation, such as Blockchain (Wan, Gao & Hu, 2022) and Big Data (Ciampi et al., 2021). The other adopts a more comprehensive and integrated view of digital technologies (Blichfeldt & Faullant, 2021; Usai et al., 2021). Many studies, however, concentrate on the direct effects of digital technologies on innovation while paying limited attention to mediating mechanisms. Zhou et al. (2023) argue that firms' knowledge bases play a crucial mediating role in digital technology-driven innovation, reflecting higher-order capabilities that support digital technology adoption. Emerging digital technologies may enhance and accelerate innovation by inducing organizational transformations, including changes in structures, the use of digital platforms to interact with users, the opening of new sales channels, and the emergence of new business models (Kastelli et al., 2024; Scuotto et al., 2022).

For firms to undertake digital transformation, Kastelli et al. (2024) contend that they must build digital capability, understood as the ability to integrate and actively use digital technologies in support of innovation and organizational change.

Usai et al. (2021) adopt a critical stance toward the predominantly positive view of digital technologies' effects on innovation, noting that much of the evidence relies on qualitative analyses rather than rigorous quantitative testing (Boeker et al., 2021; Verstegen, Houkes & Reymen, 2019; Brock & von Wangenheim, 2019; Warner & Wager, 2019; Galindo-Martín, Castano-Martínez & Mendez-Picazo, 2019; Urbinati et al., 2020). Challenging the dominant narrative, they argue that although digital technologies may increase efficiency and productivity in the short term, they can also undermine learning and relational capabilities. In particular, they suggest that the generative and combinatorial properties of digital technologies may inhibit innovation by reinforcing codified, reusable, and easily imitable knowledge. Moreover, they criticize prior research for failing to differentiate the impacts of distinct groups of digital technologies and for largely ignoring how these technologies interact with different patterns of R&D activity. Kastelli et al. (2024) echo this concern, arguing that fostering innovative performance requires strengthening firms' idiosyncratic knowledge bases, internally and through collaboration with external partners, while Heredia et al. (2022) emphasize that digital technologies operate as configurators of capabilities and resources and do not necessarily yield positive innovation outcomes in all contexts. This debate frames the contribution of the Brazilian evidence presented here, which examines whether a broad digital portfolio mitigates the potentially adverse effects highlighted by these authors.

Chen et al. (2024) argue that digitalization can significantly reshape innovation practices in firms from emerging economies and identify three main channels. First, digital technologies relax time and space constraints by connecting internal and external resources through open and shared platforms, thereby injecting dynamism into corporate innovation systems. Second, their strong penetration and compatibility with other technologies increase opportunities for recombination, enhancing innovative performance. Third, digital technologies can raise the efficiency of new product development by improving coordination and knowledge exchange among participants, thus reducing R&D costs and time while improving the quality of outcomes. Chen et al. (2024) also emphasize the public-good attributes of technological innovation and R&D, highlighting the need for policy support—such as subsidies—to overcome innovation constraints and strengthen firms' ability to cope with risk (Ivanov, Dolgui & Sokolov, 2019). In the Brazilian context, this leads to a further question: is the innovation dividend from digitalization concentrated among firms that adopt a broad portfolio of technologies, or can the adoption of a single technology yield measurable innovation gains? The answer bears directly on the design of Brazil's digital industrial policy.

Most research on the impact of digital technologies on the innovation process conceptualizes “digital innovation” as an outcome, embodied in new products, processes, services, or business models (Urbinati et al., 2022). Parallel work, however, considers digital innovation as a process shaped by firms' innovation capabilities, organizational structures, and technology management practices. According to Radicic and Petkovic (2023), the implementation of digital technologies can affect all stages of the innovation process, from inputs (for example, R&D expenditures and other innovation investments) to outputs (product and process innovations). Digitalization also supports the development and acquisition of new skills, competencies, and knowledge that can, in turn, foster new products and processes (Nambisan et al., 2020). By enhancing access to existing knowledge and enabling new knowledge creation—through, for example, Big Data analytics—digitalization expands firms' absorptive capacity and increases the likelihood of generating new products and processes (Agostini et al., 2020).

More recent studies also explore the relationship between firm-level digital technology adoption and productivity (Massini et al., 2024). Although the adoption of new technologies is expected to raise productivity, a “productivity paradox” has been documented—initially in connection with ICT adoption in the 1990s and now extended to new digital technologies such as Artificial Intelligence (Brynjolfsson et al., 2021). The OECD (2023) reports only modest productivity effects, whereas Benassi et al. (2022) find that firm productivity is positively associated with investments in modern digital technologies, while profitability remains largely unaffected. Gaglio et al. (2022) link this debate to the complex relationships among innovation, digitalization, and productivity, building on the Crépon–Duguet–Mairesse (CDM) model that traces the sequence from R&D to innovation to productivity (Crépon, Duguet & Mairesse, 1998). Their work aligns with studies that extend CDM-type models to assess the role of ICTs and digital technologies as inputs to innovation (Van Leeuwen & Farooqui, 2008; Polder et al., 2010; Aboal & Tacsir, 2018; Alvarez, 2016).

Applied studies that examine the relationship between digital technology adoption and the innovative performance of industrial firms typically consider variables in four dimensions: (i) digital technology adoption, (ii) business innovation, (iii) moderating or mediating factors, and (iv) control variables (Zhou et al., 2023). This section has identified recent contributions along these lines, which differ in objectives, hypotheses, data sources, methods, and empirical strategies. Table 1 provides a non-exhaustive systematization of these analyses, documenting the different proxies used to measure firms' digital capacity and the range of technologies considered.

The studies summarized in Table 1 converge on the idea that digital technologies matter for innovation, but they differ in how they conceptualize both “digitalization” and “innovative performance.” Some analyses focus on specific technologies or narrow bundles (for example, ICTs, Industry 4.0 tools, or particular platforms), while others adopt broader indices of digital capability spanning infrastructure, use intensity, and organizational changes. Innovation is variously measured as product or process innovation, patenting, R&D-based indicators, or composite innovation scores, which partly explains why results range from clearly positive effects to modest or mixed impacts.

There is also substantial heterogeneity in mechanisms and mediating factors. Several contributions stress that digital technologies enhance innovation by improving information processing, coordination, and knowledge recombination, often mediated by absorptive capacity,

organizational learning, or complementary investments in skills and R&D. Others emphasize structural conditions such as firm size, sector, export orientation, or participation in value chains, showing that digitalization amplifies existing advantages rather than uniformly lifting all firms. A number of studies adopt CDM-type or multi-equation models to trace sequential links from digital adoption to innovation and then to productivity, while others rely on cross-sectional regressions or qualitative evidence, leading to different degrees of causal identification.

Despite the growing literature on digitalization and firm performance, three gaps remain. First, relatively few studies explicitly distinguish between isolated adoption and full digital portfolios. A notable recent exception is Cucculelli et al. (2025), who show for a panel of Italian manufacturing firms that antecedent technologies and closely related technological skills reinforce each other in shaping the adoption of Industry 4.0 technologies (robotics, IoT, big data analytics and additive manufacturing), largely overlapping with the technology set examined here, with this complementarity intensifying following an economic shock. This evidence, however, remains confined to a mature European economy. Second, evidence from emerging economies remains more limited than evidence from Europe and China. Third, the literature rarely examines whether endogeneity differs between partial and comprehensive adoption strategies. Addressing these gaps, the present article tests three propositions. P1 states that the innovation effects of digitalization are stronger under broad and complementary adoption than under isolated adoption. P2 states that digitalization is more strongly associated with the joint occurrence of product and process innovation than with narrowly separated innovation outcomes. P3 states that partial adoption is more likely to be endogenous to innovation behaviour than comprehensive digital transformation.

Table 1
– A summary of recent analysis of the digitalization-innovation nexus (non-exhaustive)

Author	Country	Data Source	Dependent Variables	Independent Variables	Other variables	Methodology	Results
Li et al (2023)	China	Stock Market Accounting Research (CSMAR). 8,709 observations	Level of corporate innovation measured through invention patent applications	Business digitalization measured by keyword frequency analysis in firms' annual reports	Regional level of digital industry innovation	Fixed Effects Regression Models	Digitalization and the level of digital industry innovation have a beneficial impact on firm innovation. The digital industry innovation level negatively moderates the relationship between firm digitalization and innovation.
Usai et al (2021)	Europe	Eurostat data: CIS-2015 innovation data and ICT usage survey focused on e-business	Degree of "radicalness" of innovations	ICT use as a proxy for digital technologies (internal process integration, integration with customers, suppliers and supply chains, cloud computing, big data analytics, 3D printing, robotics)	Variable distinguishing firms with closed vs. open innovation (internal and external R&D)	Principal Component Analysis (PCA) and Multivariate Multiple Regression (MANOVA)	The use of digital technologies does not lead to higher innovative performance.
Blichfeldt et al (2021)	Europe (Germany, Austria, Switzerland, Denmark, Netherlands)	European Manufacturing Survey (EMS); 747 manufacturing firms	Product and service innovation; Return on Sales (ROS)	Breadth and depth of adoption of 10 different digital base technologies		Correlation matrices between variables	Positive impact of digital technology implementation on product and service innovation. Differences across firms according to their level of technological intensity.
Ferreira et al (2019)	Portugal	Telephone survey of 938 Portuguese firms	Adoption of new digital processes; number of product, process and service innovations; turnover	Importance attributed by firms to new digital processes		Logistic regression model (logit transformation)	Some specific factors have a statistically positive influence on the adoption of new digital processes.
Gaglio et al (2022)	South Africa	711 industrial SMEs in Johannesburg	Stage 1: Innovation; Stage 2: Productivity	Stage 1: Digital technologies and R&D activities; Stage 2: Innovation; Adoption of digital technologies		Adapted CDM sequential model; Two-Stage Least Squares (2SLS)	ICT adoption positively affects innovation. Innovation conditioned on ICT use positively affects labor productivity.
Álvarez (2016)	Chile	Longitudinal Enterprise Survey (ELE) – two waves; 2,300 firms (manufacturing and services)	Stage 1: Decision to innovate; Stage 2: Productivity	Stage 1: Investment in digital technologies and R&D; Stage 2: Innovation		Adapted CDM sequential model; Three-stage regression	ICT contributes positively to innovation. ICT investment directly increases productivity. ICT

Author	Country	Data Source	Dependent Variables	Independent Variables	Other variables	Methodology	Results
							adoption improves innovation outcomes regardless of innovation measures and industries.
Radacic & Petkovic (2023)	Germany	Mannheim Innovation Panel (MIP); 2,854 SMEs (industry and services)	Introduction of product and process innovations (binary indicators)	Three types of digitalization: production and logistics; digital value chains; big data analytics	Internal R&D	Binary probit model	The impact of digitalization on innovation activities is heterogeneous, depending on the type of technology and innovation. Internal R&D weakens the effects of digitalization.
Kastelli et al (2024)	Greece	1,014 industrial firms	Product, process or marketing innovation (binary variables)	Industry 4.0 digital technologies: product-based (PbT) and management-based (MbT)	Digital capability (DC); Absorptive capacity	Partial Least Squares Structural Equation Modeling (PLS-SEM)	Positive direct contribution of absorptive capacity and, to a lesser extent, digital capability to innovative performance. Absorptive capacity mediates the positive effects of digitalization.
Massini et al (2024)	England	Adoption of Digital Technologies and Skills Survey (AdiTS); 120 firms (from a universe of 2,800 in Manchester)	Consequences of digital technology adoption on firm productivity	Adoption of six advanced digital technologies: AI, Big Data, Cloud Computing, 3D Printing, IoT and Robotics	Firm characteristics and skills	Machine learning techniques; Logistic regression models	Digital technologies show strong complementarity. Adoption by SMEs and younger firms, combined with adequate skills, significantly influences productivity levels.
Cuin et al (2024)	Germany	Mannheim Innovation Panel (ZEW); 1,100 SMEs	Innovative performance: number and types of innovations (product, process, marketing, organizational)	Digital diffusion index based on PCA of 11 digital technologies	Absorptive capacity (PCA of R&D intensity, R&D workforce share, highly skilled labor)	Multinomial and multivariate probit estimates	Digital diffusion is a positive trigger for innovation in SMEs. Absorptive capacity moderates the relationship only for product innovation. Firms with strong R&D and high-quality human capital use digital technologies more effectively for product innovation.
Brea (2021)	Australia	Telephone survey (197 respondents from 807 firms)	Five different measures of innovative performance	Four AI-related technologies: advanced data analytics, AI using unstructured data, cognitive computing,	Innovation modes (STI vs. DUI)	Logistic and ordered logistic regression models	Positive and significant relationship between cognitive technology use and innovative performance.

Author	Country	Data Source	Dependent Variables	Independent Variables	Other variables	Methodology	Results
				conversational computing			Cognitive technologies positively moderate the effect of the STI mode on product innovation.
Chen et al (2024)	China	7,505 listed private firms	Number of invention patents	Digital transformation index (Dt); innovation incentive policy (Sub)	Regional development level	Python-based content analysis; Logistic regression with robustness tests	Digital transformation promotes innovation in private firms, with stronger effects in economically developed regions. Innovation incentive policies reinforce this impact.
Peng & Tao (2022)	China	China Stock Market & Accounting Research; 1,578 listed firms (527 digitally transformed; 1,051 not)	ROA, ROE and innovation output	Digital transformation		Logistic regression with fixed effects (FE) and random effects (RE) models	Digital transformation significantly improves firm performance and stimulates corporate innovation.

Source: Own elaboration.

3 The methodological approach

3.1 The Semi-annual PINTEC surveys

The database used in this study is the “Pesquisa de Inovação Semestral” (PINTEC Semestral), which conducted seven rounds of surveys on innovation and related topics among Brazilian firms employing 100 or more persons in the extractive and manufacturing industries. This article draws on one survey on the adoption of advanced digital technologies and one innovation survey, both referring to the year 2022. PINTEC Semestral disseminates results in a timely manner: data collection lasts three months and publication takes place within the subsequent three months. To ensure both speed and quality in the information gathered on innovation and corporate strategies, the survey employs short, objective and self-explanatory questionnaires administered through a self-completion system, thereby ensuring standardisation and conceptual clarity.

The population under investigation comprises industrial firms with 100 or more employees, considered representative of economically significant dimensions. In 2021, this group accounted for 85.6% of Industrial Transformation Value (VTI), 85.9% of Net Sales Revenue (RLV), and 62.2% of total employment, although it represented only 2.8% of all industrial firms. It also concentrated 85.7% of total expenditure on innovation activities and 95.1% of total investment in R&D.

The sample is updated annually based on the IBGE’s Basic Selection Register (Cadastro Básico de Seleção - CBS). In 2022, the target population comprised 9,584 firms. Stratified sampling by economic activity (CNAE 2.0) was employed, resulting in 25 natural strata: one for the extractive industry and the remainder defined according to the two-digit divisions of the manufacturing industry. Each stratum was subdivided into a take-all stratum (probability equal to 1) and a sampled stratum (random selection).

To increase efficiency, the stratification method for skewed populations proposed by Hidiroglou (1986) was adopted, establishing specific cut-off points for each stratum to minimise sample size for a predetermined level of relative precision (a coefficient of variation of 8% for total employment).

In 2022, 1,532 firms were selected, of which 687 constituted the take-all stratum and 845 the randomly selected stratum. At the end of each survey cycle, sampling weights are recalibrated to ensure consistency with the updated register; consequently, the same firm may have different weights across cycles within the same reference year.

3.2 Firm Selection Procedures and Variables

As mentioned above, for the purposes of this article, a database was constructed comprising firms common to both survey cycles and for which the necessary information from the 2022 Annual Industrial Survey (PIA- Enterprise) was also available.

Of the 1,532 firms included in the sample for the 2022 reference year, 1,444 were common to both survey cycles. However, nine firms lacked the required 2022 PIA- Enterprise information for the proposed modelling. Consequently, a reference database was created containing variables from both survey cycles together with the relevant PIA- Enterprise 2022 information, totalling 1,435 firms.

Thus, the final dataset used in this article comprises 1,435 firms and includes all variables from the two survey cycles, in addition to a selected set of variables from PIA- Enterprise 2022, enabling the application of the proposed modelling strategy and discussion of the research questions. All models were estimated at the microdata level, without applying sampling weights to represent the overall population of firms. It is important to emphasise that, although the information was collected in separate cycles through two distinct questionnaires, the variables were designed in a comparable manner for the same set of firms. The integration of the datasets and joint use of variables therefore provide essential elements that enhance the analysis and understanding of the phenomena under investigation.

Following the selection of the firm-level dataset, a descriptive analysis was conducted by cross-tabulating variables from the two PINTEC Semestral survey cycles. This analysis yielded initial evidence of relationships between firms' innovation activities and digitalisation. Subsequently, econometric estimations were carried out. Four indicators related to the innovation process were considered as dependent variables, as presented in Table 2.

Table 2
– Dependent variables: types of innovation

Variable	Description
Product and/or business process innovation (InovProdProc)	Firms that answered "yes" to product innovation and/or process innovation, provided they also answered "yes" to categories related to production activities (goods production, logistics, and IT)
Product innovation (InovProd)	Firms that innovated only in products, i.e., those that answered "yes" to product innovation and "no" to all business process innovations.
Process innovation (InovProc)	Firms that innovated only in business processes exclusively related to production activities (goods production, logistics, and IT).
Product and business process innovation (InovProd_&_Proc)	Firms that answered "yes" to both product and process innovation, provided they also answered "yes" to categories related to production activities (goods production, logistics, and IT).

Source: Own elaboration.

Table 3 presents the two key digitalization indicators. The first identifies firms that adopt all six advanced digital technologies simultaneously and captures comprehensive digital transformation (Digital). The second identifies firms that adopt at least one of these technologies and captures partial or entry-level digital adoption (Digital2). This distinction is central to the article's empirical strategy because it allows a direct test of whether innovation gains depend on breadth and complementarity rather than on mere exposure to individual tools.

Unlike much of the previous empirical literature, the analysis does not reduce digitalization to a single technology or to a broad but opaque index. Instead, it compares two analytically distinct states: limited digital adoption and comprehensive portfolio adoption. This distinction is essential to evaluating whether digital transformation influences innovation linearly or whether its effects become stronger only when multiple technologies are combined.

Table 3
–Independent variables reflecting the adoption of digital technologies by firms

Variable	Description
Digitalization (Digital)	Binary variable equal to 1 if the firm reported using all six advanced digital technologies investigated in the survey (Big Data analytics, Cloud Computing, Artificial Intelligence, Internet of Things, additive manufacturing, and robotics).
Digitalization2 (Digital2)	Binary variable equal to 1 if the firm reported using at least one of the advanced digital technologies investigated in the survey (Big Data analytics, Cloud Computing, Artificial Intelligence, Internet of Things, additive manufacturing, or robotics).

Source: Own elaboration.

Table 4 presents the remaining explanatory variables used in this article.

Table 4
– Other explanatory variables

Variable	Description
Number of employees (lnNE)	Natural logarithm of the number of employees.
Number of employees ² (NE2)	Number of employees squared (number of employees × number of employees).
Foreign capital (ForCap)	Binary variable equal to 1 if the firm has foreign or predominantly foreign capital.
R&D (RD)	Binary variable equal to 1 if the firm incurred R&D expenditures > 0.
Cooperation (Coop)	Binary variable equal to 1 if the firm was involved in cooperative arrangements with other organization(s) to develop innovative product or business process activities in 2022.
Public support (Support)	Binary variable equal to 1 if the firm used any public support instruments for its innovative activities.
Acquisition of machinery and equipment / Net sales revenue (ME)	Continuous variable equal to the value of machinery and equipment acquisition divided by net sales revenue in 2022.
High and Medium-High Intensity (HMH)	Binary variable equal to 1 if the firm is classified within high and medium-high digital intensity sectors (dummy variable).

Source: Own elaboration.

Based on the probit regression, eight (08) models were generated, presenting estimates of the inverse normal distribution function. These estimates are not probabilities per se, but values that can be observed in the normal table, the z-table (z-score). In this sense, a formula was applied based on the mean of the density of the normal distribution of the predicted values of each model multiplied by their coefficients—referred to as probabilities and marginal effects—. Such procedure makes possible to “translate” these coefficients into predicted probabilities and marginal effects. Thus, in addition to the effects observed in the z-score, the model presents marginal probabilities through the different regressor variables. Finally, the Akaike Information Criterion (AIC) was also used, which, according to Dobson & Barnett (2018), is a goodness-of-fit statistic based on the likelihood function, with a penalty for the number of estimated parameters.

Next, endogeneity was tested using an instrumental variable probit model (ivprobit). Endogeneity arises when an independent variable correlates with the error term—often due to omitted variables or measurement error—leading to biased coefficient estimates and incorrect conclusions. Instrumental variables offer a way to both detect and correct for this issue..

Accordingly, the instrumental variable digitalindex was created. It is strongly correlated with the digitalization indicators and only weakly correlated with the innovation outcomes, which supports its use in the ivprobit estimations. Testing endogeneity is especially relevant in this context because innovative firms may be more likely to adopt digital tools, particularly when such adoption is selective or limited. For this reason, the instrumental-variable models are used not only as a robustness exercise, but also as a way to determine whether partial and comprehensive digitalization differ in their causal structure.

Finally, Table 5 informs the instrumental variable used in the probabilistic model.

Table 5
– Instrumental Variable used in the probabilistic model

Industrial Sector Digitalization Intensity Index (digital_index)	Continuous variable calculated as the ratio between the sum of the number of firms adopting at least one advanced digital technology and the total number of firms in the sector (two-digit CNAE code).
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Source: Own elaboration.

Based on the methodology and variables described, the next section develops an analysis of the results obtained through descriptive statistics and econometric estimations.

4. Results

4.1 Descriptive Analysis

This section presents the descriptive and econometric evidence on the relationship between digitalization and innovation. The descriptive analysis characterizes the profiles of innovative and digitally advanced firms, while the econometric models test whether innovation effects differ between comprehensive and partial digital adoption.

Table 6 presents the number of firms with foreign capital, the number of firms that invested in R&D, that received government support, and that engaged in cooperative activities. The data show that the group of firms innovating in product and/or process represents the largest group, with 832 firms in a sample of 1,435. The smallest group consists of firms innovating only in processes (39 firms). Regarding innovation efforts, firms that develop product and/or process innovations are among the highest spenders in R&D (75.6% of firms). Within the group of firms innovating in both product and process (177 firms), 85.5% of this group invests in R&D. Firms innovating in both product and process also stand out for their high frequency of receiving government benefits (support), with about 70% of firms benefiting (145 firms), as well as for engaging in cooperative arrangements, with 68% of firms participating.

Table 6
Number of firms that carried out innovation, by type and characteristics

Types of Innovation	Number of Firms	Foreign Capital	R&D	Public Support	Cooperation
Product and/or Process Innovation	832	219	629	487	446
Product Innovation	191	59	118	94	63
Process Innovation	39	16	24	16	19
Product and Process Innovation	207	52	177	145	142

Source: Own elaboration.

Table 7 presents the number of employees, net sales revenue, the amount spent on the acquisition of machinery and equipment, and R&D investment values. Additionally, it is possible to construct the labour productivity variable from the ratio between industrial output value and number of employees. This table shows that the group of firms innovating in product and/or process exhibits higher indicators compared to the other groups, followed by the group of firms innovating in both product and process. Firms innovating only in processes have higher expenditures on machinery and equipment (M&E) and lower R&D spending compared to the group of firms innovating only in products.

Table 7
Characteristics of firms that carried out innovation, by type

Types of Innovation	Number of Employees	Net Sales Revenue (R\$ mil)	M&E (R\$ mil)	P&D spending (R\$ mil)	Labour Productivity
Product and/or Process Innovation	2.062.979	3.127.583.646	63.768.412	26.679.034	602.462
Product Innovation	282.910	238.812.812	5.068.195	2.336.615	277.325
Process Innovation	105.897	144.952.009	8.271.195	251.345	373.168
Product and Process Innovation	796.893	997.433.594	14.936.574	6.079.326	375.604

Source: Own elaboration.

The labour productivity gap between firms that innovate in both product and process (375,604 R\$/worker) and those that innovate only in products (277,325 R\$/worker) suggests that process innovation generates productivity returns independently of product innovation – a hypothesis partially tested by the econometric models below. This raises the question: does digitalization contribute to innovation-led productivity, or does it primarily enable the appearance of innovation without the underlying productivity transformation?

Table 8 presents the results of the tabulation, allowing for the analysis of the number of firms using each advanced digital technology. Among firms that carried out product and/or process innovation, cloud computing is the most adopted technology among those analysed. The prevalence of cloud computing adoption among innovative firms (across all innovation types) is consistent with its role as an enabling infrastructure for all other digital technologies – a platform upon which AI, Big Data, and IoT operations run. This raises the question of whether cloud computing operates as a necessary (though not sufficient) condition for the innovation effects of the broader digital portfolio. Future research using interaction terms could test this mediation hypothesis directly.

The second most adopted technology is the Internet of Things, followed by robotics and Big Data. It is worth noting that the least adopted digital technologies by Brazilian firms innovating in product and/or process are additive manufacturing and artificial intelligence. The other innovation categories (product only, process only, and product and process) follow the same pattern regarding the two most used advanced technologies: cloud computing is first, followed by the Internet of Things.

Table 8
Number of firms that carried out innovation, by use of digital technology

Types of Innovation	Big Data	Cloud Comput.	AI	IoT	Additive Manufactur.	Robotics	Digital	Digital 2
Product and/or Process Innovation	394	713	315	502	320	443	126	781
Product Innovation	69	155	57	97	70	88	19	174
Process Innovation	17	34	17	28	9	15	2	36
Product and Process Innovation	117	186	100	146	106	131	47	198

Source: Own elaboration.

The descriptive evidence suggests that the two digitalization variables capture qualitatively different types of firms. The group classified under *Digital*, which adopts all six technologies simultaneously, is much smaller and more selective, consistent with a deeper form of organizational transformation. By contrast, Digital2 includes a much broader set of firms that have adopted at least one technology and therefore captures a more heterogeneous and less demanding form of digitalization.

Table 9 reinforces this distinction. Firms with comprehensive digital portfolios are larger, more R&D-intensive, more cooperative, more likely to receive public support, and more frequently associated with foreign capital than firms in the broader partial-adoption group. This pattern is consistent with the interpretation that full digital portfolios are linked to stronger capabilities and to a more structured transformation trajectory.

Table 9
Characteristics of firms that adopted digital technologies,
by category

Variables	Digital (1)	Digital2 (2)
Number of Employees (average)	5441,79	2111,83
Foreign Capital (%)	41,61%	25,12%
R&D (%)	86,13%	53,74%
Cooperation (%)	73,72%	38,53%
Public Support (%)	81,75%	42,98%
HMH (%)	41,61%	39,47%
ME (average)	0,0306	0,0330
Number of firms	137	1282

Source: Own elaboration.

Firms that adopt all six digital technologies simultaneously (Digital) generally show higher economic indicators (column 01) compared to firms that adopt at least one digital technology (Digital2), as shown in column 02.

On average, Digital firms are larger and have a higher incidence of foreign capital participation (41.6% of firms). Regarding innovation effort indicators, Digital firms predominantly engage in R&D activities (86% of firms), cooperate for innovation more frequently (73.7%), and more regularly receive government support (81.7%). The only indicator where firms adopting at least one digital technology (Digital2) perform better is the acquisition of machinery and equipment relative to net sales (ME). Digital firms spend 3.05% of net sales revenue on machinery and equipment, while Digital2 firms spend slightly more on average, at 3.3% of net sales revenue.

5. Econometric Analysis

5.1 Estimation of probabilistic models

Unlike logit regression, probit regression returns estimates through the inverse normal distribution function. This means that the results seen in the "Estimates" (Estim.) columns of Tables 10 and 11 are not probabilities per se, but values that can be read in the normal table, the z-table (hence commonly called the z-score). These interpretations are not intuitive and there is no odds-ratio equivalent, because the model does not produce probability or log-probability coefficients directly.

Therefore, to interpret the estimates correctly - i.e., in terms of changes in probability—formulas are used to translate these coefficients into predicted probabilities and marginal effects. For this reason, a third column was added to all estimations/models presented in Tables 10 and 11, making them interpretable. Additionally, no values indicated multicollinearity among variables in any model, and most data points fell within the simulated envelope (similar to a QQ-plot, but for non-normal data). Regarding model comparisons, the Akaike Information Criterion (AIC) was used to assess which model better fits the data. The following models present their estimates, p-values (significance level $\alpha = 0.05$), and marginal probabilities.

Table 10 presents the results of the estimations of probabilistic models considering four dependent variables: product and/or process innovation, product innovation, process innovation, and product and process innovation. In these models, the main explanatory variable is Digital, measured by the adoption of all six advanced digital technologies.

Tables 10 and 11 present the core econometric results. Their comparison provides the main empirical test of the article. If digitalization matters primarily through complementarity, the comprehensive portfolio variable should outperform the partial-adoption variable. This is exactly what the evidence indicates.

The results using Digital show that comprehensive digital transformation is positively associated with product and/or process innovation and, more specifically, with the joint occurrence of product and process innovation. By contrast, the coefficients for product-only and process-only innovation are not statistically significant. This pattern supports the argument that the innovative effects of digitalization are strongest when technologies are adopted in broad and coordinated combinations and when innovation is understood in a more systemic sense.

The models using Digital2 show no significant effect in the baseline probit specifications. This contrast is substantively important. It suggests that partial or isolated digital adoption does not automatically translate into measurable innovation gains. In other words, the innovation return to digitalization appears to depend less on the existence of at least one digital tool than on the breadth and complementarity of the technological portfolio.

From the results presented in columns (1), (2), and (3), it is possible to analyse the probability of a firm innovating in product and/or production process through the different regressors. The use of the six advanced technologies (Digital) is associated with an increase of 0.77 in the z-score of a firm innovating in product and/or process. In terms of marginal effects, the adoption of these six advanced digital technologies is associated with an increase of approximately 19.73% in the probability that the firm innovates in product and/or production process.

Considering the foreign capital variable, firms with foreign capital are associated with a decrease of 0.22 in the z-score of innovating in product and/or process. In marginal effects, this corresponds to a decrease of 5.67% in the probability of innovating in product and/or process. The results for the other explanatory variables indicate that R&D expenditure, public support, cooperation for innovation, and high-tech intensity sectors increase the probability of a firm innovating in product and/or process. R&D expenditure stands out: investment in these activities is associated with an increase of approximately 33.51% in the probability of innovating in product and/or process.

In the model testing the effect of Digital on the probability of innovating in product only, the associated coefficient is positive but not significant, as observed in columns (4), (5), and (6). A similar pattern is seen for the model testing the effect of Digital on the probability of innovating in process only. In that case, the coefficient is negative but not significant, as shown in columns (7), (8), and (9).

The results in columns (10), (11), and (12) show that the adoption of digital tools affects the probability of a firm innovating in both product and production process. The adoption of six advanced digital technologies is associated with an increase of 0.24 in the z-score for product and process innovation. In terms of marginal effects, this corresponds to an increase of approximately 4.5% in the probability that a firm innovates in both product and process. Other explanatory variables - R&D expenditure, public support, cooperation for innovation, and high-tech intensity sector - also increase this probability. Notably, R&D expenditure is associated with an increase of approximately 11.83% in the probability of innovating in both product and process.

Table 11 presents the results of probabilistic model estimations considering the four dependent variables: product and/or process innovation, product innovation, process innovation, and product and process innovation. In these models, the main explanatory variable is Digital2, measured by the adoption of at least one of the six digital technologies (Big Data, Cloud Computing, Artificial Intelligence, Internet of Things, Additive Manufacturing, and Robotics). Across the four models, there is no evidence that the use of at least one digital technology affects the probability of firms innovating.

The contrast between the Digital and Digital2 results is the article's central empirical contribution: while the adoption of any single digital technology does not statistically improve the probability of innovation (Digital2 is insignificant in all non-IV models), the adoption of the full portfolio of six technologies raises the probability of product-and/or-process innovation by approximately 19.7 percentage points. This threshold effect — where digitalization only 'pays off' innovatively once it reaches system-wide breadth — has direct implications for how industrial policy should target digital adoption support

In summary, comparing the results from Tables 10 and 11, it can be inferred that digital technologies generate positive and significant effects on the probability of firms innovating when used jointly, in combination (Digital variable), as also highlighted by Li et al. (2023) and Massini et al. (2024). Moreover, positive effects are observed in firms that innovate in product and/or process as well as in firms that innovate in both product and process, indicating that digital technologies, when adopted, have a transversal effect, simultaneously influencing both types of innovation (product and process). This finding aligns with Chen et al. (2024), who emphasize that the use of digital technologies can enhance process efficiency while simultaneously supporting the development of new products.

Table 10
– Estimations of probabilistic models by type of innovation using the “Digital” variable

Coef.	Product and/or Process Innovation			Product Innovation			Process Innovation			Product and Process Innovation		
	Estim. (1)	P-value (2)	Marg. Prob. (3)	Estim. (4)	P-value (5)	Marg. Prob. (6).	Estim. (7)	P-value (8)	Marg. Prob. (9)	Estim. (10)	P-value (11)	Marg. Prob. (12)
Intercept	-0,49	< 0,05	-	-0,91	< 0,05	-	-2,05	< 0,05	-	-2,55	< 0,05	-
Digital	0,77	< 0,05	0,1972	0,01	0,95	0,0021	-0,41	0,18	-0,0245	0,24	0,08	0,0450
InNE	-0,04	0,21	-0,0109	-0,07	0,08	-0,0141	0,001	0,99	4,09E-05	0,11	< 0,05	0,0209
NE2	3,05E-10	0,57	7,82E-11	-6,01E-10	0,51	-1,26E-10	1,06E-10	0,48	6,41E-12	8,94E-11	0,47	1,70E-11
ForCap	-0,22	< 0,05	-0,0567	0,20	< 0,05	0,0413	0,40	< 0,05	0,0240	-0,23	< 0,05	-0,0440
RD	1,31	< 0,05	0,3351	0,36	< 0,05	0,0763	0,17	0,38	0,0102	0,62	< 0,05	0,1183
Coop	0,65	< 0,05	0,1674	-0,26	< 0,05	-0,0552	0,28	0,11	0,0167	0,43	< 0,05	0,0814
Support	0,29	< 0,05	0,0747	0,15	0,17	0,0321	-0,24	0,18	-0,0148	0,19	0,10	0,0355
ME	0,43	0,40	0,1105	-0,01	0,96	-0,0027	-0,48	0,70	-0,0287	-0,06	0,85	-0,0107
HMH	0,18	< 0,05	0,0461	0,06	0,51	0,0119	-0,18	0,24	-0,0107	0,16	0,09	0,0300
	AIC = 1327,7			AIC = 1114,1			AIC = 363			AIC = 1011,5		

Table 11
– Estimations of probabilistic models by type of innovation using the “Digital2” variable

Coef.	Product and/or Process Innovation			Product Innovation			Process Innovation			Product and Process Innovation		
	Estim. (1)	P-value (2)	Marg. Prob. (3)	Estim. (4)	P-value (5)	Marg. Prob. (6).	Estim. (7)	P-value (8)	Marg. Prob. (9)	Estim. (10)	P-value (11)	Marg. Prob. (12)
Intercept	-0,73	< 0,05	-	-0,96	< 0,05	-	-1,96	< 0,05	-	-2,67	< 0,05	-
Digital2	0,17	0,18	0,0435	0,08	0,61	0,0158	0,03	0,91	0,0017	0,00	0,98	0,0009
InNE	-0,03	0,45	-0,0067	-0,07	0,07	-0,0144	-0,02	0,75	-0,0011	0,13	< 0,05	0,0244
NE2	5,37E-10	0,45	1,39E-10	-5,92E-10	0,51	-1,24E-10	1,22E-10	0,42	7,40E-12	8,10E-11	0,52	1,55E-11
ForCap	-0,19	0,06	-0,0485	0,20	< 0,05	0,0408	0,40	< 0,05	0,0241	-0,22	< 0,05	-0,0425
RD	1,29	< 0,05	0,3332	0,36	< 0,05	0,0753	0,17	0,38	0,0103	0,62	< 0,05	0,1188
Coop	0,67	< 0,05	0,1732	-0,27	< 0,05	-0,0560	0,25	0,15	0,0153	0,44	< 0,05	0,0848
Support	0,33	< 0,05	0,0856	0,15	0,17	0,0322	-0,27	0,14	-0,0165	0,21	0,07	0,0395
ME	0,51	0,33	0,1309	-0,02	0,95	-0,0033	-0,53	0,67	-0,0320	-0,04	0,90	-0,0071
HMH	0,18	< 0,05	0,0459	0,06	0,52	0,0118	-0,18	0,22	-0,0111	0,16	0,08	0,0310
	AIC = 1342,1			AIC = 1113,8			AIC = 365,1			AIC = 1014,6		

5.2 Estimations of probabilistic models with instrumental variables

Endogeneity is characterized by the correlation between an independent variable and the error term of a dependent variable, and it may lead to biased coefficient estimates, incorrect conclusions, and other issues. To address the potential presence of endogeneity, the instrumental variable “digital_index” was constructed, whose correlation proved to be high with the variables “Digital” and “Digital2” and low with the response variables “InovProdProc,” “InovProd_E_Proc,” “InovProd,” and “InovProc.”

Since the estimated models are non-linear probabilistic (probit), standard linear endogeneity tests are not applicable; we therefore rely on the Wald test. This test evaluates the null hypothesis “There is no endogeneity” against the alternative hypothesis “There is endogeneity.” If the p-value obtained in the test is greater than the significance level $\alpha = 0.05$, the null hypothesis is not rejected, indicating the absence of endogeneity in the estimated model.

In addition, the same concept of marginal effects was assessed through marginal probabilities, as discussed in other sections. It was also necessary to standardize the variable NE2, since numerical issues were observed in the model estimation, possibly related to multicollinearity and/or the scale of the variable. Therefore, NE2 was standardized by subtracting its mean and dividing by its standard deviation.

Thus, tests were conducted for the eight models presented in the previous section, and the model estimates as well as the p-values of the Wald test are shown in Tables 12 and 13.

Table 12 presents the results of the estimations of probabilistic models using instrumental variables, considering the four dependent variables: product and/or process innovation, product innovation, process innovation, and product and process innovation. In these models, the main explanatory variable is Digital, measured by the adoption of all six advanced digital technologies.

To verify the presence of endogeneity in the models, it is necessary to analyse the results of the Wald tests. It is observed that all models estimated with the Digital variable do not present endogeneity at the 5% significance level. Therefore, the results presented in Table 10 (probabilistic models) are the most appropriate for analysing the relationship between the Digital variable and the four types of innovation.

Table 13 presents the results of the estimations of probabilistic models considering the four dependent variables: product and/or process innovation, product innovation, process innovation, and product and process innovation. In these models, the main explanatory variable is Digital2, measured by the adoption of at least one of the six digital technologies (Big Data, Cloud Computing, Artificial Intelligence, Internet of Things, Additive Manufacturing, and Robotics).

To verify the presence of endogeneity in these models, it is necessary to analyse the results of the Wald tests. Among the models estimated with the Digital2 variable, only the one considering product and/or process innovation (Table 13) shows endogeneity at the 5% significance level (p-value = 0.0373) (column 03). The Wald test results for the other models do not indicate the presence of endogeneity; therefore, the results presented in Table 11 (probabilistic models) are the most appropriate for analysing the relationship between the Digital2 variable and the other types of innovation: product innovation, process innovation, and product and process innovation.

Based on the results presented in columns (1), (2), and (3) of Table 13, after using the instrumental variable and correcting for the endogeneity problem, it is possible to verify that the adoption of at least one of the six digital technologies (Big Data, Cloud Computing, Artificial Intelligence, Internet of Things, Additive Manufacturing, and Robotics), Digital2, is associated with an increase of 1.8715 in the z-score of a firm innovating in product and/or production process. In terms of marginal effects, it is observed that the adoption of at least one of the six digital technologies is associated with an increase of approximately 66.4% in the probability that the firm innovates in product and/or production process.

The instrumental-variable results add a second key layer to the argument. For the models based on Digital, the Wald tests do not indicate endogeneity at the 5% level. This suggests that comprehensive digital portfolios behave as relatively stable strategic commitments rather than as simple reactions to contemporaneous innovation outcomes.

By contrast, endogeneity is detected in the model that links Digital2 to product and/or process innovation. After correction, the estimated effect becomes positive and large. Rather than invalidating the baseline contrast, this result refines it. It indicates that partial digital adoption may be strongly intertwined with pre-existing innovation behaviour: firms that are already innovating may selectively adopt one or a few digital technologies. This reinforces the interpretation that isolated adoption is a noisier and more endogenous measure of digital transformation than full digital portfolios.

Table 12
– Estimations of probabilistic models with instrumental variables by type of innovation using the “Digital” variable

Coef.	Product and/or Process Innovation			Product Innovation			Process Innovation			Product and Process Innovation		
	Estim. (1)	P-value (2)	Marg.Prob. (3)	Estim. (4)	P-value (5)	Marg. Prob. (6).	Estim. (7)	P-value (8)	Marg. Prob. (9)	Estim. (10)	P-value (11)	Marg. Prob. (12)
Intercept	0.1404	0.7041	-	-0.1321	0.76	-	-1.2784	0.19	-	-2.7543	< 0.05	-
Digital	2.4316	< 0.05	0.7702	2.0109	< 0.05	0.6369	1.3134	0.41	0.4160	-0.5989	0.63	-0.1897
InNE	-0.1301	< 0.05	-0.0412	-0.1625	< 0.05	-0.0512	-0.0893	0.35	-0.0282	0.1509	< 0.05	0.0478
NE2	0.0842	0.56	0.0267	-0.1370	0.56	-0.0434	0.0382	0.39	0.0121	0.0211	0.59	0.0067
ForCap	-0.2577	< 0.05	-0.0816	0.1026	0.33	0.0325	0.2946	0.13	0.0933	-0.1987	0.09	-0.0629
RD	1.1643	< 0.05	0.3688	0.3226	< 0.05	0.1022	0.1644	0.35	0.0521	0.6029	< 0.05	0.1909
Coop	0.4452	< 0.05	0.1410	-0.3708	< 0.05	-0.1174	0.1287	0.57	0.0408	0.4788	< 0.05	0.1517
Support	0.1176	0.39	0.0373	-0.0344	0.79	-0.0109	-0.3559	0.05	-0.1127	0.2477	0.07	0.0785
ME	0.2743	0.57	0.0869	-0.0948	0.70	-0.0300	-0.5085	0.66	-0.1611	-0.0202	0.95	-0.0064
HMH	0.1292	0.12	0.0409	0.0088	0.92	0.0028	-0.1894	0.17	-0.0599	0.1709	0.06	0.0541
AIC = 1637 Log Veros. = -796,56			AIC = 1423 Log Veros. = -689,55			AIC = 674,96 Log Veros. = -315,48			AIC = 1324 Log Veros. = -639,96			
		Qui-Quad	P-value		Qui-Quad	P-value		Qui-Quad	P-value		Qui-Quad	P-value
	Wald Test	3.41	0,0647	Wald Test	3,73	0,0534	Wald Test	0,84	0.3598	Wald Test	0,42	0,5173

Table 13
– Estimations of probabilistic models with instrumental variables by type of innovation using the “Digital2” variable

Coef.	Product and/or Process Innovation			Product Innovation			Process Innovation			Product and Process Innovation		
	Estim. (1)	P-value (2)	Marg. Prob. (3)	Estim. (4)	P-value (5)	Marg. Prob. (6).	Estim. (7)	P-value (8)	Marg. Prob. (9)	Estim. (10)	P-value (11)	Marg. Prob. (12)
Intercept	-1.7551	< 0.05	-	-1.9927	< 0.05	-	-2.6191	< 0.05	-	-2.3898	< 0.05	-
Digital2	1.8715	< 0.05	0.6640	1.8233	< 0.05	0.6469	1.2442	0.41	0.4415	-0.3925	0.74	-0.1393
lnNE	-0.0636	0.06	-0.0226	-0.1017	< 0.05	-0.0361	-0.0484	0.46	-0.0172	0.1369	< 0.05	0.0486
NE2	0.1303	0.48	0.0462	-0.1475	0.54	-0.0523	0.0388	0.39	0.0138	0.0226	0.57	0.0080
ForCap	-0.2295	< 0.05	-0.0814	0.1035	0.33	0.0367	0.3236	0.09	0.1148	-0.2065	0.08	-0.0733
RD	1.0090	< 0.05	0.3580	0.2129	0.12	0.0755	0.0918	0.66	0.0326	0.6404	< 0.05	0.2272
Coop	0.4655	< 0.05	0.1652	-0.3379	< 0.05	-0.1199	0.1653	0.43	0.0587	0.4658	< 0.05	0.1653
Support	0.2549	< 0.05	0.0904	0.0961	0.37	0.0341	-0.2779	0.11	-0.0986	0.2119	0.06	0.0752
ME	0.3199	0.49	0.1135	-0.0958	0.70	-0.0339	-0.5535	0.64	-0.1964	-0.0181	0.95	-0.0064
HMH	0.1295	0.11	0.0459	0.0192	0.81	0.0068	-0.1905	0.18	-0.0676	0.1678	0.07	0.0595
	AIC = 1931 Log Veros. = -943,33			AIC = 1703 Log Veros. = -829,60			AIC = 957,51 Log Veros. = -456,75			AIC = 1607 Log Veros. = -781,71		
		Qui-Quad	P-value		Qui-Quad	P-value		Qui-Quad	P-value		Qui-Quad	P-value
	Wald Test	4,34	0,0373*	Wald Test	3,51	0,0611	Wald Test	0,51	0,4763	Wald Test	0,12	0,7324

Source: Own elaboration.

6. Final remarks

6.1 Summary of findings

This study contributes to three bodies of knowledge. First, it adds to innovation theory by providing evidence that digital technologies operate as a system, not as discrete inputs – the estimates indicate that complementarity is empirically relevant. Second, it enriches the emerging-economy innovation literature by showing that Brazilian industrialisation dynamics appears to be influenced by similar technology-innovation mechanisms to those in China and OECD countries, though with important heterogeneities worth exploring. Third, it contributes to the nascent empirical literature using firm-level survey data to operationalise digital portfolios, establishing PINTEC Semestral as a methodological reference for future comparative work.

Drawing on a representative sample of 1,435 Brazilian industrial firms from the PINTEC Semestral 2022 dataset, this article addressed a central question in the digitalization-innovation debate: does it matter whether firms adopt one digital technology or many? Of these firms, 832 innovate in product and/or process, 177 in both product and process jointly, and 39 in process alone; firms with product and/or process innovation are also the most R&D-intensive and most frequently adopt cloud computing, followed by the Internet of Things and robotics.

The econometric results reveal a clear asymmetry between the two forms of digital adoption. Comprehensive digital portfolios (Digital, all six technologies) are positively and significantly associated with product and/or process innovation and with the joint occurrence of both, with the effect more pronounced for this joint outcome than for isolated product or process innovation. By contrast, adopting at least one digital technology (Digital2) shows no significant effect in the baseline models. The instrumental-variable estimates refine this picture: none of the Digital models show evidence of endogeneity at the 5% level, consistent with comprehensive portfolios reflecting a stable strategic commitment rather than a response to pre-existing innovation behaviour. Among the Digital2 models, only the one for product and/or process innovation shows endogeneity ($p = 0.0373$); once corrected, this effect becomes positive and large (an estimated 66.4 percentage-point increase in probability), suggesting that partial adoption is closely intertwined with firms’ pre-existing innovation activity rather than an independent driver of it.

These results are consistent with the wider literature emphasising complementarity among digital technologies and between digital technologies and firms' existing capabilities, and with the view that digital transformation affects product and process innovation jointly rather than each in isolation.

Beyond the central role of digital portfolios, the results show that firms' innovation performance is strongly conditioned by more traditional capabilities, policy instruments and structural attributes. R&D expenditure, cooperation with external partners and access to public support exert sizeable, statistically significant effects on the probability of product and process innovation, often exceeding the marginal impacts of digitalisation itself and indicating that denser knowledge and policy networks enhance firms' ability to leverage digital technologies. Sectoral technological regimes also matter: firms in high- and medium-high technology industries display higher innovation probabilities, suggesting that the returns to digital transformation are uneven across sectors. In addition, firm size, foreign capital participation and the intensity of investment in machinery and equipment shape innovation outcomes, with larger and more capital-intensive firms generally innovating more, while foreign ownership is associated with lower innovation likelihood in some specifications. Collectively, these lateral findings indicate that digital portfolios operate within a broader configuration of R&D, collaboration, policy support, sectoral context and firm structure that critically mediates the innovation payoffs from digitalisation and should inform future research and policy design

6.2 Discussion and implications

The results suggest that digital transformation influences innovation not simply through the presence of advanced tools, but through their coordinated and complementary adoption. This finding is consistent with the view of digital technologies as enabling infrastructures whose value depends on integration across organizational and production domains.

For managers, the evidence implies that piecemeal adoption may be insufficient to generate robust innovation gains. Firms appear to benefit more when digital technologies are adopted as part of an articulated transformation strategy connected to R&D, cooperation and organizational capability-building. This pattern is consistent with D'Amico et al. (2025), who find for UK firms that AI adoption enhances innovation performance specifically when it complements firms' own R&D investment, while also substituting for certain forms of external knowledge collaboration.

For policymakers, the findings caution against support instruments narrowly focused on single technologies. Subsidies or incentives for isolated tools may have limited innovation effects if they are not embedded in broader capability and transformation programs. In emerging economies such as Brazil, digital industrial policy may be more effective when it promotes systemic upgrading, complementarities across technologies, and linkages with innovation-support institutions, a conclusion that resonates with broader diagnoses of the structural barriers facing Brazilian innovation policy, including low business R&D investment (Queiroz, Vonortas & Canuto, 2025).

7. Conclusions

This article examined whether the innovation effects of digitalization in Brazilian industrial firms arise from isolated digital technologies or from the integrated adoption of complementary digital portfolios. Using firm-level data from PINTEC Semestral 2022 and PIA- Enterprise for 1,435 industrial firms, the evidence indicates that comprehensive digital adoption is positively associated with product and/or process innovation and with the joint introduction of product and process innovation, whereas partial adoption does not generate consistent effects in baseline models.

The article's main contribution is to show that digitalization should not be treated as a binary condition in which any adoption automatically improves innovation performance. Instead, the results point to a complementarity threshold: digital technologies become more innovation-relevant when they are deployed in broad and coordinated combinations. The instrumental-variable analysis further refines this conclusion by showing that partial adoption is more vulnerable to endogeneity, which suggests that isolated digital tools may often be adopted as a response to pre-existing innovation dynamics.

These findings contribute to the literature on digital transformation and innovation in emerging economies by offering Brazilian evidence based on direct observation of six advanced technologies at the firm level. They also underscore that digital transformation interacts with more traditional innovation drivers, especially R&D, cooperation and public support. Future research may build on this analysis by testing interaction effects between digital portfolios and absorptive capacity, by exploring sectoral heterogeneity in greater depth, and by extending the empirical design to productivity outcomes.

Declarations

Author Contribution

A.P.M.A., J.B., and J.C.F. contributed to the study conception (conceptualization). A.P.M.A., J.B., F.P., and L.D. carried out the investigation and formal analysis. A.P.M.A., J.B., F.P., L.D., and J.C.F. developed the methodology. F.P. performed data curation. J.C.F. and M.S. supervised the study (supervision). A.P.M.A., J.B., and J.C.F. wrote the original draft. A.P.M.A., J.C.F., and M.S. reviewed and edited the manuscript. All authors reviewed and approved the final manuscript.

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Data Availability

Yes. This study uses firm-level microdata from two surveys conducted by the Brazilian Institute of Geography and Statistics (IBGE): the Pesquisa de Inovação Semestral (PINTEC Semestral, 2022 round) and the Pesquisa Industrial Anual – Empresa (PIA-Empresa, 2022). These are confidential firm-level microdata subject to statistical secrecy under Brazilian law, and are not publicly available. Access is restricted to authorized researchers under IBGE's controlled data-access protocols. Researchers interested in accessing the data should contact IBGE directly (<https://www.ibge.gov.br>) to inquire about the applicable access procedures. Aggregate statistics derived from these surveys are publicly available at <https://www.ibge.gov.br/estatisticas/multidominio/ciencia-tecnologia-e-inovacao/35867-pesquisa-de-inovacao-semestral.html>.

References

1. Aboal, D., & Tacsir, E. (2018). Innovation and productivity in services and manufacturing: the role of ICT. *Ind Corp Chang*, 27(2), 221–241.
2. Agostini, L., Galati, F., & Gastaldi, L. (2020). The digitalization of the innovation process. Challenges and opportunities from a management perspective. *Eur J Innov Manag*, 23(1), 1–12. <https://doi.org/10.1108/EJIM-11-2019-0330>
3. Alvarez, R. (2016). The impact of R&D and ICT investment on innovation and productivity in Chilean firms. *Inter-American Development Bank Technical Note Series*. IDB-TN-1056.
4. Benassi, M., Grinza, E., Rentocchini, F., & Rondi, L. (2022). Patenting in 4IR technologies and firm performance. *Industrial and Corporate Change*, 31(1), 112–136. <https://doi.org/10.1093/icc/dtab041>
5. Blichfeldt, H., & Faullant, R. (2021). Performance effects of digital technology adoption and product & service innovation – A process-industry perspective. *Technovation*, 105. <https://doi.org/10.1016/j.technovation.2021.102275>
6. Boeker, W., Howard, M. D., Basu, S., & Sahaym, A. (2018). Interpersonal relationships, digital technologies, and innovation in entrepreneurial ventures. *Journal of Business Research*, 125 November 495–507. 2021. <https://doi.org/10.1016/j.jbusres.2019.09.003>
7. Brea, E. (2021). An empirical exploration of the role of artificial intelligence in enhancing innovation performance in organisations. In: *Proceedings of the 18th International Schumpeter Society Conference*. International Joseph Schumpeter Society, Italy.
8. Brock, J. K. U., Von Wangenheim, F., & Demystifying, A. I. (2019). What Digital Transformation Leaders Can Teach You about Realistic Artificial Intelligence. *California Management Review*, 61(4), 110–134.
9. Brynjolfsson, E., Rock, D., Syverson, C., & The Productivity, J.-C. (2021). How Intangibles Complement General Purpose Technologies. // *American Economic Journal-Macroeconomics*, 13(1), 333–372. <https://doi.org/10.1257/mac.20180386>
10. Chen, P., & Kim, S. (2023). The impact of digital transformation on innovation performance - The mediating role of innovation factors. *Heliyon*, 9. <https://doi.org/10.1016/j.heliyon.2023.e13916>
11. Chen, L., Tu, R., Huang, B., Zhou, H., & Wu, Y. (2024). Digital transformation's impact on innovation in private enterprises: Evidence from China. *Journal of Innovation & Knowledge*, 9. <https://doi.org/10.1016/j.jik.2024.100491>
12. Ciampi, F., Demi, S., Magrini, A., Marzi, G., & Papa, A. (2021). Exploring the Impact of Big Data Analytics Capabilities on Business Model Innovation: The Mediating Role of Entrepreneurial Orientation. *Journal of Business Research*, 123, 1–13.
13. Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly*, 35(1), 128–152. <https://doi.org/10.2307/239355>
14. Crépon, B., Duguet, E., & Mairesse, J. (1998). Research, Innovation, and Productivity: An Econometric Analysis at the Firm Level. *Economics of Innovation and New Technology*, 7(2), 115–158.
15. Cucculelli, M., Lamperti, F., Mondolo, J., Pompei, F., & Venturini, F. (2025). Firm adoption of Industry 4.0 technologies in times of economic turmoil: the role of enabling factors. *Journal of Technology Transfer*, 51(4), 2455–2485. <https://doi.org/10.1007/s10961-025-10263-1>

16. Cui, J. (2023). Impact of Digital Transformation on Corporate Innovation– Empirical evidence from public companies. *SHS Web of Conferences* 169, 01046. <https://doi.org/10.1051/shsconf/202316901046>
17. D'Amico, E., Belitski, M., Braga, A., & Savoie, R. (2025). Enhancing knowledge spillover of innovation through artificial intelligence: an empirical investigation. *Journal of Technology Transfer*, 51(4), 2222–2250. <https://doi.org/10.1007/s10961-025-10217-7>
18. Dobson, A. J., & Barnett, A. G. (2018). *An Introduction to Generalized Linear Models* (4th ed.). CRC.
19. Ferreira, J. J. M., Fernandes, C. I., & Ferreira, F. A. F. (2019). To be or not to be digital, that is the question: Firm innovation and performance. *Journal of Business Research*, 101, 583–590.
20. Gaglio, C., Kraemer-Mbula, E., & Lorenz, E. (2022). The effects of digital transformation on innovation and productivity: Firm-level evidence of South African manufacturing micro and small enterprises. *Technological Forecasting & Social Change*, 182. <https://doi.org/10.1016/j.techfore.2022.121785>
21. Galindo-Martín, M. A., Castano-Martínez, M. S., & Mendez-Picazo, M. T. (2019). Digital transformation, digital dividends and entrepreneurship: A quantitative analysis. *Journal of Business Research*, 101, 522–527. <https://doi.org/10.1016/j.jbusres.2018.12.014>
22. Hassan, S. S., Meisner, K., Krause, K., Bzhalava, L., & Moog, P. (2024). Is digitalization a source of innovation? Exploring the role of digital diffusion in SME innovation performance. *Small Business Economics*, 62, 1469–1491. <https://doi.org/10.1007/s11187-023-00826-7>
23. Heredia, J. (2022). How do digital capabilities affect firm performance? The mediating role of technological capabilities in the new normal, *Journal of Innovation & Knowledge* (JIK), ISSN 2444-569X, Elsevier, Amsterdam, Vol. 7, Iss. 2, pp. 1–10, <https://doi.org/10.1016/j.jik.2022.100171>
24. Hidiroglou, M. A. (1986). The construction of a self-representing stratum of large units in survey design. *The American Statistician*, Vol. 40, No. 1, pp. 27–31, American Statistical Association. https://www.researchgate.net/publication/239799358_The_Construction_of_a_SelfRepresenting_Stratum_of_Large_Units_in
25. Pesquisa de Inovação, I. B. G. E. (2022). Semestral 2021 – Indicadores básicos. Rio de Janeiro: Instituto Brasileiro de Geografia e Estatística – IBGE, Available at: <https://www.ibge.gov.br/estatisticas/multidominio/ciencia-tecnologia-e-inovacao/35867-pesquisa-de-inovacao-semestral.html>. Accessed: July 2024.
26. Pesquisa de Inovação, I. B. G. E. (2023). Semestral 2022 – Indicadores temáticos. Rio de Janeiro: Instituto Brasileiro de Geografia e Estatística – IBGE, Available at: <https://www.ibge.gov.br/estatisticas/multidominio/ciencia-tecnologia-e-inovacao/35867-pesquisa-de-inovacao-semestral.html>. Accessed: July 2024.
27. Pesquisa de Inovação, I. B. G. E. (2024). Semestral 2022 – Indicadores básicos. Rio de Janeiro: Instituto Brasileiro de Geografia e Estatística – IBGE, Available at: <https://www.ibge.gov.br/estatisticas/multidominio/ciencia-tecnologia-e-inovacao/35867-pesquisa-de-inovacao-semestral.html>. Accessed: July 2024.
28. Ivanov, D., Dolgui, A., & Sokolov, B. (2019). The impact of digital technology and Industry 4.0 on the ripple effect and supply chain risk analytics. *International journal of production research*, 57(3), 829–846. 10.1080/00207543.2018.1488086. <https://www.tandfonline.com/doi/abs/>
29. Jung, J., & Gómez-Bengoechea, G. A. literature review on firm digitalization: drivers and impacts. *Estudios sobre la Economía Española* 2022/20. Septiembre de 2022.
30. Kastelli, J., Dimas, P., Stamopoulo, D., & Tsakanikas, A. (2024). Linking Digital Capacity to Innovation Performance: the Mediating Role of Absorptive Capacity. *Journal of the Knowledge Economy*, 15, 238–272. <https://doi.org/10.1007/s13132-022-01092-w>
31. Kohli, R., & Melville, N. P. (2019). Digital innovation: A review and synthesis. *Information Systems Journal*, 29(1), 200–223. <https://doi.org/10.1111/isj.12193>
32. Li, S., Gao, L., Han, C., Gupta, B., Alhalabid, W., & Almakdie, S. (2023). Exploring the effect of digital transformation on Firms' innovation performance. *Journal of Innovation & Knowledge*, 8. <https://doi.org/10.1016/j.jik.2023.100317>
33. Liu, W., Wang, Z., Shi, Q., & Bao, S. (2024). Impact of the digital transformation of Chinese new energy vehicle enterprises on innovation performance. *Humanities and Social Sciences Communications*, 11. <https://doi.org/10.1057/s41599-024-03109-y>
34. Liu, Y., Dong, J., Mei, L., & Shen, R. (2023). Digital innovation and performance of manufacturing firms: An affordance perspective. *Technovation*, 119. <https://doi.org/10.1016/j.technovation.2022.102458>
35. Luo, J., & Study of the Effect of Digital Transformation on Firm Performance. (2023). A - Based on the Mediating Effect of Green Technology Innovation. In: Y. Jiao et al. (Eds.), *Proceedings of the 3rd International Conference on Internet Finance and Digital Economy (ICIFDE 2023)*, Atlantis Highlights in Economics, Business and Management, 1. https://doi.org/10.2991/978-94-6463-270-5_17
36. Massini, S., Sanchez-Barrioluengo, M., Yu, X., & Salehnejad, R. (2024). Digital transformation in firms: determinants of technology adoption and implications for performance. *MloIR Working Paper Series*, No.01.
37. Nambisan, S., Lyytinen, K., & Yoo, Y. (2020). *Handbook of Digital Innovation*. Edward Elgar Publishing.

38. Nwankpa, J. K., & Roumani, Y. (2016). IT Capability and Digital Transformation: A Firm Performance Perspective. Thirty Seventh International Conference on Information Systems, Dublin.
39. OECD. Employment Outlook (2023). : Artificial Intelligence and the labour market. 2023. https://www.oecd-ilibrary.org/employment/oecd-employment-outlook-2023_08785bba-en
40. Peng, Y., & Tao, C. (2022). Can digital transformation promote enterprise performance? —From the perspective of public policy and innovation. *Journal of Innovation & Knowledge*, 7. <https://doi.org/10.1016/j.jik.2022.100198>
41. Polder, M., van Leeuwen, G., Mohnen, P., Raymond, W., & Product (2010s-28). Process and Organizational Innovation: Drivers, Complementarity and Productivity Effects. CIRANO - Scientific Publications, 2010.
42. Queiroz, S., Vonortas, N., & Canuto, O. (2025). Global changes and effectiveness of innovation policy in Brazil. *Journal of Technology Transfer*, 51(4), 2486–2505. <https://doi.org/10.1007/s10961-025-10264-0>
43. Radicic, D., & Petkovic, S. (2023). Impact of digitalization on technological innovations in small and medium-sized enterprises (SMEs). *Technological Forecasting & Social Change*, 191. <https://doi.org/10.1016/j.techfore.2023.122474>
44. Scuotto, V., Magni, D., Palladino, R., & Nicotra, M. (2022). Triggering disruptive technology absorptive capacity by CIOs. Explorative research on a micro-foundation lens. *Technological Forecasting and Social Change*, 174, 121234.
45. Urbinati, A., Chiaroni, D., Chiesa, V., & Frattini, F. (2020). The role of digital technologies in open innovation processes: An exploratory multiple case study analysis. *R&D Management*, 50(1), 136–160. <https://doi.org/10.1111/radm.12313>
46. Urbinati, A., Manelli, L., Frattini, F., & Bogers, M. L. A. M. (2022). The digital transformation of the innovation process: Orchestration mechanisms and future research directions. *Innovation*, 24, 65–85. <https://doi.org/10.1080/14479338.2021.1963736>
47. Usai, A., Fiano, F., Messeni Petruzzelli, A., Paoloni, P., Farina Briamonte, M., & Orlando, B. (2021). Unveiling the impact of the adoption of digital technologies on firms' innovation performance. *Journal of Business Research*, 133, 327–336. <https://doi.org/10.1016/j.jbusres.2021.04.035>
48. Van Leeuwen, G., & Farooqui, S. ICT investment and productivity. In: Eurostat Final Report Information Society: ICT Impact Assessment by Linking Data From Different Sources, pp. 163–189. 2008. Working Paper.
49. Verstegen, L., Houkes, W., & Reymen, I. (2019). Configuring collective digital-technology usage in dynamic and complex design practices. *Research Policy*, 48(8), 103696. <https://doi.org/10.1016/j.respol.2018.10.020>
50. Wan, Y., Gao, Y., & Hu., Y. (2022). Blockchain Application and Collaborative Innovation in the Manufacturing Industry: Based on the Perspective of Social Trust. *Technological Forecasting and Social Change*, 177, 121540. [10.1016/j.techfore.2022.121540](https://doi.org/10.1016/j.techfore.2022.121540)
51. Wang, Z., Lin, S., Chen, Y., Lyuliyov, O., & Pimonenko, T. (2023). Digitalization Effect on Business Performance: Role of Business Model Innovation. *Sustainability*, <https://doi.org/10.3390/su15119020>
52. Wang, X., Wang, Y., & Chen, D. (2024). How Does Digitalization Influence Innovation Performance of Manufacturing Enterprises in Emerging Countries? The Perspective of Dual Innovation Synergy. *Polish Journal of Environment Studies*, 33(3). <http://doi.org/10.15244/pjoes/174838>
53. Warner, K. S., & Wager, M. (2019). Building dynamic capabilities for digital transformation: An ongoing process of strategic renewal. *Long Range Planning*, 52(3), 326–349.
54. Yoo, Y., Boland, R. J. Jr, Lyytinen, K., & Majchrzak, A. (2012). Organizing for innovation in the digitized world. *Organization science*, 23(5), 1398–1408.
55. Zittrain, J. (2006). The generative Internet. *Harvard Law Review*, 119, 1974–2040.
56. Zhou, Y., Yang, C., Liu, C., & Gong, L. (2023). Digital technology adoption and innovation performance: a moderated mediation model, *Technology Analysis & Strategic Management*, May. [10.1080/09537325.2023.2209203](https://doi.org/10.1080/09537325.2023.2209203)

Footnotes

1. The PINTEC Semestral initiative contemplated 7 rounds of surveys to industrial firms with at least 100 employees between 2022 and 2025. Four surveys covered innovation efforts, 2 the adoption of advanced digital technologies and one, the environment practices adopted by Brazilian industrial firms. This project was carried out by the Brazilian Statistical Office, IBGE, in partnership with the Brazilian Agency for Industrial Development (ABDI) and the Institute of Economics, of the Federal University of Rio de Janeiro (IE/UFRJ). The series of surveys is categorised by IBGE as “experimental statistics”. <https://www.ibge.gov.br/en/statistics/multi-domain/science-technology-and-innovation/35884-pesquisa-de-inovacao-semestral-2.html?edicao=38062>
2. <https://www.ibge.gov.br/en/statistics/economic/industry-and-construction/16903-annual-survey-of-industry-product.html?=&t=o-que-e>
3. The sectoral control variable by digital intensity was constructed based on the OECD classification. The sectors classified as having high and medium-high digital intensity are: Transport equipment; Furniture; Other manufacturing; Computer repair; Computer, electronic and optical products; Machinery and equipment; Electrical equipment; Wood and paper products; and Printing.