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ARTICLE

The dual effects of digitalization on SMEs: export gains and learning losses

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Abstract
Longstanding debates persist about the impact of new technologies on firms, particularly as it relates to internationalization. Some scholars suggest that digitalization will enhance the benefits of export activity by facilitating connections with partners and customers. Others, however, suggest that digitalization will simply fail to live up to the hype—or perhaps even worse. This debate is especially relevant for SMEs given that export activity is the primary route to global markets for such firms. We propose that digitalization will exert dual effects on SMEs: on the "bright" side, larger investments in digital technologies will lead to *greater* export activity (i.e., higher export sales); on the "dark" side, however, digitalization-induced export activity will generate *fewer* learning opportunities from export partners (i.e., smaller productivity gains). The proposed hypotheses were tested and supported using detailed firm-level panel data from 20,133 Portuguese firms from 2010 to 2019. Additional analyses and case studies corroborate the proposed mechanisms and point to hybrid approaches as one possible way to balance these dual effects of digitalization. Taken together, the findings shed new light on the debate about the role of digitalization in internationalization efforts.

Keywords Digitalization · Internationalization · Learning-by-exporting · Productivity · SMEs

Introduction

Firms seem eager to adopt the latest digital technologies. This is especially true among small and medium-sized enterprises (SMEs) engaged in internationalization efforts; such firms are now shifting core processes—inventory management, quality control, customer billing, and more—to cloud-based systems that synchronize data across markets in real time. AI-driven translation and customer-support chatbots enable resource-constrained firms to engage with buyers in multiple languages, thereby broadening reach without proportional staffing. Participation in cross-border e-commerce marketplaces equips these firms with ready-made logistics, payment, and localized storefronts, thereby opening new export channels. Collectively, these scalable applications promise to reduce barriers to foreign markets by lowering fixed costs and complexity—and SMEs are buying into that promise by investing in digital technologies.

Scholars, however, suggest that digitalization is perhaps more of a mixed bag. On one hand, many scholars have extolled its benefits, suggesting that digital technologies enable firms to more effectively engage in the international landscape by helping them to overcome physical distance

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(Nambisan et al., 2019), institutional differences (Deng et al., 2017), and language barriers (Brynjolfsson et al., 2019). Others, however, have warned that these technologies will fail to live up to the hype (Acemoglu et al., 2014)—or lead to unexpected negative consequences (Nambisan et al., 2019). These conflicting perspectives have led to various calls for a more balanced view, that is, understanding the "bright" *and* "dark" sides of digital globalization (Verbeke & Hutzschenreuter, 2021).

The aim of this study is to examine how digitalization impacts export activity. We focus on exporting, given that it continues to be one of the most common forms of firm internationalization, especially among SMEs. Nearly a third of global gross domestic product can be attributed to exports (World Bank, 2025). Export activity not only allows firms to enter new markets with minimal up-front investment (de Oliveira et al., 2021), it also facilitates interactions with foreign clients, suppliers, and other agents; these interactions provide firms with valuable new knowledge that is not available in the home market (Tse et al., 2017), which can be used to improve productivity levels (for a review of "learning-by-exporting," see Freixanet & Federo, 2023). Exporting thus represents an important set of strategic decisions relevant for competitiveness abroad and capabilities at home.

Our core thesis is that investments in digital technologies will exert a dual effect on exporters: higher levels of digitalization will be associated with *increased* export activity but also *decreased* learning from export partners. On the "bright" side, digitalization will enhance firms' capabilities to search for, identify, and connect with trade partners, thereby increasing levels of export activity. On the "dark" side, however, digitalization will hamper firms' capabilities to richly engage in human-to-human interactions and interorganizational knowledge transfer processes, thereby deriving less learning from export partners. We thus propose that digitalization will generate expected benefits but also unexpected drawbacks.

These hypotheses were tested using detailed firm-level management and accounting data from 20,133 Portuguese firms from 2010 to 2019—a period book-ended by the financial crisis and the global pandemic but rather stable throughout from an economic perspective and, importantly, encompassing the rise of digitalization in the global economy (Kohtamäki et al., 2022). Our findings show that investments in digital technologies indeed enabled firms to enjoy greater levels of export activity; at the same time, however, export activity induced by such investments led to smaller productivity gains compared to export activity not facilitated by digitalization. Additional analyses and case studies corroborate the proposed mechanisms. Taken together, these findings provide evidence of the proposed dual effect.

This study offers at least two theoretical contributions. First, it contributes to the burgeoning stream of research at the intersection of digitalization and globalization (Banalieva & Dhanaraj, 2019; Hennart, 2019; Luo, 2022; Luo & Zahra, 2023; Meyer et al., 2023) while heeding calls to offer a more balanced view of global digitalization (Nambisan et al., 2019; Teece, 2025; Verbeke & Hutzschenreuter, 2021). These calls have emerged from "a pressing need for IB scholars to provide a more nuanced understanding of the identified risks" of digitalization (Luo, 2022: 345), considering longstanding debates over whether new technologies live up to their hype (see Acemoglu et al., 2014). Our findings highlight a new type of benefit (i.e., greater export activity) as well as drawback (i.e., smaller productivity gains), thereby pointing to the merits of a "both/and" rather than an "either/or" perspective on the impacts of digitalization. Second, it contributes to learning-based views of internationalization theory (Johanson & Vahlne, 2009) by leveraging classic theories of organizational learning (e.g., Levitt & March, 1988) as well as new perspectives on the role of technology in learning (e.g., Balasubramanian et al., 2022) to respond to calls for a better understanding of the strategic value of SME participation in the export market (Freixanet & Federo, 2023; Tse et al., 2017). Our findings point to a counterintuitive hurdle to learning-by-exporting: digitalization. As a bridge between these two bodies of research, this study can be seen as situated within the broader phenomenon of factors that exert dual and potentially contradictory effects on key outcomes. Our study also employs new analytical techniques that not only enhance the rigor of the present analysis but also serve as a guide for future research. These findings point to important practical implications and exciting avenues for future inquiry.

Theoretical background

Digitalization in international business

Digitalization refers broadly to "the process of transforming the essence of an organization's products, services, and processes into Internet-compatible data packages that can be created, stored, and transferred in bits and bytes, along with the information associated with them, for marketing, sales, and distribution" (Banalieva & Dhanaraj, 2019: 1373). It has rapidly evolved over the past few decades and now includes such technologies as e-commerce platforms, artificial intelligence, "smart" and "connected" products, automation, remote monitoring, cloud-based storage and services, and more (see Banalieva & Dhanaraj, 2019; Jean et al., 2021). Trends suggest the continued adoption of digital technologies among firms (Nambisan et al., 2019; Verbeke & Hutzschenreuter, 2021).

Digitalization plays a key role in international business. Several editorials (Meyer et al., 2023), commentaries

(Hennart, 2019; Teece, 2025), and special issues (Autio et al. 2021) have focused on digital globalization, that is, “a form of globalization that digitally connects businesses across nations with flows of data, information and knowledge, and digitally enabled flows of goods, services, investment, and capital” (Luo, 2022: 345; also see Nambisan & Luo, 2021). Most scholars seem to agree that digitalization has reshaped international business—and will continue to do so—in fundamental ways. However, these same scholars seem to point in different directions about *how* digitalization will do so.

On one hand, these latest digitalization trends might enhance operations for international firms. For example, digital tools enable firms to more easily compete across domestic and international markets (Erdey et al., 2024). Firms reconfigure offerings based on customer feedback gathered through e-platforms and online forums (Jean et al., 2021) and strengthen export participation (Añón Higón & Bonvin, 2024). Digital tools have also changed how firms relate to one another. Firms communicate more easily and quickly, thereby expanding networks and making firm boundaries more fluid (Nambisan et al., 2019). These two changes—adaptation of offerings and interfirm relationships—operate in tandem; for example, firms now modularize offerings such that multiple players connect through digital platforms to deliver value to customers (Banalieva & Dhanaraj, 2019). Many scholars convey a taken-for-granted assumption that digitalization has and will continue to produce benefits for firms.

On the other hand, a less idyllic picture may emerge. Some have suggested that digitalization will simply fail to live up to the hype and thus be a mere disappointment (Acemoglu et al., 2014; Brynjolfsson et al., 2019). Others have warned that digitalization may lead to unintended costs, risks, or other negative consequences (Nambisan & Luo, 2021; Natarajan et al., 2026; Verbeke & Hutzschenreuter, 2021). Indeed, internationalized firms may be uniquely exposed to such risks—such as cyberattacks, supply chain disruptions, and regulatory challenges—due to their international strategies, geographic diversity, and digital interdependence (Luo, 2022). In sum, an increasing number of voices have called for research to shed light on the possible downsides of digitalization in international business.

Of course, both perspectives are likely true even if neither in isolation tells the full story. Hence, there is a need to understand the “bright” *and* “dark” sides of digitalization. We do so in the context of exporting given its prevalence and importance for the global economy in general and SMEs in particular.

The role of exporting for SMEs

Exporting provides strategic value to firms for two complementary reasons. First, it enables them to explore a range of new possibilities abroad. Internationalization is inherently uncertain and risky (Luo, 2021, 2022; Miller, 1992). Yet exporting requires firms to allocate relatively few resources to any particular foreign market opportunity (Helpman et al., 2004). Firms thus manage internationalization risk by placing “bets” on multiple markets at the same time (Håkanson & Kappen, 2017). Firms then commit further resources over time to markets where the bets pay off (Johanson & Vahlne, 2009). Exporting thus enables firms to access a larger and more diverse customer base and establish a larger global footprint (de Oliveira et al., 2021), thereby experimenting abroad.

Second, exporting facilitates new lessons that can be exploited at home. At a basic level, exporting often leads to higher production volumes, allowing firms to sell surpluses and use inventories more efficiently (Mesquita & Lazzarini, 2008). Moreover, export activity entails interactions with a range of foreign agents, including clients, suppliers, competitors, and others. According to the learning-by-exporting hypothesis, these interactions enable exporters to “acquire knowledge of new production methods, inputs, and product designs” that is unavailable in the home market and thus inaccessible to “insulated domestic counterparts” (Aw et al., 2000: 65; also see Freixanet & Federo, 2023; Salomon & Shaver, 2005; Xie & Li, 2018). This knowledge can be translated into increased productivity levels in the home market (Grossman & Helpman, 1991). Exporters, consequently, enjoy quicker and greater productivity gains compared to non-exporters (Tse et al., 2017). Exporting is thus also a way for firms to gain efficiencies at home.

Presumably, the benefits abroad are the motivating factor for firms to initiate export activity. This would seem to be particularly true for SMEs—especially those in smaller or developing economies (Vendrell-Herrero et al., 2022)—given that exporting represents a pathway to larger markets and more customers. At the same time, however, such firms stand to enjoy benefits at home—if they learn new lessons from trade partners.

Hypothesis development

A critical question arises: Has the strategic value of exporting shifted in the age of digitalization? We suggest that firm-level investments in digital technologies will have a dual effect. That is, digitalization will create anticipated advantages by boosting export activity even as digitalization-induced export activity will create unintended disadvantages by dampening learning from export partners.

This tension highlights a trade-off between short-term benefits and long-term challenges. Interestingly, individual-level analogies point to similar conclusions. Recent research has warned that ChatGPT helps students earn higher grades yet harms long-term learning outcomes (Bastani et al., 2024); ChatGPT similarly helps employees solve simple tasks but inhibits performance on complex problems (Dell'Acqua et al., 2026); artificial intelligence helps physicians detect imaging anomalies yet inhibits the accrual of expertise (Lebovitz et al., 2022); and autopilot technology helps pilots navigate in normal conditions yet degrades the ability to recover from an undesirable state (FAA, 2013). Similarly, we posit that firm-level investments in digital technologies offer short-term benefits and long-term drawbacks.

The "bright" side of digitalization for export activity

The identification of new export markets and trade partners involves organizational search. Identifying and choosing among opportunities, however, is difficult and costly (Felin et al., 2023). Importantly, firms are better able to engage in search to the extent that decision makers possess a "superior representation of the environment" (Gavetti & Menon, 2016: 208). Such firms can identify opportunities not obvious to others (Felin et al., 2023) and enjoy greater returns on the effort.

We posit that investments in digital technologies will enable firms to more effectively engage in such a search. First, digitalization will enable exporters to more effectively search for export destinations. Digital technologies provide enhanced tools for continuous monitoring of market conditions, competitor activities, and regulatory changes, allowing firms to more quickly identify opportunities that might arise due to contextual factors (Meyer et al., 2023). Similarly, these technologies have significantly enhanced firms' ability to continuously monitor international markets and adapt distribution channels, enabling growth in diverse and previously inaccessible regions (Brouthers et al., 2022). This flexibility is particularly advantageous in complex and dynamic contexts where traditional trade and distribution routes are often disrupted (Autio et al., 2021). Indeed, firms have leveraged digital tools and web-based platforms to monitor shifting conditions (Jean et al., 2021) and to facilitate access to foreign markets (Añón Higón & Bonvin, 2024).

Second, digitalization will enable exporters to more effectively connect with trade partners. Connections with local partners, distributors, and customers are vital for facilitating information exchange and navigating market dynamics, cultural nuances, and regulatory requirements (Johanson & Vahlne, 2009). Developing and maintaining these relationships can be challenging due to geographical distance, cultural differences, and diverse business practices; however, digital technologies help firms overcome these hurdles (Brynjolfsson et al., 2019; Deng et al., 2017; Luo & Zahra, 2023; Nambisan et al., 2019). Furthermore, such technologies enable firms to connect with trade partners without third parties or other intermediaries. As Luo (2022: 962) put it: "Digital global connectivity is not only an overwhelming feature of the new era for international business but also a golden thread that ties businesses together around the world…" thereby granting connected firms a competitive advantage.

Taken together, we propose that investments in digital technologies will enable firms to more effectively search for, identify, and connect with new trade partners in new markets. Additionally, digitalization may also lead to longer-lasting relationships with trade partners owing to enhanced trust. Trust is broadly defined as the extent to which one has positive expectations about another's motives and actions; importantly, trust can be understood in terms of two different dimensions (Das & Teng, 1998). Competence-based trust is linked to performance risk and refers to "the expectation that partners have the ability to fulfill their roles" whereas goodwill-based trust is linked to relational risk and refers to "the expectation that a partner intends to fulfill their role in the relationship" (Lui & Ngo, 2004: 474). Firm capabilities related to the formalization of trade relationships via contracts, technology, and the like, have been shown to enhance competence-based trust, in particular, by portraying predictability and thus reducing performance risk (Shen et al., 2019). We suggest that digitalization will convey to trade partners such capabilities as digital technologies standardize inputs and automate processes so that data are recorded more securely and accurately, retained over longer periods, and readily available for verification. The formation of competence-based trust will, in turn, lead to more operationally effective relationships with trade partners and thus higher levels of export activity. We therefore propose:

Hypothesis 1: To the extent that a firm invests in digital technologies, it will enjoy greater export activity (i.e., higher export sales performance).

The "dark" side of digitalization for learning-by-exporting

The learning-by-exporting hypothesis posits that export activity exposes firms to international agents; these interactions enable firms to acquire valuable knowledge unavailable in the domestic market (Grossman & Helpman, 1991) that can then be translated into efficiency gains (Freixanet & Federo, 2023; Tse et al., 2017; Vendrell-Herrero et al., 2022). Learning-by-exporting amounts to vicarious learning, that is, learning from others' experiences (Levitt & March, 1988) rather than the firm's own experiences (Argote & Epple, 1990). Such lessons might be derived by either observing the actions and outcomes of other firms (i.e., "observational learning") or by understanding the beliefs that have arisen from those experiences (i.e., "knowledge transfer"); importantly, there must be "sufficient opportunities for rich interaction between [the two firms] … for this differential wisdom to be exploited through vicarious learning" (Park & Puranam, 2024: 2999). Put differently, knowledge transfer hinges on rich interaction.

We posit that digital technologies will lead to interactions between partners that are less rich—and thus dampen learning-by-exporting. Digital technologies often replace human decision-making with machine-based decision-making, which risks decreasing the richness of learning opportunities (Murray et al., 2021). According to Balasubramanian et al. (2022), richness is diminished in two ways. First, the diversity of routines is reduced as digitalization narrows choice sets via standardized processes, automatized outputs, and algorithms (Ransbotham et al., 2017). In doing so, digitalization precludes humans from learning opportunities that arise from the natural diversity that occurs when humans make decisions in heterogeneous ways and then discover optimal approaches. Opportunities for vicarious learning in the form of observational learning are thus reduced because digitalization reduces the range of actions and outcomes trade partners might observe in and from one another.

Second, contextual and causal knowledge is reduced as machines and algorithms do not enjoy the same background experiences as humans. Consequently, digital technologies often miss key details, contingencies, or likely outcomes that humans might notice (Choudhury et al., 2020). This is especially true as digitalization shifts sensemaking from human-to-human collaborations to human-to-machine problem-solving exercises (Raisch & Fomina, 2025). Moreover, users often see digital technologies as a "black box" that increases epistemic uncertainty about causal relationships between inputs and outputs (Lebovitz et al., 2022). Of course, such causal inferences are critical for learning (Levitt & March, 1988).

In the context of exporting, contextual and causal knowledge is reduced because digitalization tends to decrease the observability and interpretability of partners' assumptions and decision processes. Using marketplace fulfillment and automated pricing tools, for example, allows exporters to see only finalized orders; the platform conceals negotiation threads, exception-handling, and buyer rationales, preventing decision makers from inferring the subtleties apparent in human-to-human communication. Such limited visibility into processes and contexts creates information asymmetries that particularly disadvantage SMEs with limited boundary-spanning resources. As Kellogg et al. (2020: 366) put it, digital technologies "transform input data into desired outputs in ways that tend to be more encompassing, instantaneous, [and] interactive…than prior technological systems" but also—critically— "more opaque". These technologies obscure how trade partners make decisions by enclosing decision-making within "black boxes" that do not reveal underlying beliefs. As a result, the ability to engage in vicarious learning via knowledge transfer (see Park & Puranam, 2024) is limited.

Taken together, we propose that digitalization will impede learning-by-exporting by limiting vicarious learning via observational learning and knowledge transfer. The latter will be further hampered due to reductions in trust. As noted, firm capabilities related to the formalization of trade relationships between trade partners enhance competence-based trust; at the same time, however, such capabilities also reduce goodwill-based trust by implying instrumentality and thus heightening relational risk (Shen et al., 2019). Similarly, digitalization risks undermining goodwill-based trust by engendering perceptions of instrumentalism rather than communalism (van Houwelingen & Stoelhorst, 2023). Indeed, digitalization is a subpar substitute for interpersonal relationships (Verbeke & Hutzschenreuter, 2021), which are necessary for such trust (Das & Teng, 1998) and knowledge transfer (Park & Puranam, 2024). The weakening of goodwill-based trust will thus hamper learning-by-exporting. We therefore propose:

Hypothesis 2: Exports induced by digitalization will lead to less learning-by-exporting (i.e., smaller gains in firm productivity) compared to exports not induced by digitalization.

To summarize, we have hypothesized that investments in digital technologies will have a dual effect such that higher levels of investments will lead to *greater* levels of export activity (Hypothesis 1) yet *fewer* opportunities for learning from export partners (Hypothesis 2).

Research methods

Data

Data was sourced from an integrated database (Sistema de Contas Integradas das Empresas; "SCIE") jointly developed by the Portuguese National Institute of Statistics (Instituto Nacional de Estatistica; "INE") and the Bank of Portugal. This database includes comprehensive firm-level data, including balance sheet information and income statements, which—critically—offers data on annual investments in digital technologies. It encompasses complete yearly observations of all manufacturing firms based in Portugal from 2010 to 2019, a period that spans a relatively stable economic phase, covering the aftermath of the global economic crisis through the year preceding the COVID-19 pandemic. It also captures a time of global digital disruption that significantly impacted manufacturing business models (Kohtamäki et al., 2022). Portugal's small domestic market makes exports a structural growth driver; export intensity rose from 30% of GDP in 2010 to over 43% in 2019 (and nearly 47% today).

Although Portugal's technological base and R&D intensity remain relatively modest, private R&D nearly doubled between 2015 and 2022 to 1.1% of GDP (Heitor, 2023). Concurrently, Portugal has become a dynamic IT hub and foreign direct investment (FDI) host, with over one third of FDI projects in software and IT services, offering a relevant benchmark for SMEs from similarly small, export-oriented economies. The data and context thus make it ideal for testing the proposed hypotheses.

The database includes all manufacturing firms active throughout the study period, resulting in a balanced panel dataset. The original dataset included 22,811 firms. Two restriction criteria were used. First, we excluded companies with profits or losses from subsidiaries to ensure that observed effects were due to exporting rather than other forms of internationalization, such as FDI; 2466 firms were excluded. Second, we excluded size outliers—firms for which the average number of employees or sales deviated by more than two standard deviations from the mean—to ensure comparability across firms; 212 firms were excluded (131 due to employees, 21 due to sales, and 60 due to both). The final sample included 20,133 firms, representing 88.3% of Portuguese manufacturing firms active throughout the period.[1] Notably, the sample is composed of SMEs: the average workforce was 13 full-time-equivalent employees. Approximately 95% of firm-year observations corresponded to small firms (< 50 employees) and the remaining 5% to medium firms (50–250 employees). Finally, the analysis uses a 2-year lag for the treatment variable (details below); the sample for analysis thus comprises data from 20,133 firms from 2012 to 2019 (i.e., 161,064 firm-year observations).

Variables

Export intensity

This is the dependent variable in tests of Hypothesis 1 and the independent variable in tests of Hypothesis 2. It was calculated as the ratio of foreign to total sales (Wulff & Villadsen, 2020) with a 1-year lag (Salomon & Shaver, 2005). Roughly 39% of firm-year observations indicate the presence of exporting activity. On average, exporting firms allocate 27% of total sales to foreign markets.

Total factor productivity (TFP)

This is the dependent variable in tests of Hypothesis 2. It was computed using gross value added at market prices as a proxy for output, personnel expenses for labor input, cost of materials consumed as intermediate inputs, and net book value of tangible fixed assets (machinery, vehicles, buildings, land) as capital (Levinsohn & Petrin, 2003). The translog functional form is used for its flexibility in substitution elasticities and returns to scale while addressing functional dependence. TFP has a mean value of 3.39 and a standard deviation of 2.08.

Digitalization investments

This is a key independent variable in both hypothesis tests. It is measured as firm-level investments in computer and/or machinery software (Luo, 2022). The mean and median levels of investment are approximately €8800 and €1300, respectively; 1% of positive observations show annual investment above €100,000.

Figure 1 illustrates the adoption rate and median digitalization investment over time by class size. The adoption rate is lower for small companies (approximately 5%) and higher for medium companies (approximately 20%). The overall adoption rate has remained relatively stable throughout the period, though medium firms exhibit a slight increase over time. The median investment has risen for both groups. Approximately one-quarter of firms invested in digitalization at least once during the period; the conditional probability that a firm invests in the current year if it did so in the previous year is 38%.

We use two alternative measures to ensure the robustness of the results and to enable a wider range of robustness checks: a binary and a continuous measure. The binary measure is a dummy variable that equals 1 when a firm reports a nonzero investment in software for a given year, and 0 otherwise. Because the data includes many zeros, the binary measure is appropriate for distinguishing between adopters and non-adopters—a common feature in digitalization studies. To account for the potential lagged effect of investments on firm outcomes, we computed two versions: the standard version as described above ("1-year digitalization") and a transformed version ("3-year digitalization"); the latter takes on the value of 1 for the year of the investment and the subsequent 2 years.[2] All hypothesis tests using the dummy variable report models with both versions.[3] The continuous measure, in contrast, takes on the observed

[1] The results remain qualitatively consistent even when including outliers.

[2] Tests with 4- and 5-year windows yielded qualitatively consistent results.

[3] The 1-year digitalization variable contains 10,174 treated firm-year observations, while the 3-year digitalization variable contains 19,169 treated firm-year observations. Note that the latter is only 1.88 times higher than the former because the transformation results in fewer changes in some cases. For instance, a company with two consecutive years of digitalization investment will have only two additional treatment years after the transformation.

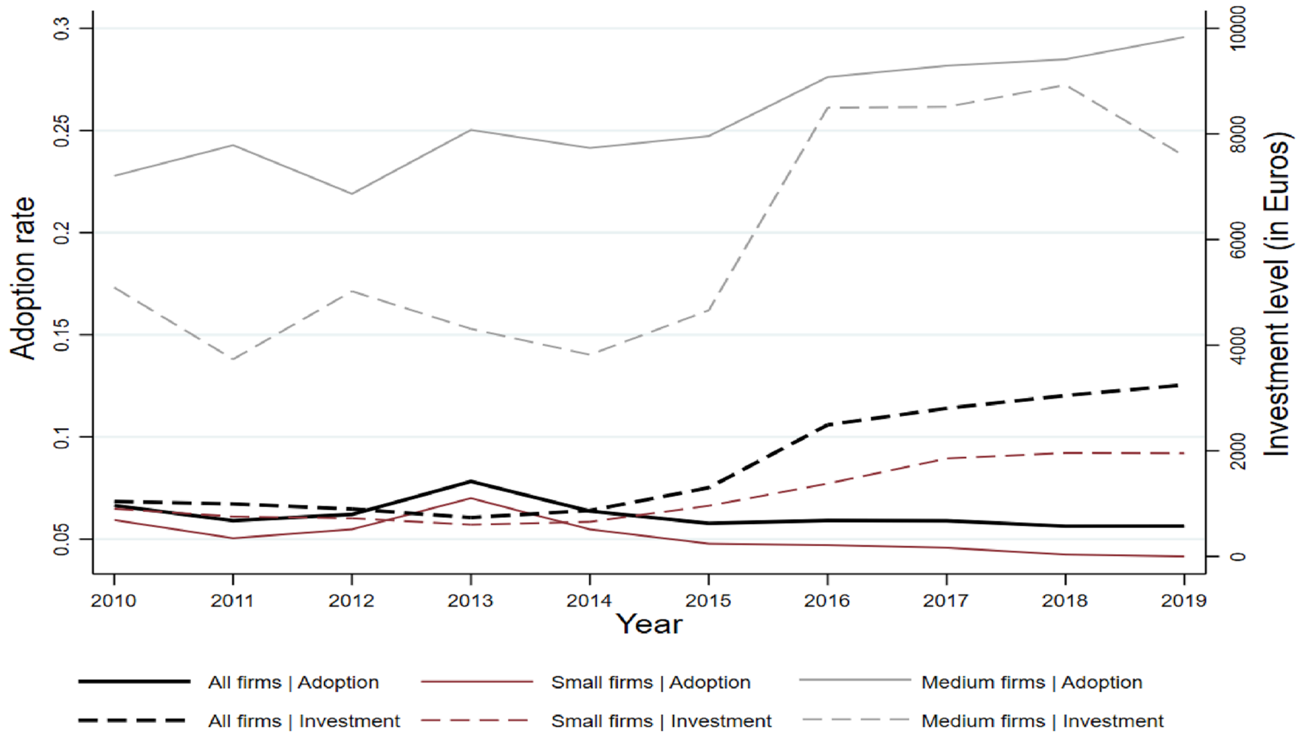

Fig. 1 Digitalization adoption rate and investment level by year. *Notes* The investment level refers to the median value of investment amongst adopters only. The small category includes those firms with 1–49 employees, whereas the medium category includes those firms with 50+ employees

monetary value of the investment. Given the skewness of the distribution, the continuous treatment effect is estimated using two marginal increases—referred to hereafter as deltas—of €500 and €1000. As detailed below, these two measures are associated with complementary sets of analyses.

Control variables

Estimations also included the following variables: (1) firm size, measured by the *number of employees*; (2) the *Out-of-EU ratio*, defined as the percentage of exports outside the European Union; (3) *service intensity*, measured as the percentage of service sales relative to total sales; (4) level of *intangible assets*, defined as the ratio of intangible to total assets; (5) *import intensity*, measured as the ratio of imported goods to total purchases; and (6) research and development (*R&D*) efforts, represented by the percentage of R&D workers relative to total workers. Fixed effects included (7) *firm*; (8) *year*; (9) *region* according to the Nomenclature of Territorial Units for Statistics classification (NUTS-2), which encompasses North (50.1%), Centre (26.4%), Lisbon (14.4%), Alentejo (5.2%), Algarve (1.8%), Azores (0.9%), and Madeira (1.1%); and (10) *industry*, which differentiates between the 22 industries represented in the data. The ten industries with the highest representation in the dataset are as follows: fabricated metal products (18.84%), food products (14.45%), apparel (9.75%), non-metallic mineral products (7.01%), wood and cork products (6.93%), furniture (5.83%), textiles (5.15%), printing and reproduction of media (5.09%), leather products (4.47%), and repair and installation of machinery (4.59%); these industries account for a majority of observations (roughly 82%). The remaining industries include sectors such as pharmaceuticals, motor vehicles, and electronics.

Table A1 in the online appendix presents year-by-year descriptive statistics and correlations for key variables. Digitalization is positively and significantly associated with export intensity across all years, suggesting that digital technologies enhance export activity. Interestingly, export intensity and productivity growth are generally negatively correlated but positive in 2018–2019. The correlations between digitalization and productivity growth are generally negative albeit non-significant.

Research design

We used a two-stage regression design to account for the dual effects of digitalization. The first stage estimates the effect of firm investments in digitalization on export intensity. The second stage tests whether export activity induced by digitalization leads to different productivity gains compared to what would have occurred in the absence of digitalization; accordingly, we decompose observed export intensity into digitalization-induced and counterfactual components to evaluate their differential effects.

Stage 1: Digitalization and export activity

Hypothesis 1 proposes that investments in digitalization increase firms' export activity. Three complementary approaches were used to estimate the average treatment effect (ATE) of digitalization on export intensity in the first stage: (1) a binary treatment model, (2) a continuous treatment model, and (3) a matched binary treatment model using propensity score matching (PSM). We discuss each in turn.

First, we estimate ATE using a binary treatment specification in which firms are classified as digitalized or non-digitalized depending on whether they invest in digital technologies as follows:

$$\mathrm{ATE} = E\left[\mathrm{XI}_{t-1} \middle| \mathrm{DIG}_{t-2} = 1\right] - E\left[\mathrm{XI}_{t-1} \middle| \mathrm{DIG}_{t-2} = 0\right] \quad (1)$$

where ATE specifies the net effect of the treatment variable in t–2 (i.e., digitalization, DIG) on the outcome variable in t–1 (i.e., export intensity, XI) and E refers to expected value; controls are included for firm size, R&D investment, and industry, year, and region fixed effects, thereby accounting for systematic differences in firms' export capacity. ATE represents the average change in export intensity associated with digitalization investments, that is, the expected difference in export intensity between treated and untreated observations (Holland, 1986); we refer to the latter as the Baseline Untreated Level (Baseline).[4]

Second, we estimate ATE using a continuous treatment framework to account for variation across firms and years. Following Hirano and Imbens (2004), we estimate the generalized propensity score (GPS), implemented through the Stata command developed by Bia and Mattei (2008). The covariate specification mirrors the binary treatment model. The resulting GPS estimates are then used to construct a dose–response function that models export intensity as a quadratic function of digitalization investment, the GPS, and their interaction term. The specification includes the untransformed investment variable, while the estimation procedure applies a logarithmic transformation of the treatment variable. This specification allows us to evaluate how marginal increases in digitalization investment affect export intensity. ATE is computed by estimating the expected change in export intensity associated with small increases in digitalization investment (delta, denoted as δ). These estimates capture the marginal impact of digitalization investment on export activity across different levels of treatment intensity as follows:

$$ATE = \left(\sum_i^n \begin{matrix} E\left[XI_{i,t-1} \mid DIGINV_{t-2} = Inv_{i,t-2} + \delta\right] - \\ E\left[XI_{i,t-1} \mid DIGINV_{t-2} = Inv_{i,t-2}\right] \end{matrix} \right) / n \quad (2)$$

where $E[\cdot]$ is based on the estimated dose–response function and n is the number of treated firms.

Third, we estimate ATE using propensity score matching (PSM) to approximate a quasi-experimental comparison between treated and untreated firms. The panel structure inherent in the first two approaches controls for time-invariant heterogeneity; however, firms that invest in digitalization may systematically differ from those that do not. PSM accounts for such selection bias. Matching procedures are sensitive to the structure of panel data because the same firm may appear as both treated and untreated in different years. We therefore transform the panel dataset by estimating eight separate cross-sectional models corresponding to the 8 years of the panel while maintaining the lag structure of the treatment and outcome variables. This approach ensures that treated firms are matched with comparable untreated firms within the same period, preventing firms from being matched with themselves in different years and preserving the temporal order of the treatment and outcome variables. Propensity scores are estimated using a Probit model that includes lagged firm productivity, firm size, and industry and regional dummies (Chang & Chung, 2017). A kernel-based matching estimator is then used to construct the synthetic control group. The kernel function calculates the distance between the treated observation and each untreated observation to determine these weights.[5] The treatment effect from the matching procedure is equivalent to Equation 1) but produces a cleaner comparison between treated and untreated firms.

Computation of induced versus counterfactual effects

The first stage estimates distinguish between export activity attributable to digitalization from that which would have occurred in the absence of digitalization investments (Golovko et al., 2022; Hottenrott & Lopes-Bento, 2014).

[4] Some statistical packages refer to this as the "Potential Outcome Mean."

[5] The kernel-based specification is particularly well-suited because it allows for the retention of nearly all observations, preserving critical information such as the proportion of adopters for the second stage. Alternative PSM methods that do not rely on weights (e.g., 1:1 matching) are suitable for the first-stage models but would alter the frequency of the treatment group, rendering them unsuitable for robust second-stage models.

We decompose observed export intensity into two components—digitalization-induced (DXI) and counterfactual (CXI)—as follows for the binary and continuous treatment analysis:

$$\mathrm{DXI}_{i,t-1} = \begin{cases} \mathrm{TE}_{i,t-1} & \text{if } \mathrm{DIG}_{i,t-2} = 1 \\ 0 & \text{if } \mathrm{DIG}_{i,t-2} = 0 \end{cases} \tag{3}$$

$$\mathrm{CXI}_{i,t-1} = \begin{cases} \mathrm{XI}_{i,t-1} - \mathrm{TE}_{i,t-1} & \text{if } \mathrm{DIG}_{i,t-2} = 1 \\ \mathrm{XI}_{i,t-1} & \text{if } \mathrm{DIG}_{i,t-2} = 0 \end{cases} \tag{4}$$

where ($\mathrm{TE}_{i,t-1}$) is the specific estimated treatment effect for each treated firm; firms that did not invest in digitalization are given a value of zero.

Kernel-based PSM generates counterfactual observations by assigning weights (ω) to control observations based on their similarity to the treated observation, with higher weights given to more similar control observations. The treatment effect is therefore adjusted using the weights assigned to treated firms, which determines the induced and counterfactual export components as follows:

$$\mathrm{DXI}_{i,t-1} = \begin{cases} \mathrm{XI}_{i,t-1} - \sum_{j\epsilon C(i)} \omega_{ij,t-1} \times \mathrm{XI}_{j,t-1} & \text{if } \mathrm{DIG}_{i,t-2} = 1 \\ 0 & \text{if } \mathrm{DIG}_{i,t-2} = 0 \end{cases} \tag{5}$$

$$\mathrm{CXI}_{i,t-1} = \begin{cases} \sum_{j\epsilon C(i)} \omega_{ij,t-1} \times \mathrm{XI}_{j,t-1} & \text{if } \mathrm{DIG}_{i,t-2} = 1 \\ \mathrm{XI}_{i,t-1} & \text{if } \mathrm{DIG}_{i,t-2} = 0 \end{cases} \tag{6}$$

Stage 2: Learning-by-exporting

Hypothesis 2 predicts that exports induced by digitalization generate less learning-by-exporting than exports not induced by digitalization. We thus estimate a dynamic fixed effects panel model relating firm productivity to lagged export activity while controlling for prior productivity and firm characteristics. Following convention (see Salomon & Shaver, 2005), productivity is modeled as a function of lagged productivity and lagged export activity. To evaluate whether digitalization-induced exports generate different learning effects, we decompose export intensity into the two components derived in the first stage—digitalization-induced (DXI) and counterfactual (CXI) exports—as follows:

$$TFP_{i,\ t} = \gamma + \beta_{DXI} \times DXI_{i,t-1} + \beta_{CXI} \times CXI_{i,t-1} + \delta \times TFP_{i,t-1} + \Omega_{i,\ t} + \vartheta_i + \vartheta_s + \vartheta_t + \vartheta_r + \varepsilon_{j,t} \tag{7}$$

where $\mathrm{TFP}_{i,t}$ is current productivity, $\mathrm{TFP}_{i,t-1}$ is 1-year lagged productivity, $\mathrm{XI}_{i,t-1}$ is the export intensity of firm i at time $t\text{-}1$, and $\Omega_{j,t}$ is a vector of the control variables: ϑ_i, ϑ_s, ϑ_t and ϑ_r indicate firm, industry, time, and region dummies, respectively; $\varepsilon_{j,t}$ is the error term.[6]

This specification allows us to compare productivity effects associated with export activity due to digitalization investments (DXI) versus export activity independent of such investments (CXI). Hypothesis 2 proposes that CXI will exceed DXI. Of course, these tests assume that export intensity is the main channel through which digitalization affects productivity. In principle, both direct (e.g., via internal process automation and back-office efficiency) and indirect (i.e., learning-by-exporting) effects may occur. If so, this assumption suggests the findings represent a conservative test, as any direct effects of digitalization would bias the estimates against detecting the proposed "dark side" of digitalization.

Results

Two-stage regression analysis with panel data

Hypothesis 1 is tested using ATE in the first-stage models. Table 1 presents the two-stage analysis for the binary treatment, including both versions of the variable (1- and 3-year). ATE yields a value of 0.0733 ($p = 0.000$) for the 1-year measure (Model 1) and 0.0604 ($p = 0.000$) for the 3-year measure (Model 3). These findings imply that digitalization indeed boosts export intensity; firms that invested in digitalization enjoyed an additional increase in export intensity of approximately 6–7% the following year. The *Baseline Untreated Level* is informative as a reference point. These parameters together indicate firms that invest in digitalization enjoy an increase in export intensity from a baseline of approximately 11% to 17–18% the year after their investment. In relative terms, this represents an increase of 55–65% compared with the baseline. When benchmarked against the average export intensity among exporters in our sample (27%), the effect corresponds to roughly one quarter of the cross-sectional mean, demonstrating that the effect is both statistically significant and economically meaningful.

Table 2 presents the two-stage analysis for the continuous treatment, including both delta values (€500, €1000). Using the firm-level treatment effects, we compute ATE: 0.00079 for €500 and 0.00162 for €1000 (in both cases, $p = 0.000$). Assuming a linear pattern, these estimates imply an average increase in export intensity of 0.00079 and 0.00162 above the baseline untreated level of 0.116 (i.e., the export intensity of firms that do not invest in digitalization) for each additional €500 and €1000 invested.

[6] The Hausman test indicates that the firm fixed effects model is indeed appropriate. That is, we reject the null hypotheses that the difference in coefficients between firm fixed effects and random effects models is not systematic ($p < 0.001$).

Figure 2 presents the dose–response and treatment functions for the continuous treatment analysis. The dose–response function shows considerable growth in export intensity at low levels of digitalization investment; above €2000, however, the relationship becomes considerably less pronounced. This result suggests that the shift between non-digitalized and digitalized status is particularly relevant, giving more merit to the binary treatment analysis. The treatment effect function is shown by level of investment for specific delta values: €500 and €1000. These estimates reflect the change in export intensity associated with an increased investment, conditional on the firm's current investment. The results show proportionality: the €500 coefficients are approximately half those of €1000. The treatment effects are consistently positive; above €2000, however, the marginal benefit of additional investment plateaus.

Overall, the positive relationship between digitalization and export intensity is robust across multiple specifications—two binary treatments (1- and 3-year digitalization measures) and two continuous treatments (€500 and €1000 deltas)—providing consistent support for Hypothesis 1.

Hypothesis 2 was tested using the differences between counterfactual (CXI) and digital-induced (DXI) export intensity in the second-stage models, which are indeed significantly different from one another for the binary treatment in Table 1 (Model 2 [1-year]: β_{CXI}–$\beta_{DXI}=0.2373$, $p=0.011$; Model 4 [3-year]: β_{CXI}–$\beta_{DXI}=0.1701$, $p=0.049$) and continuous treatment in Table 2 (Model 2 [€500]: β_{CXI}–$\beta_{DXI}=0.8531$, $p=0.039$; Model 4 [€1000]: β_{CXI}–$\beta_{DXI}=0.4263$, $p=0.039$).

The effect sizes are quite substantial. Consider two hypothetical firms: Firms Digital and Analogue both realized 17% of sales in export markets in year t; the former invested in digitalization in year t–1 (i.e., treated) but the latter did not (i.e., untreated). Based on the 3-year specification (Models 3 and 4 in Table 1), Digital will realize a productivity gain of 0.0077 units whereas Analogue will realize a gain of 0.0119 units; put differently, Analogue will enjoy over 1.6 times the learning-by-exporting. Although the absolute difference (0.0042) appears small, it represents roughly 0.20% of one standard deviation of TFP in the sample (SD = 2.08), which corresponds to around one fifth of the average annual productivity growth observed nationally (≈1%)[7], highlighting the economic significance of the effect. Taken together, these findings are robust across specifications, lending support to Hypothesis 2.

Two-stage regression analysis with propensity score matching

Table 3 presents a summary of the two-stage analysis using PSM; the year corresponds to the final year of each 3-year period (e.g., 2012 refers to 2010–2012). The analysis produced a substantial reduction bias in the two continuous variables used during matching; initially, treated firms were larger and less productive, but this bias is markedly diminished across all models. It also shows that the kernel function allows for the retention of nearly all observations: the sum of treated and untreated observations closely aligns with the total number of firms in the full sample. The PSM technique thus produced a weighted synthetic control group that is comparable to the treated firms in terms of productivity, size, industry, and region. The table presents a summary of key parameters from first- and second-stage analyses across all 32 estimated models: 16 for the 1-year measure and 16 for the 3-year measure.[8]

Hypothesis 1 is again tested via the first-stage models. All parameters for ATE are positive and significant ($p < 0.001$ in all cases), indicating that digitalization enhances export intensity, irrespective of the year in which the investment is made. Furthermore, the magnitude of this effect increases over time (e.g., ATE = 0.0450 in 2012 and 0.0751 in 2019) and is greater for the 1-year digitalization measure compared to the 3-year digitalization measure. Hypothesis 1 thus receives further strong support.

Hypothesis 2 is again tested via the second-stage models and receives strong support; the difference between the counterfactual and induced effects is positive and significant in nearly all cases, except 2013 for the 3-year measure (β_{CXI}–$\beta_{DXI}=0.0474$, $p=0.154$).

This year-by-year analysis also reveals an interesting longitudinal pattern: The gap between the counterfactual (CXI) and induced (DXI) effects increases over time, suggesting that the "dark side" of digitalization grows dimmer and the learning gap widens as dependence on digital technologies increases. Figure 3 illustrates this evolution; it depicts the difference between β_{CXI} and β_{DXI} from Table 3 alongside a country-level indicator of the strength of the digital infrastructure, specifically, the Digital Economy and Society Index (DESI)[9] by the European Commission. It shows that greater availability of digitalization is associated with a growing disparity between the effects of induced and counterfactual exports. Although the digital infrastructure may support firms' export activity (i.e., β_{CXI} increases over time; see Table 3), investments in digitalization produce decreasing benefits (i.e., the difference between β_{CXI} and

[7] See https://www.caixabankresearch.com/en/economics-markets/activity-growth.

[8] This analysis is cross-sectional and thus excludes firm fixed effects.

[9] See https://digital-strategy.ec.europa.eu/en/policies/desi.

Table 1 Two-stage fixed effects regression analysis: binary treatment

	(1)	(2)	(3)	(4)
Model description	1-year digitalization		3-year digitalization	
	First stage	Second stage	First stage	Second stage
Dependent variable	Export Intensity *EI (t−1)*	Total Factor Productivity *TFP (t)*	Export Intensity *EI (t−1)*	Total Factor Productivity *TFP (t)*
Average treatment effect	0.0733		0.0604	
(digitalization)	(.00336)		(0.00235)	
	0.000		*0.000*	
Baseline untreated level	0.1128		0.1100	
(no digitalization)	(0.00065)		(0.00067)	
	0.000		*0.000*	
Digital-induced export intensity		− 0.1672		− 0.0999
DXI *(t–1)*		(0.0968)		(0.0973)
		0.084		*0.304*
Counterfactual export intensity		0.0701		0.0702
CXI *(t–1)*		(0.0339)		(0.0339)
		0.039		*0.038*
Total factor productivity		0.3997		0.3997
TFP (t-1)		(0.0104)		(0.0104)
		0.000		*0.000*
Service intensity		0.3015		0.3015
		(0.0367)		(0.0367)
		0.000		*0.000*
Out-of-EU ratio		0.0135		0.0135
		(0.0130)		(0.0130)
		0.295		*0.297*
Number of employees		− 0.0200		− 0.0200
		(0.0011)		(0.0011)
		0.000		*0.000*
Intangible assets		− 0.0907		− 0.0920
		(0.3063)		(0.3063)
		0.767		*0.764*
Import intensity		− 0.0045		− 0.0045
		(0.0332)		(0.0332)
		0.892		*0.891*
R&D		0.0933		0.0924
		(0.0823)		(0.0824)
		0.257		*0.262*
Constant		2.0608		2.0606
		(0.2819)		(0.2817)
		0.000		*0.000*
β_{CXI}–β_{DXI}		0.2373		0.1701
		0.011		*0.049*
Firm FE	No	Yes	No	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
R-squared (within)	–	0.193	–	0.193
Observations	161,064	161,064	161,064	161,064
Number of firms	20,133	20,133	20,133	20,133

Robust standard errors in parentheses. *p* values in italics

Table 2 Two-stage fixed effects regression analysis: continuous treatment

	(1)	(2)	(3)	(4)
Model description	Delta = +500€		Delta = +1000€	
	First stage	Second stage	First stage	Second stage
Dependent variable	Export Intensity EI *(t−1)*	Total Factor Productivity TFP *(t)*	Export Intensity EI *(t−1)*	Total Factor Productivity TFP *(t)*
Average treatment effect	0.00079		0.00162	
(digitalization)	(0.00004)		(0.00007)	
	0.000		*0.000*	
Baseline untreated level	0.1163		0.1160	
(no digitalization)	(0.00063)		(0.00063)	
	0.000		*0.000*	
Digital-induced export intensity		− 0.7834		− 0.3566
DXI *(t–1)*		(0.4828)		(0.2385)
		0.105		*0.135*
Counterfactual export intensity		0.0697		0.0697
CXI *(t–1)*		(0.0339)		(0.0339)
		0.040		*0.040*
Total factor productivity		0.3997		0.3997
TFP (t–1)		(0.0104)		(0.0104)
		0.000		*0.000*
Service intensity		0.3016		0.3016
		(0.0367)		(0.0367)
		0.000		*0.000*
Out-of-EU ratio		0.0135		0.0135
		(0.0130)		(0.0130)
		0.298		*0.298*
Number of employees		− 0.0200		− 0.0200
		(0.0011)		(0.0011)
		0.000		*0.000*
Intangible assets		0.0936		0.0936
		(0.0823)		(0.0823)
		0.255		*0.255*
Import intensity		− 0.0914		− 0.0914
		(0.3063)		(0.3063)
		0.765		*0.765*
R&D		− 0.0047		− 0.0047
		(0.0332)		(0.0332)
		0.887		*0.887*
Constant		2.0590		2.0590
		(0.2818)		(0.2818)
		0.000		*0.000*
$\beta_{CXI}–\beta_{DXI}$		0.8531		0.4263
		0.039		*0.039*
Firm FE	No	Yes	No	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
R-squared (within)	–	0.193	–	0.193
Observations	161,064	161,064	161,064	161,064
Number of firms	20,133	20,133	20,133	20,133

Robust standard errors in parentheses. *p* values in italics

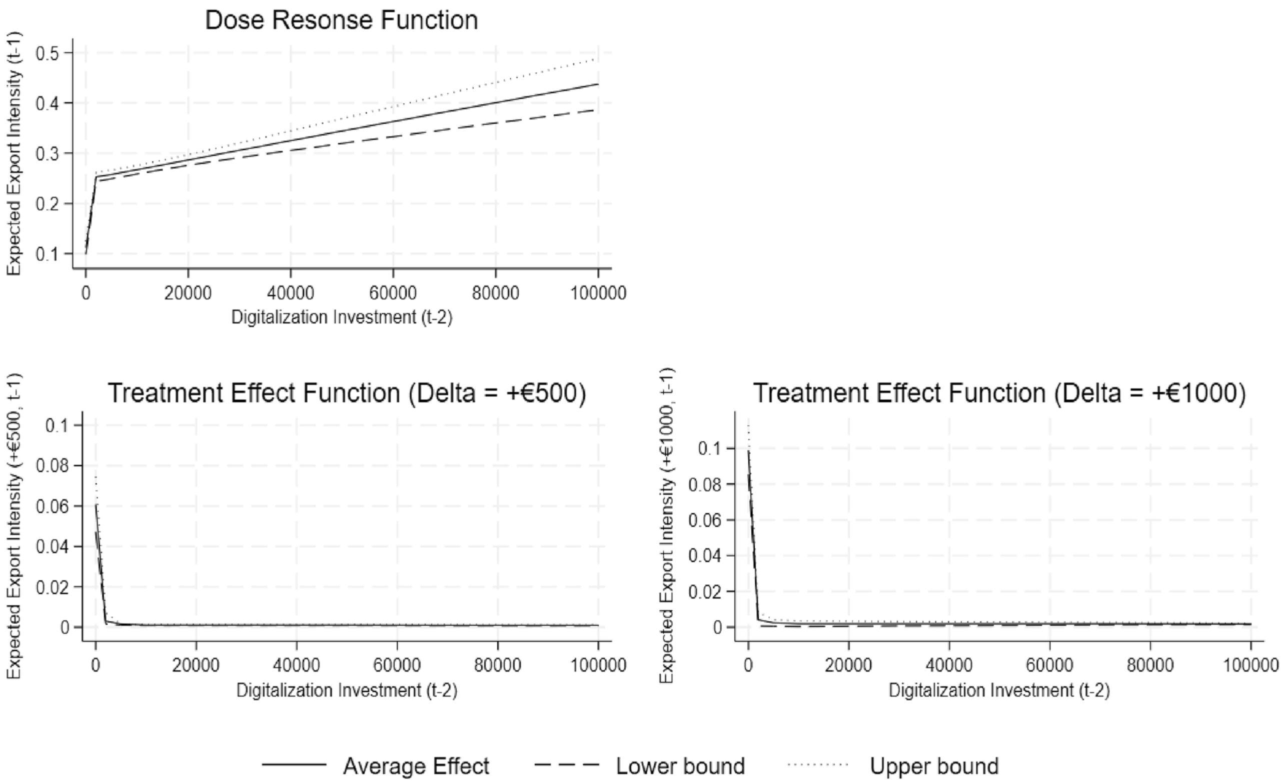

Fig. 2 Estimated dose–response and treatment functions for the continuous treatment variable. *Notes* Confidence bounds at 95% level. The dose–response function represents a linear prediction

β_{DXI} increases over time; see Table 3). Put differently, the unintended downside seems to strengthen over time.

Additional analysis

The main analysis included two robustness checks by design: two measures of digitalization (binary and continuous; for the former, 1- and 3-year specification) and a synthetic control group. Three additional robustness tests were conducted. First, we acknowledge the significant heterogeneity in levels of investment in digitalization; some firms make very small or merely symbolic investments. Notably, the effect of digitalization on exports is particularly strong for low levels of investment (see Fig. 2). We therefore adjusted the variable by trimming it at the 1st, 5th, and 10th percentiles, replacing it with zero for investment amounts within each percentile. The appendix includes alternative versions of Table 1 (Tables A2 and A3) and Table 3 (Tables A4 to A6); these findings qualitatively mirror the main results. Interestingly, the induced effect (i.e., DXI) is negative and significant in more cases, lending even stronger support for Hypothesis 2. Second, a small proportion of firms report very large investments. We therefore applied the K-8 transformation (Schaffrath Rosario et al., 2006), which partitions the continuous treatment into eight optimized percentile groups (see Table A7). These findings also lend consistent support for both hypotheses. Third, we replicated the PSM analysis using radius-based specifications to ensure the results were not sensitive to the kernel-based specifications (see Table A8). The results, too, are consistent with the main analysis. Overall, the robustness tests lend further confidence in the findings.

Additional analysis was also conducted to detect some evidence for the proposed mechanisms. Our central thesis is that digitalization diminishes learning because it reduces the richness of interactions between trade partners. If so, digitization should have especially pernicious effects in contexts that are particularly reliant upon human-to-human interactions, such as the provision of services (see Visnjic-Kastalli & Van Looy, 2013). Accordingly, we conducted heterogeneity analyses to examine whether the negative effects of digitalization on learning-by-exporting are stronger among firms with a greater orientation toward services rather than products (see Table A9). As expected, the negative effect of digitalization on learning-by-exporting increases with service intensity, thereby corroborating the proposed mechanisms.

Table 3 Summary of two-stage year-on-year regression analysis with kernel-weighted PSM

Digitalization	Year	Reduction Bias T: TFP W: Workers	Number of observations T: Treated U: Untreated	First-stage models DV: Export Intensity (*t*–1)		Second-stage models DV: Total Factor Productivity (*t*)		
				Average Treatment Effect *Digitalization*	Baseline Untreated Level *No Digitalization*	Digital-Induced Export Intensity DXI *(t–1)*	Counterfactual Export Intensity CXI *(t–1)*	Difference β_{CXI}–β_{DXI}
1-year	2012	T: 81.2% W: 72.8%	T: 1336 U: 18,795	0.0450 (0.0087) *0.000*	0.1639 (0.0037) *0.000*	0.0151 (0.0483) *0.755*	0.0994 (0.0397) *0.012*	0.0843 *0.044*
1-year	2013	T: 82.5% W: 72.3%	T: 1189 U: 18,943	0.0653 (0.0097) *0.000*	0.1839 (0.0042) *0.000*	– 0.0395 (0.0417) *0.343*	0.0440 (0.0287) *0.125*	0.0835 *0.025*
1-year	2014	T: 77.3% W: 73.1%	T: 1249 U: 18,882	0.0583 (0.0088) *0.000*	0.1755 (0.0037) *0.000*	– 0.0271 (0.0311) *0.383*	0.0615 (0.0235) *0.009*	0.0886 *0.012*
1-year	2015	T: 82.8% W: 75.9%	T: 1574 U: 18,557	0.0520 (0.0079) *0.000*	0.1785 (0.0036) *0.000*	– 0.0435 (0.0360) *0.227*	0.03865 (0.0214) *0.071*	0.08215 *0.025*
1-year	2016	T: 84.4% W: 78.1%	T: 1281 U: 18,850	0.0611 (0.0090) *0.000*	0.1953 (0.0042) *0.000*	– 0.0428 (0.0322) *0.184*	0.0841 (0.0191) *0.000*	0.1269 *0.000*
1-year	2017	T: 87.9% W: 81.0%	T: 1162 U: 18,970	0.0579 (0.0099) *0.000*	0.2117 (0.0048) *0.000*	– 0.0443 (0.0372) *0.274*	0.1112 (0.0304) *0.000*	0.1555 *0.000*
1-year	2018	T: 92.5% W: 84.6%	T: 1191 U: 18,941	0.0650 (0.0102) *0.000*	0.2258 (0.0053) *0.000*	– 0.0811 (0.0378) *0.032*	0.1509 (0.0359) *0.000*	0.2320 *0.000*
1-year	2019	T: 93.4% W: 81.7%	T: 1187 U: 18,944	0.0751 (0.0104) *0.000*	0.2240 (0.0054) *0.000*	– 0.0377 (0.0365) *0.302*	0.1747 (0.0453) *0.000*	0.2124 *0.000*
3-year	2012	T: 81.2% W: 72.8%	T: 1336 U: 18,795	0.0450 (0.0087) *0.000*	0.1639 (0.0037) *0.000*	0.0151 (0.0483) *0.755*	0.0994 (0.0397) *0.012*	0.0843 *0.044*
3-year	2013	T: 94.3% W: 78.9%	T: 2071 U: 18,059	0.0532 (0.0074) *0.000*	0.1728 (0.0037) *0.000*	– 0.0122 (0.0366) *0.734*	0.0352 (0.0285) *0.217*	0.0474 *0.154*
3-year	2014	T: 98.5% W: 80.7%	T: 2714 U: 17,417	0.0514 (0.0064) *0.000*	0.1684 (0.0035) *0.000*	– 0.0089 (0.0354) *0.801*	0.0774 (0.0300) *0.010*	0.0863 *0.032*
3-year	2015	T: 98.0% W: 82.5%	T: 2,843 U: 17,288	0.0475 (0.0062) *0.000*	0.1685 (0.0035) *0.000*	– 0.0105 (0.0337) *0.755*	0.0648 (0.0221) *0.003*	0.753 *0.031*
3-year	2016	T: 98.0% W: 81.9%	T: 2846 U: 17,284	0.0459 (0.0062) *0.000*	0.1679 (0.0035) *0.000*	– 0.0023 (0.0307) *0.940*	0.0602 (0.0198) *0.002*	0.625 *0.044*
3-year	2017	T: 99.5% W:85.4%	T: 2695 U: 17,437	0.0485 (0.0066) *0.000*	0.1770 (0.0039) *0.000*	– 0.0782 (0.0411) *0.057*	0.0865 (0.0249) *0.000*	0.1647 *0.000*
3-year	2018	T: 96.9% W: 86.7%	T: 2395 U: 17,736	0.0583 (0.0073) *0.000*	0.1911 (0.0045) *0.000*	– 0.0766 (0.0288) *0.008*	0.1293 (0.0302) *0.000*	0.2059 *0.000*
3-year	2019	T: 94.8% W: 86.8%	T: 2260 U: 17,871	0.0690 (0.0079) *0.000*	0.1983 (0.0049) *0.000*	0.0059 (0.0370) *0.873*	0.1799 (0.0408) *0.000*	0.1740 *0.001*

Refer to the text for full model specifications. Robust standard errors in parentheses. *p* values in italics

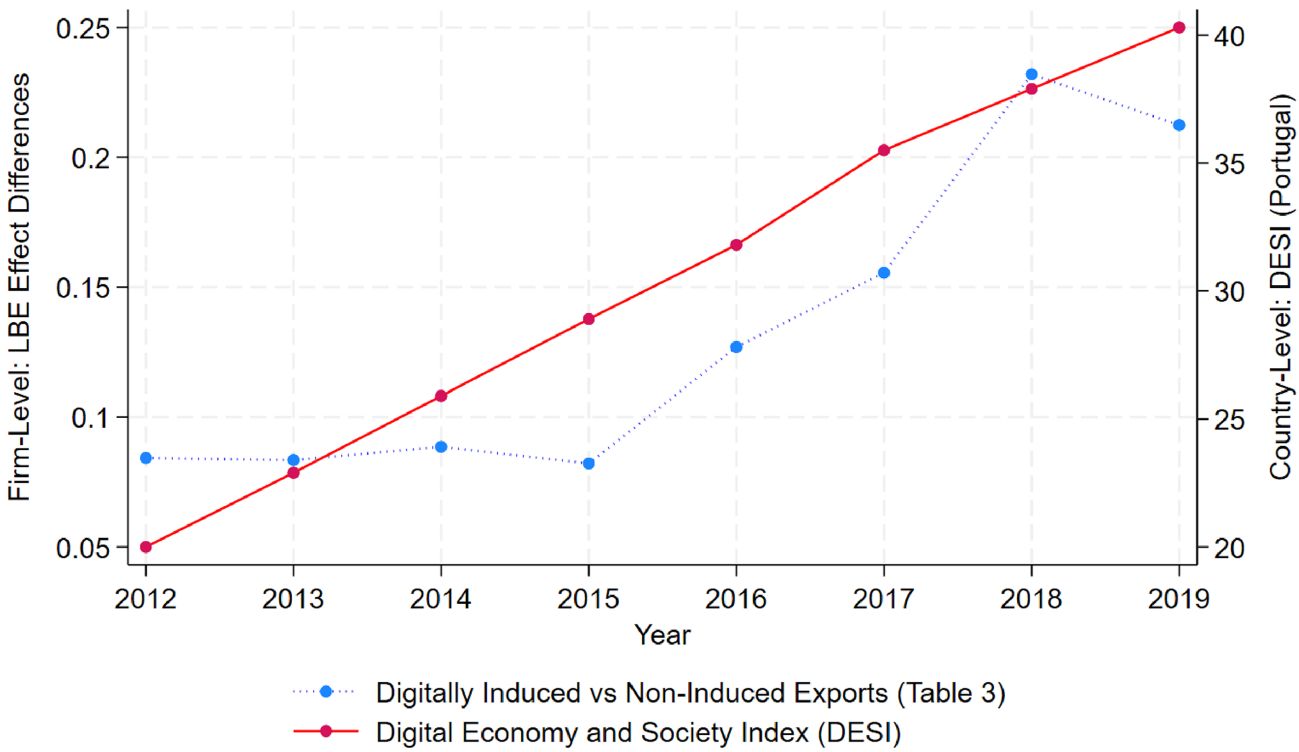

Fig. 3 Firm-level digitalization effects and country-level trends over time. *Notes* The *blue line* depicts the difference between the digitally induced (β_{DXI}) and counterfactual (β_{CXI}) export effect as reported in Table 3. The *red line* depicts the Digital Economy and Society Index (DESI) as reported by the European Commission. Note that DESI was reported from 2014 to 2022; accordingly, a linear prediction was used to impute data for 2012 and 2013

Case insights

Qualitative case studies were conducted to shed additional light on the mechanisms behind the observed statistical relationships. Although econometric results confirm that digitalization investments are positively associated with export intensity (Hypothesis 1) and that such digitally induced export growth may limit learning (Hypothesis 2), case studies allow us to better understand how these dynamics might unfold. We identified four firms in the dataset that met the following criteria: (i) engaged in export activity, (ii) invested in digitalization at various levels, (iii) varied in size, and (iv) from different sectors. The firms thus represent a convenience sample but are also representative of the broader population.

Table 4 includes an overview of the cases. Alpha manufactures competition-grade kayaks and canoes for professional rowing teams, Beta sells and services customized HVAC solutions, Gamma sources and sells frozen seafood, and Sigma produces organic health and wellness products; Table A10 includes detailed vignettes. All four firms invested in customer relationship management (CRM) and/or enterprise resource planning (ERP) platforms; Beta additionally incorporated remote monitoring. Moreover, three firms had the resources and technical knowledge to build proprietary or customized systems, while the smallest firm subscribed to an off-the-shelf platform. The investment levels range from modest annual fees to tens or hundreds of thousands of euros. The cases suggest that, at least in this context, digitalization most often takes the form of CRM- and ERP-based platforms.

Importantly, these cases enable us to unpack the proposed mechanisms at play. Across the firms, investments in digitalization were indeed associated with subsequent increases in export sales (i.e., Hypothesis 1). Alpha enjoyed stronger customer loyalty and increased repeat sales soon after its investments, suggesting that digitalization fostered competence-based trust and reliable performance. Beta, in contrast, experienced a longer lag before the full range of benefits materialized; while remote monitoring systems improved product reliability and service delivery right away, the delayed export benefits suggest that competence-based trust took longer to develop. For Gamma and Sigma, which produce more standardized B2C products, the effects of digitalization on export intensity were immediate and visible. Gamma attributed a 14% year-on-year increase in exports in 2023 to CRM- and ERP-based investments. Sigma, despite its micro size, leveraged digital platforms during the COVID-19 pandemic to broaden its consumer reach, reporting a steady 10% annual sales increase. These cases reinforce the quantitative evidence but also highlight different pathways: for some firms, digitalization fosters customer loyalty and incremental export growth; for other firms, it acts as a direct accelerator of export growth.

All four cases also suggest that digitalization-induced export growth hampers interorganizational learning (i.e., Hypothesis 2). Alpha's CEO explained that "less conversation" took place when distributors and clients interacted through the firm's proprietary platform, thereby limiting informal exchanges critical for the development of goodwill trust. Beta's Marketing and Sales Director described a similar dynamic: digital tools improved routine interactions with established customers but proved far less effective in generating the trust needed to deepen international relationships, leading to a decline in knowledge transfer opportunities. Gamma's COO noted that "virtual meetings now replace 60% of in-person visits," reducing their ability to sense subtle shifts in consumer preferences or emerging trends. Sigma provides a clear illustration: digitalization led to a sharp decline in human-to-human interaction, both in the form of international trips as well as phone calls. What is perhaps most striking across all four cases is the consistency of this finding: managers in all firms explicitly recognized that digitalization, while offering some benefits and engendering additional export growth, tended to reduce the richness of human relationships, weakening the capacity to learn from partners and clients in international markets.

Interestingly, managers at all four firms sought ways to counterbalance the downsides of digitalization. Rather than allowing digital tools to fully substitute personal relationships, they created mechanisms to preserve opportunities for rich interaction. Alpha, for instance, continued to use its platform for routine exchanges but reinstated structured in-person distributor visits to address complex issues and strengthen trust. Beta resumed personal visits "as much as possible," making it clear that digitalization should complement—not replace—relationships. Gamma went even further by designing quarterly "hybrid roadshows" that combined travel to regional hubs with online streaming. Even though Sigma remained primarily dependent on digital tools, its manager noted the limits of digital interactions and has experimented with selective personal touchpoints. In short, all managers responded to digitalization by reverting—albeit to varying degrees—to face-to-face exchanges with foreign clients.

Taken together, these cases corroborate the econometric analysis even as they begin to illuminate underlying mechanisms. Investments in digitalization enhance export intensity as expected but also dampen opportunities for learning-by-exporting in unexpected ways. Digital tools—though efficient—tend to displace the informal yet rich human-to-human interactions through which knowledge is most often transferred. All four firms eventually adopted a hybrid approach, thereby highlighting a dual effect: Digitalization-driven export growth is real and measurable, but it may come at the cost of eroding the very learning processes that underpin long-term international success; firms must thus remain adaptive.

Discussion and implications

As new technologies emerge and develop—and as many firms embrace them with open arms—greater clarity is needed about whether these technologies will live up to their promises. This is especially true regarding firm internationalization efforts in an increasingly global economy. This study suggests that investments in digitalization are a mixed bag: Firms that invested in digital technologies enjoyed higher levels of export activity but learned less from export partners. These "bright" and "dark" sides of digitalization present at least two theoretical contributions.

First, this study contributes to the growing stream of research at the intersection of digitalization and globalization. Most scholars have implied that the continued march toward digitalization is all but inevitable (Banalieva & Dhanaraj, 2019; Hennart, 2019; Luo & Zahra, 2023; Raisch & Krakowski, 2021). Although most scholars have highlighted the apparent benefits of such trends (e.g., Luo, 2022; Meyer et al., 2023; Nambisan et al., 2019), a few have issued warnings about the potential downsides. As Verbeke and Hutzschenreuter (2021: 607; emphasis added) put it:

> The literature may thus have given undue weight to the opportunities and benefits of digital globalization, i.e., the *bright side* … rather than to its *dark side*, which we see as the limited capacity of digital assets to function as FSAs [firm-specific advantages] in a wide variety of cross-border contexts, and the potential negative impact on the relationships between [firms].

Our findings show that such warnings are well founded. Firm investments in digital technologies had a dual effect: on the "bright" side, larger investments led to greater levels of export activity; on the "dark" side, digitalization-induced export activity generated fewer learning opportunities. Notably, previous studies have mainly emphasized such risks as cyberattacks, supply chain disruptions, and regulatory challenges (Luo, 2022); our study highlights a different but complementary risk: diminished inter-organizational learning that firms might otherwise derive from export activity. This study thus points to the merits of a "both/and" rather than an "either/or" perspective on the impacts of digitalization.

Table 4 Summary of case studies

Case	1	2	3	4
Company	Alpha	Beta	Gamma	Sigma
Interviewee's role	Founder/CEO	Mktg/Sales Director	COO	Managing director
Orientation	B2C/B2B	B2B	B2C	B2C
No. employees	150 (medium)	70 (medium)	20 (small)	2 (micro)
Foundation year	1978	2008	1997	2014
Started exporting	1980	2008	1997	2016
NAICS	3366	3329	4244	4244
Main products	Competition-Grade Kayaks and Canoes	Customized HVAC Solutions	Frozen Fish and Seafood	Organic Health and Wellness Products
Digitalization investment: year(s)	2018–2021	2017 onward	2019 onward	2021 onward
Digitalization investment: type	Proprietary Customized Platform	Proprietary Customized Platforms and Remote Monitoring Systems	Proprietary Customized ERP-based Systems	Subscription to External Standardized Platform
Digitalization investment: monetary value	€70–80k	~2% of turnover	Variable; €20,000 example	Initial €1800; €400 annually
Impact of digitalization: export performance	"Boosted customer loyalty and repeat sales"	"Considerable export growth," especially since 2022	"14% YoY export jump in 2023" attributed to digitalization and efficiency	Reduced overhead with "a 10% annual increase in sales" post-COVID in 2021
Impact of Digitalization: Interorganizational Relationships	"Less conversation as everything done on the platform," impacting F2F relationships and trust-building	Digital tools were helpful for existing consumers but less effective in building trust with new customers	"Virtual meetings now replace 60% of in-person visits," weakening tacit feedback and delay in detecting consumer trends	Reduction in deep client insights due to less frequent in-person feedback and interactions
Impact of digitalization: behavioral change	Implemented structured distributor visits, maintaining digital tools for routine tasks but prioritizing in-person complex discussions	Resumed personal visits "as much as possible," using digitalization mainly for routine interactions	Introduced quarterly "hybrid roadshows" with travel to regional hubs while streaming to smaller distributors	Reduced travel and increased online interactions, while exploring a balance between digital tools and personal touchpoints

Pseudonyms are used for company names. See Table A10 for detailed vignettes

Second, this study contributes to learning-based perspectives of firm internationalization. International business scholars have long pointed to the role of learning in globalization (Johanson & Vahlne, 2009), which is even more critical in today's knowledge economy. The learning-by-exporting hypothesis posits that export activity enables firms to both explore foreign markets and learn from trade partners. For years, studies presented compelling theoretical arguments but inconclusive findings. More recently, scholars have focused on identifying contingencies of the learning-by-exporting effect (Freixanet & Federo, 2023). We extend these findings by drawing a connection between learning-by-exporting and vicarious learning (Park & Puranam, 2024), positing that digitalization will hinder the sort of knowledge transfer at the root of vicarious learning. This study thus highlights a contingency of the learning-by-exporting effect previously unexplored: digitalization. Yet unlike other contingencies, digitalization points to an inherent tension, hence, the "bright" and "dark" sides.

This study also contributes to the long line of mainstream research on organizational learning. Recent theoretical perspectives have suggested that digital technologies like artificial intelligence and machine learning will fundamentally change decision-making (Raisch & Fomina, 2025) and learning (Balasubramanian et al., 2022), raising questions about automation versus augmentation (Raisch & Krakowski, 2021), among others. Recent empirical findings at the individual level have similarly highlighted a trade-off between short-term benefits and long-term challenges of digital technologies (Bastani et al., 2024; Lebovitz et al., 2022). Yet the impact of digitalization on vicarious learning via interfirm knowledge transfer remains unexplored. This study represents one step on this front by showing that access to partners via digital tools does not necessarily translate into learning, perhaps because digitalization does not enable firms to enjoy the full benefits of interpersonal relationships.

More generally, the notion of a "bright" and "dark" side of digitalization fits within the broader phenomenon of strategic or organizational factors that exert dual and potentially contradictory effects on key outcomes. For example, family governance has been shown to reduce firms' internationalization and innovation inputs even as it enhances the efficiency with which knowledge gained abroad is converted into innovation outcomes (Freixanet et al., 2021). Similarly, institutional development can both enhance and constrain the innovation benefits of exporting: stronger R&D support amplifies learning-by-exporting even as greater market openness dampens these gains (Xie & Li, 2018). Understanding these sorts of dual effects is critical given the range of outcomes associated with digitalization and the inherent trade-offs dual effects force upon managers as competing expectations are formed (see Battilana et al., 2022).

From this vantage point, acknowledging the "bright" and "dark" sides of digitalization opens the door to new research questions. One particularly promising direction is to consider how the tension between the benefits and drawbacks of digitalization might manifest in other domains. We focused here on export activity, given that it continues to be one of the most common forms of firm internationalization, especially among SMEs. Yet the underlying mechanisms would presumably apply to other types of intra- and inter-organizational relationships, not just trade partners, thereby producing similar dual effects. Future research should also consider how digitalization might pose dual effects on other forms of internationalization, such as FDI entry modes, including mergers and acquisitions, and joint ventures.

Another promising direction for future research is to consider boundary conditions. For example, the effects may vary depending on firm type. Our additional analysis suggests that the detrimental effects of digitalization on learning-by-exporting are exacerbated among digitalized firms with an orientation toward services, presumably because such firms depend even more strongly on human-to-human interaction. Future research should consider other firm differences that might exacerbate or mitigate the effects. Alternatively, the findings may vary depending on the type of digitalization. Our case studies suggest that firms that rely on standardized or "off-the-shelf" digital platforms may be more exposed to the downsides of digitalization compared to those that employ proprietary tools or adopt hybrid models of digitalization coupled with human-to-human interaction. Indeed, the critical distinction seems to be whether digitalization is viewed as a substitute for or a complement of human relationships. Future research should consider whether some types of digital tools are better suited than others for facilitating the sort of trust-based relationships that foster learning. Finally, the findings may depend on the level of digitalization investment within the broader technological environment. Our analysis suggests that the beneficial effects of digitalization are stronger at lower levels of investments, which is akin to other findings have suggested the possibility of so-called "threshold effects" (Capelleras et al., 2025; Erdey, et al., 2024) or even the delayed benefits of digitalization (the "J-curve" effect; Brynjolfsson et al., 2021). Future research would benefit from further examining such heterogeneities.

This study also provides a methodological toolkit for other researchers. First, we show how comparisons of induced versus counterfactual effects, which have typically been restricted to binary treatments, can be extended to continuous treatments. Second, we show how PSM, which is conceptually designed for cross-sectional data, can be used with balanced panel data by implementing a lag structure and performing matching over multi-year windows. To our knowledge, these extensions have not been applied in management or international business research. With the growing availability of long panel datasets and rich treatment variables, these methods stand to aid future management research endeavors.

Despite its merits, this study is not without limitations. Most critically, the archival data did not allow us to conclusively detect the proposed mechanisms. Additional analysis provided suggestive evidence and case studies further corroborated the notion that investments in digitalization may enhance firms' ability to search for and identify foreign trade partners even as it may hamper their ability to learn from them. Nevertheless, a useful next step is to capture and test these mechanisms via alternative paradigms, such as surveys or other qualitative methods. Second, the data also do not distinguish between different types of digital technologies. As noted, such heterogeneity represents a promising avenue for future inquiry. At the same time, it is important to note that the measure of digitalization used here is not necessarily specific to export activity; it may also capture investments aimed primarily at domestic operations. If so, such heterogeneity would seem to bias the estimates against detecting a strong effect; as such, the findings reported here may be viewed as conservative tests. Nevertheless, future research would do well to investigate such heterogeneities. Third, the analysis does not enable us to conclusively rule out the possibility of residual endogeneity. Alternative identification strategies, such as instrumental variables and natural experiments, would complement the present analysis. Fourth, the data do not allow us to answer important questions about generalization. Even though the database contains the full population of SME manufacturing firms for a small, developed economy, we are unable to generalize to larger multinational firms or those from larger economies. Nevertheless, the robustness tests lend a reasonable degree of confidence in the conclusions drawn from the findings.

This study also points to important practical implications. For managers, it should prompt careful consideration of digitalization investments, especially within SMEs as it relates to internationalization. Such investments may yield short-term benefits but also longer-term costs. Our case studies suggest that managers might adapt to these dual outcomes by adopting forms of hybrid approaches. In this way, the "dark side" is not an inevitable side effect of the "bright side". Rather, managers may be able to couple the adoption of digitalization with new routines to prioritize human-to-human and face-to-face interactions (see Mintzberg, 2026)—both within and across organizational boundaries—and thereby engender new learning opportunities.

For policymakers, it should prompt a recalibration of export promotion programs to leverage digitalization's benefits while mitigating downsides. Our findings suggest that one possible mechanism to increase global trade via exports might be to subsidize digital technologies or provide digitalization training to promote export activity. Yet digitalization can enhance market access while dampening learning, necessitating hybrid policies that pair digital support with mechanisms for knowledge transfer between trade partners. For example, export promotion program design and funding should shift from one-size-fits-all to segmented, evidence-based allocation that matches firms by digitalization level, size, and international experience, supported by rigorous evaluation and monitoring systems (Freixanet, 2022). Such a balanced, data-driven approach maximizes public returns and better serves exporters in an increasingly digitalized yet relationship-dependent international marketplace. In sum, this study highlights some of the potential promises of digitalization in a global economy even as it warns of possible pitfalls.

Conclusions

This study broadens the conversation around digitalization and its impact on internationalization efforts, shedding light on both its empowering as well as its limiting effects. Although digitalization appears to equip firms to more effectively navigate export markets, it seems also to hamper the potential for learning from those export activities. This duality underscores the tension between the "bright" and "dark" sides of global digitalization. As digitalization continues to evolve, future research will be essential to understand how firms might effectively balance this inherent tension.

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