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Privacy protection laws, national culture, and artificial intelligence innovation around the world

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Abstract
A substantial body of research highlights how stringent regulations disrupt innovators' incentives and increase transaction costs, yet their information processing implication remains understudied. Building on information processing theory, we study how the interplay between formal and informal institutions shapes inventors' information processing in developing artificial intelligence (AI) innovation. We examine the effect of stringent privacy regulations on AI innovation by exploiting the European Union's General Data Protection Regulation (GDPR) announcement. We argue that, following the GDPR announcement, GDPR-affected countries experience lower national AI innovation rates than unaffected countries. Further, we postulate that this negative effect is weaker in GDPR-affected countries, marked by higher levels of individualism, masculinity, and indulgence, but stronger in the affected countries with higher levels of uncertainty avoidance, power distance, and long-term orientation. Our difference-in-differences analysis supports the proposed framework. Our research contributes to the international business literature by developing novel theoretical predictions at the intersection of comparative institutional analysis and national culture, explaining how privacy protection laws and cultural factors shape AI inventors' information processing. Finally, this study provides insights into how inventors and entrepreneurs in countries with stringent privacy laws can leverage national culture to shape their AI innovation strategies and inform strategic decision-making.

Keywords Artificial intelligence · Culture · Difference-in-differences · GDPR · Information processing theory · Privacy protection laws

Introduction

Artificial intelligence (AI) innovation[1] is essential in today's digital economy because it is crucial for businesses to enhance efficiency, improve decision-making, and maintain a competitive edge (Choi et al., 2025; Kemp, 2023; Krakowski et al., 2023). AI as an enabling, general-purpose technology is expected to provide breakthroughs and opportunities to drive the Fourth Industrial Revolution, which will

[1] AI is a collection of technologies that simulate intelligence by leveraging algorithms, data, and computational power (Wang, 2019). AI innovation encompasses a broad spectrum of advancements, including patenting in fields such as machine learning, natural language processing, computer vision, speech technology, knowledge processing, AI hardware, evolutionary computation, and planning and control (Giczy et al., 2021). These patents are filed by various entities, including firms, universities, and other organizations. To gain a comprehensive understanding of AI innovations worldwide, we follow the common practice in the literature of aggregating patents at the country level (e.g., Furman et al., 2002; Taylor & Wilson, 2012; Yoon et al., 2024). We refer to these aggregated values as AI innovation or national AI innovation rates.

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bring about a fundamental and disruptive change in the way we live, work, and socialize (Chalmers et al., 2021; Lundvall & Rikap, 2022; Luo, 2022; Miller, 2019). However, as AI becomes increasingly pervasive and ubiquitous across markets, it serves the economic interests of businesses at the expense of data privacy (Acemoglu, 2021; Acemoglu et al., 2022; Choi et al., 2025; West, 2019). This has sparked a growing debate on (stringent) privacy protection laws[2] regulating AI (e.g., Luo, 2022; Russell et al., 2015).

Prior studies examining the implications of stringent privacy protection laws, such as the General Data Protection Regulation (GDPR), have yielded mixed results. Some studies indicate that firms and inventors quickly adapt to the new regulatory environment by increasing investments in R&D and filing more patents (e.g., Frey & Presidente, 2024). In contrast, other studies show how stringent privacy protection laws can bolster the position of large incumbent firms on online platforms, raising entry barriers for newcomers (e.g., Geradin et al., 2021). Such laws have been associated with innovative app exits (Janssen et al., 2022), reduced venture capital in tech firms (Jia et al., 2021), and a shift from radical to incremental innovation (Blind et al., 2024).

To expand upon existing views on the implications of privacy protection laws, a more fine-grained institutional analysis is necessary, considering the interplay between formal and informal institutions. Indeed, formal and informal institutions are deeply interconnected, reinforcing one another or creating conflicting views on imposed rules (Posner, 2009; Rosen, 2006). Accordingly, we pose the following research question: *How does the interplay between formal and informal institutions influence inventors' information processing in the development of AI innovation?* This inquiry is crucial because the extent to which AI inventors anticipate continued access to private information and data to build new algorithms is a necessary condition for successful AI innovation (Berente et al., 2021; Choi et al., 2025; Kemp, 2023). From a theoretical standpoint, while prior studies have focused on the logic of transaction costs to understand how privacy protection laws determine the incentive structure for inventors by focusing on entry cost (Janssen et al., 2022) and compliance costs (Blind et al., 2024; Geradin et al., 2021), the information processing implications of privacy protection laws require more attention (Egelhoff, 1991; Luo, 2022).

Drawing on insights from information processing theory, we argue that stringent privacy protection laws such as GDPR influence AI inventors because they anticipate administrative and financial hurdles associated with these laws when gathering private information to develop and commercialize their AI innovations. Thus, we expect AI inventors to respond by re-evaluating their innovation activities in GDPR-affected countries. Moreover, given that informal institutions such as national culture influence AI inventors' perceptions of the bureaucratic hurdles imposed by the GDPR, which limit information processing, we draw from the six national culture dimensions of Hofstede[3] to theorize

[2] (Stringent) privacy protection laws are defined as "omnibus data protection laws that provide individuals with a set of rights related to private sector record-keeping practices and provide a basis for the government to protect citizens from abuses in the private sector" (Culnan, 1993, p.343).

[3] Our theoretical framework is based on Hofstede's cultural dimensions rather than GLOBE (House et al., 2004) or Schwartz (2006, 2008), due to its extensive use and better alignment with our study context – AI innovation. For instance, GLOBE's in-group collectivism emphasizes family orientation (Brewer & Venaik, 2010; Venaik & Brewer, 2010), which has limited relevance to AI innovation. Further, Schwartz Value Survey's dimensions (1994, 2004, 2006, 2008) are not perfectly compatible or comparable with Hofstede's framework or with the arguments of our study. While Hofstede and Schwartz dimensions are both values-based, they differ in several important ways. Key among them is that the Schwartz model captures seven dimensions (Harmony, Embeddedness, Hierarchy, Mastery, Affective Autonomy, Intellectual Autonomy, Egalitarianism), with some overlapping and some being unique relative to Hofstede's 6 dimensions. Given the research questions of our study, Schwartz measures would thus not be compatible with our arguments and proposed relationships. Therefore, Hofstede's dimensions are more applicable, useful, and suitable for the current study.

Hofstede first developed four dimensions of national culture using employee survey data from IBM subsidiaries across 70 countries between 1968 and 1973, which he collected while working at the company in personnel management (Hofstede, 1980). The measures originally encompassed 40 countries, as only those with at least 50 respondents were retained. The four ensuing dimensions were individualism (vs. collectivism), power distance, uncertainty avoidance, and masculinity (vs. femininity). Bond and colleagues then conducted a separate survey of 23 countries, using Chinese researchers, where they identified an additional cultural dimension, which they labeled Confucian dynamism (Bond, 1988; Chinese Culture Connection, 1987; Hofstede & Bond, 1988). Building on work with Minkov and others, Hofstede incorporated this 5th dimension into his model (naming it Long-Term Orientation [Hofstede, 1991]) and extended the countries covered to 93 using data from the World Values Survey (WVS) (Hofstede et al., 2010; Minkov & Hofstede, 2012). Minkov's (2011) work using WVS data also led to the development of the 6th and final cultural dimension in Hofstede's model: indulgence (vs. restraint).

The literature has identified a number of strengths and weaknesses (or limitations) in Hofstede's model. Some of the major strengths are: that the dimensions are highly intuitive and easy to understand; that by using company data for the first four dimensions it captures work values and not just social values, as the latter are often more relevant in management work; that by using a single company data for the first four dimensions, it avoids confounding factors that may vary by company, such as corporate culture; and that it uses an etic approach (cf., Pike 1954), which argues for a universally applicable and generalizable psychology for humanity, and which thus allows for cultural comparisons across countries.

At the same time, some of the major criticisms of this model are: that it uses single country data (within a single industry); that the results are time-dependent (as the data was collected in the 1960s and 1970s); that the measures are not dynamic in that they do not account for change in culture over time; that they are at the country level, while culture can vary significantly at the sub-national level; that the measures are not exhaustive, as it does not cover all possible cultural dimensions; that it only covers a portion of the world's countries; and that it has a Western bias (particularly the way the first four dimensions were constructed). Moreover, another important limitation is that Beugelsdijk and Welzel (2018)'s work suggests that Hofstede's how national culture conditions the impact of GDPR on AI innovation. Specifically, we posit that the negative effect of GDPR on AI innovation is less pronounced in countries with stringent privacy protection laws and higher levels of individualism, masculinity, and indulgence, but more pronounced in countries with higher levels of uncertainty avoidance, power distance, and long-term orientation.

We test our framework in a quasi-natural experimental setting by exploiting the announcement of the GDPR in the EU (European Union), which is widely regarded as the most stringent and comprehensive privacy protection law in the world (Human Rights Watch, 2018). Our empirical strategy is congruent with prior studies that have examined the impact of GDPR on technology venture investments (Jia et al., 2021), firm performance (Aridor et al., 2020), and productivity (Ferracane et al., 2020). In testing the baseline model in a quasi-natural experimental setting, we observe that GDPR-affected countries exhibit lower national AI innovation rates than GDPR-unaffected countries after the GDPR announcement. Moreover, using Hofstede's cultural dimensions, we find that individualism, masculinity, and indulgence attenuate the negative relationship between the stringent privacy protection law and national AI innovation rates, whereas uncertainty avoidance, power distance, and long-term orientation accentuate the relationship.

Our study makes multiple contributions. First, we speak to the literature drawn from rational choice institutionalism (North, 1990; Williamson, 1985, 2000), which postulates that economic actors (such as inventors) behave instrumentally in line with their official mandates and goals, with a focus on efficiency (Campbell, 2004). This perspective relies on key assumptions such as rational self-interested behavior, profit maximization, and bounded rationality of inventors, suggesting that they seek their own interests, yet their rationality is limited by imperfect information availability and their cognitive capacity (see Dau et al., 2022, p. 993). Our study relaxes the assumptions of bounded rationality and self-interested behavior by acknowledging the importance of informal institutions. Second, we suggest that information processing implications of institutions for inventors, such as privacy protection laws, must be considered an institutional factor in innovation. The information processing logic is distinct (Luo, 2022, p. 348) because the quality of economic institutions in lowering *transaction costs* and the information processing environment are not always aligned (Powell, 2003). Finally, the paper offers insights for managers on choosing countries that maximize AI innovation output and helps policymakers weigh the trade-offs of stringent data protection policies in balancing consumer protection and AI innovation.

Theory and hypotheses

Given the long-standing emphasis on the institutional context in IB and innovation literature, scholars have explored its implications on innovation (Bennett & Nikolaev, 2021; Furman et al., 2002; Li & Zahra, 2012; Yoon et al., 2024). A key recent development in this field is the shift of technological innovation toward emerging economies (Luo & Tung, 2007; Petricevic & Teece, 2019), which challenges traditional free-market innovation models. For instance, China's rise as a global AI leader – despite its lenient IP regulations and collectivist culture – illustrates how both formal and informal institutions jointly shape innovation outcomes (Lundvall & Rikap, 2022). This underscores the need to examine the joint effects of formal and informal institutions on AI innovation.

Formal institutions represent structural rules and standards that shape interactions among societal constituents and regulate individual behaviors (North, 1990; Scott, 1995). At a fundamental level, formal institutions are defined as the "rules of the game" that are reflected in documented laws, regulations, policies, and standards (North, 1990: 3). Working through explicit rules, incentives, and enforcement mechanisms codified into formal regulations, they constrain and enable human behavior (North, 1990) as well as influencing organizational behavior (Powell & DiMaggio, 1991). Most studies operationalize formal institutions by focusing on transaction costs logic, which helps understand how formal institutions, such as regulations, determine the incentive structure faced by innovators in society (Blind et al., 2024; Boudreaux et al., 2019; Geradin et al., 2021; Janssen et al., 2022; Nyström, 2008). As such, institutions viewed as "the humanly devised constraints that organize political, economic, and social interactions" are aimed at establishing order and minimizing uncertainty in exchanges (North, 1991, p. 97). They are essential for the smooth functioning of markets, allowing firms to carry out transactions without encountering high transaction costs.

Extending this view, we introduce the information processing implications of formal institutions for AI innovators. The information-processing theory aligns with the transaction cost economics perspective by emphasizing the importance of cost-saving in information processing (Luo, 2022). Yet, what sets it apart is its illumination of the intricate

Footnote 3 (continued)

six dimensions can be condensed into three dimensions, with individualism and power distance being opposites of each other, long-term orientation and indulgence also being opposites of each other, and uncertainty avoidance being a stand-alone dimension. For additional details on the assumptions and limitations of Hofstede's dimensions and other related cross-cultural research, see Tung & Verbeke, (2010). For a more detailed discussion of how Hofstede's measures were developed, see Hofstede (1980, 2001), Brewer & Venaik (2011), and Venaik & Brewer (2010). For a review of the IB literature using Hofstede's dimensions, see Beugelsdijk et al. (2017).

mechanisms involved in processing information (Luo, 2022). For instance, a fundamental principle of information processing theory is that the selection, acquisition, and interpretation of information are particularly demanding in complex environments characterized by high information diversity (Lord & Maher, 1990). This suggests that individuals and firms exposed to elevated risks of information breaches and external shocks necessitate more intensive information processing (Egelhoff, 1991). As such, AI innovations characterized by higher levels of information and data intensity are prone to facing increased regulatory risks.

This is the context of our study, where AI innovators anticipate bureaucratic hurdles regarding access to personal information due to stringent privacy protection laws. For instance, acquiring customer information about demographic characteristics and technological preferences is essential for increasing the likelihood of identifying customers' needs and improving sales (Berente et al., 2021; Krakowski et al., 2023). As such, the information processing aspect of formal institutions is crucial because it involves acquiring and combining new information, which can generate new business opportunities (Vaghely & Julien, 2010).

Alongside formal institutions, informal institutions generally refer to "the typically unwritten but socially shared rules and constraints that generate social behavior expectations" (Dau et al., 2022; 986). With this broad conceptualization, we focus on addressing the role of national culture, which represents a system of "collectively held values" within a society (Hofstede, 1984: 51). It "is the deeper level of basic assumptions and beliefs" (Schein, 1985: 6-7; see also, Hofstede, 1980, 1994; House et al., 2004; Tung & Verbeke, 2010). Prior studies grounded in the cross-cultural framework tend to focus on examining the effects of a few national culture dimensions, such as individualism and uncertainty avoidance on innovation (Li & Zahra, 2012; Shane, 1993) and risk-taking behavior (Kanagaretnam et al., 2011). Specifically, several studies have found that while individualism fosters innovation and risk-taking behavior, uncertainty avoidance is detrimental (Kanagaretnam et al., 2011; Shane, 1993). Yet, given that innovation emerges from inventors located in a diverse spectrum of cultures (e.g., including Japan, where indulgence is low, and China, where power distance is high), a more fine-grained analysis is necessary, considering multiple dimensions of national culture.

Integrating these insights, our study pays closer attention to the convergence between formal and informal institutions because collective values and societal beliefs encourage inventors and firms to adhere to formal rules and expectations (Helmke & Levitsky, 2004; Hofstede, 1984). In contrast, the divergence between formal and informal institutions leads to conflicting expectations and motivations (Damaraju et al., 2021; Posner, 2009; Rosen, 2006). As such, national culture, as an informal institution, is a strong determinant of the effectiveness of government policies (Posner, 2009). Building on this formal institution-national culture convergence logic, AI innovation requires considering the interplay of formal and informal institutions (Damaraju et al., 2021). For instance, whereas privacy protection laws as a formal institution regulate inventors' access to private information, culture as an informal institution determines inventors' anticipation of regulatory challenges in information processing to generate AI innovation. Accordingly, our framework for the relationship between privacy protection laws and AI innovation includes considering how that relationship might vary across countries with distinct cultures (see Online Appendix Figure I).

GDPR

Formal institutions such as the GDPR in Europe represent structural rules that safeguard human rights in the digital age (Smith, 2001). In line with the value-based definition of privacy (e.g., general privacy as a human right integral to society; Smith et al., 2011), the GDPR is "one of the strongest and most comprehensive attempts to regulate the collection and use of personal data by both governments and the private sector" (Human Rights Watch, 2018: 1). The GDPR is a comprehensive data privacy regulation adopted by the EU to protect the personal data and privacy of individuals (Goddard, 2017; Hoofnagle et al., 2019). Before GDPR, EU member states had their own data protection laws, but these varied widely in scope and effectiveness (Malgieri, 2019). However, the GDPR aimed to harmonize data protection regulations across the EU, providing a single set of rules applicable to all member states (Goddard, 2017; Hoofnagle et al., 2019). The GDPR applies uniformly across all EU member states, eliminating the necessity for national laws to enforce it. Even though there is some flexibility in how each EU member state enacts the GDPR, the privacy protection laws across different EU countries remain broadly consistent due to the GDPR (Goddard, 2017; Hoofnagle et al., 2019).

Although the enactment and enforcement of the GDPR took place in 2016 and 2018, respectively, several national governments and businesses in the EU have been preparing a long time for its adaptation. For instance, in 2011, the European Data Protection Supervisor officially communicated a comprehensive approach about personal data protection in the EU to reinitiate the reform of its 1995 data protection rules (see Online Appendix Figure II). Since 2011, many businesses have been making adaptations to conform to the key implication of GDPR, which requires "consumers to be allowed to make an informed, specific, and unambiguous consent to the processing of their data" (Aridor et al., 2020: 1). Thus, even before its formal rollout in 2018, inventors and businesses involved in AI innovation began anticipating the institutional environment shaped by the GDPR (Chalmers et al., 2021; Kolbjørnsrud et al., 2016).

Adapting to new regulations such as the GDPR is costly, demanding a substantial amount of time and requiring AI inventors to explore unknown territories. Specifically, this involves anticipating and addressing challenges related to data access restrictions, diverting attention from the primary focus of generating novel technologies and algorithms. Some businesses established divisions to manage privacy issues by anonymizing personal information and ensuring accountability (Berente et al., 2021), such that the inventors using customers' private data could avoid costly lawsuits and prevent any loss of reputation when the GDPR was deployed (Martin, 2016). After its enforcement in 2018, though, national data protection authorities in European countries that had implemented the regulation imposed various sanctions and fines (Ruohonen & Hjerppe, 2021).

AI innovation and stringent privacy protection laws: The role of GDPR

Below, we do not judge the desirability of implementing GDPR rules. It can positively affect society by protecting privacy while curbing opportunism for businesses. We simply focus on theorizing its effects on AI innovation.

AI innovation is a dynamic and experimental decision-making process that necessitates inventors to foresee forthcoming market conditions, encompassing technological requirements, consumer preferences, and projections for future growth (Acemoglu et al., 2011). For this reason, AI innovation represents a subjective judgment process wherein innovators proactively allocate resources to create innovations, guided by their evaluation of perceived technological and business opportunities (Foss et al., 2019). These assessments are significantly influenced by formal institutions, as exemplified by stringent privacy protection laws such as the GDPR.

Some postulate that formal institutions benefit innovation by guiding and forcing firms to invest in innovative activities (Furman et al., 2002). For instance, effective regulations are essential to well-functioning markets, as they establish an orderly process for conducting transactions, making investments, and protecting private property (Deeds & Hill, 1999). In contrast, regulations could lead to bureaucracy and burdensome tasks for innovators. For instance, complying with rules will likely increase costs or restrict innovators' freedom of action (Blind et al., 2024; Boudreaux et al., 2019; Geradin et al., 2021; Janssen et al., 2022). Consistent with the latter view, we focus on stringent privacy protection laws, which inventors anticipate as constraints on their access to and processing of private information when developing and commercializing AI innovations (Acemoglu, 2021; Acemoglu et al., 2022; Berente et al., 2021).

Stringent privacy protection laws such as GDPR will introduce administrative complexities by leading to prolonged procedures for accessing and processing personal data. AI inventors anticipate that obtaining explicit consent from diverse sources will be time-consuming, thereby slowing down the data acquisition process, which is critical for AI development (Aridor et al., 2020; Goldfarb & Tucker, 2012). Additionally, AI inventors will anticipate establishing procedures to handle data subject requests, such as access, rectification, erasure, and data portability (Urban et al., 2019). These information acquisition and processing procedures are resource-intensive and divert focus from core AI innovation activities. For these reasons, even with the introduction of AI data solutions as replacements for paper medical records, many hospitals and healthcare professionals are reluctant due to privacy protection regulations restricting health information sharing (Miller & Tucker, 2009). To oversee compliance with complex privacy protection laws like GDPR, organizations across different sectors, including firms and universities, have appointed data protection officers (Akhlaghpour et al., 2021). Such administrative burdens will deter inventors from effectively processing information to engage in AI innovation activities, ultimately contributing to a slowdown in the rate of AI innovation. Further, stringent privacy protection laws also increase inventors' perceptions that AI innovation is costly (Goldfarb & Tucker, 2012), leading them to fear potential penalties. As such, inventors in countries with stringent privacy protection laws will need to foresee administrative challenges and an increase in the costs of doing business while gathering private data to develop and commercialize their novel AI innovations. Hence, inventors in GDPR-affected countries are likely to view privacy protection laws as administrative and financial burdens when seeking to process information to develop AI innovations and extract value from their AI innovations.

In sum, we propose that stringent privacy protection laws such as GDPR lead to lower national AI innovation rates. Based on these arguments, we predict:

Hypothesis 1 *Stringent privacy protection laws have a negative impact on AI innovation, such that following the announcement of the GDPR, GDPR-affected countries produce fewer AI innovations than GDPR-unaffected countries.*

National culture, GDPR, and AI innovation

While we expect the information processing and bureaucratic hurdles imposed by the GDPR to act as the primary mechanism for lower national AI innovation rates, consistent with the information processing and transaction cost economics perspectives, we further argue that it is critical to consider cultural differences across countries. This consideration is crucial because regulatory interventions can be deeply influenced by a country's culture (Posner, 2009). Accordingly, we theorize how national cultures influence AI inventors' perceptions of the GDPR's potential impact on their information processing abilities.

GDPR and individualism

We argue that AI inventors in GDPR-affected countries with higher levels of individualism (collectivism) will experience less (more) compromised information processing abilities. AI inventors in countries with higher levels of individualism tend to be more autonomous and comfortable working independently (Allik & Realo, 2004; Realo et al., 2002). This tendency is salient because people in individualistic societies prefer a loosely knit social framework where they can pursue their own interests instead of prioritizing group interests and harmony (Shao et al., 2013). At the same time, individualistic societies encourage independent thinking, creativity, and risk-taking (Bennett & Nikolaev, 2021), leading AI inventors to think outside the box and find novel solutions to bureaucratic obstacles. This, in turn, will enable AI inventors to efficiently navigate information processing hurdles imposed by the GDPR. Conversely, in collectivist cultures, there is often a strong emphasis on maintaining group harmony (Hofstede, 1980, 1984, 2001). As such, collectivist cultures underscoring group harmony and cohesion create a reluctance to deviate from established norms and procedures, stifling creativity and hindering the exploration of alternative approaches (Bennett & Nikolaev, 2021). By implication, AI inventors in collectivist societies tend to prioritize consensus-building over individual initiative, which can significantly limit their capacity by conforming to information processing hurdles imposed by the GDPR.

In sum, we propose that the negative impact of the GDPR announcement on AI innovation is weaker in countries with higher levels of individualism, as AI inventors in these societies are better equipped to handle information processing challenges with greater autonomy and creativity.

Hypothesis 2 *The negative impact of the GDPR announcement on AI innovation is weaker in GDPR-affected countries with higher levels of individualism than in GDPR-affected countries with lower levels of individualism.*

GDPR and masculinity–femininity

We argue that AI inventors in GDPR-affected countries with higher levels of masculinity (femininity) will experience less (more) compromised information processing abilities. AI inventors in countries with higher levels of masculinity tend to be more assertive (Hofstede, 1980, 1984) because people in these societies, characterized by rewards and recognition for performance, celebrate success, ambition, and wealth (Hofstede, 1980, 1984). Given the salience of assertiveness in a masculine culture, there is less emphasis on expressing vulnerability or seeking support, leading to greater individual resilience and persistence (Dheer et al., 2021). Hence, AI inventors in masculine societies will assertively and persistently seek to overcome the information processing challenges imposed by the GDPR. In contrast, feminine nations prioritize values such as service, welfare, and care for others over assertiveness, achievement, and success (Dheer et al., 2021; Hofstede, 1980). Supporting this rationale, AI inventors in feminine societies are more inclined towards welfare states, favoring privacy protection. By implication, AI inventors in feminine societies are more likely to comply with stringent privacy protection regulations.

In sum, we propose that the negative impact of the GDPR announcement on AI innovation is weaker in countries with higher levels of masculinity, as AI inventors in these societies are better equipped to handle information processing challenges with greater assertiveness and resilience.

Hypothesis 3 *The negative impact of the GDPR announcement on AI innovation is weaker in GDPR-affected countries with higher levels of masculinity than in GDPR-affected countries with lower levels of masculinity.*

GDPR and uncertainty avoidance

We argue that AI inventors in GDPR-affected countries with higher levels of uncertainty avoidance will experience more compromised information processing abilities. AI inventors in countries with higher levels of uncertainty avoidance tend to be more risk-averse (Hofstede, 1980, 1984). This tendency is salient because people in these societies show a low tolerance for risk-taking activities and actions in response to uncertain or unknown situations (Li & Zahra, 2012). It manifests as a fear of uncertain situations, suppressing deviant ideas and behaviors, adopting strict behavior codes, and resisting new technologies and innovation (Steenkampet al., 1999). Likewise, the notion that "what is different is dangerous" prevails in such societies (Hofstede, 1991: 119). By implication, AI inventors in these societies are less likely to push information processing boundaries to avoid legal repercussions. In contrast, low uncertainty avoidance nations are more tolerant of ambiguities (Hofstede, 1991). Following this reasoning, AI inventors in low uncertainty avoidance societies are more likely to compromise their information processing capabilities by adhering to stringent regulatory measures.

In sum, we propose that the negative impact of the GDPR announcement on AI innovation is stronger in countries with higher levels of uncertainty avoidance, as AI inventors in these societies are troubled by information processing challenges with their fear of an uncertain future imposed by the stringent privacy protection law.

Hypothesis 4 *The negative impact of the GDPR announcement on AI innovation is greater in GDPR-affected countries with higher levels of uncertainty avoidance than in GDPR-affected countries with lower levels of uncertainty avoidance.*

GDPR and power distance

We argue that AI inventors in GDPR-affected countries with higher levels of power distance will experience more compromised information processing abilities. AI inventors in countries with higher levels of power distance are more likely to follow rules and guidelines (Daniels & Greguras, 2014) because people in these societies accept the unequal distribution of power, status, and authority (Hofstede & Bond, 1984). As such, high power distance nations are normatively inclined to obey rules (Fischer & Mansell, 2009). For this reason, AI inventors in these societies recognize the importance of adhering to these rules to ensure societal trust and compliance with legal standards. In other words, there will be heightened conformity to privacy standards in countries with higher power distance. Conversely, individuals in nations with lower power distance are less submissive, often challenging authorities and proactively participating in decision-making processes (Daniels & Greguras, 2014). Following this logic, AI inventors in societies with higher levels of power distance are more likely to adhere to the stringent privacy protection regulations, which restrict their information processing capabilities.

In sum, we propose that the negative impact of the GDPR announcement on AI innovation is more pronounced in countries with higher levels of power distance, as AI inventors in these societies are likely to conform to stringent privacy protections, thereby limiting their information processing abilities.

Hypothesis 5 *The negative impact of the GDPR announcement on AI innovation is greater in GDPR-affected countries with higher levels of power distance than in GDPR-affected countries with lower levels of power distance.*

GDPR and long-term orientation

We argue that AI inventors in GDPR-affected countries with higher levels of long-term orientation will experience more compromised information processing abilities. AI inventors in countries with higher levels of long-term orientation tend to be more pro-social by prioritizing the interests of society (Graafland & Noorderhaven, 2020). This inclination stems from the cultural emphasis on virtues oriented toward future rewards, particularly perseverance and thrift (Bond, 1988; Hofstede, 2001, p. 359). As such, AI inventors in these countries are more sensitive to the potential threats posed by rapidly evolving AI technologies. They anticipate these advancements as possible long-term risks and are committed to safeguarding the interests of future generations. Subsequently, AI inventors in countries with higher levels of long-term orientation are more likely to conform to strict privacy regulations (LaBrie et al., 2018). This adherence to privacy standards is anticipated to substantially hamper the innovative potential of AI development in these countries by restricting the information processing abilities of AI inventors. In contrast, societies characterized by a short-term orientation tend to prioritize immediate business interests over long-term considerations (Hofstede & Minkov, 2010). This focus on short-term gains empowers AI inventors to swiftly navigate information processing hurdles imposed by the GDPR, seeking quick solutions to maintain their competitive edge.

In sum, we propose that the negative impact of GDPR announcement on AI innovation is more pronounced in countries with higher levels of long-term orientation, as AI inventors in these societies are likely to conform to stringent privacy protections, thereby limiting their information processing abilities.

Hypothesis 6 *The negative impact of the GDPR announcement on AI innovation is greater in GDPR-affected countries with higher levels of long-term orientation than in GDPR-affected countries with lower levels of long-term orientation.*

GDPR and indulgence

We argue that AI inventors in GDPR-affected countries with higher levels of indulgence will experience less compromised data processing abilities. AI inventors in countries with higher levels of indulgence often prioritize activities and experiences that bring them pleasure, reflecting the broader societal preference for personal satisfaction and freedom (Hofstede, 2011). In indulgent societies, individuals tend to make decisions based on their own preferences, free from external constraints. As such, people in countries with higher levels of indulgence do not generally appreciate imposing rules and regulations that compromise their freedom (Brehm & Brehm, 2013). This cultural inclination towards enjoyment and freedom encourages inventors to pursue creative and pleasurable endeavors in their innovation activities, even under strict privacy regulations. In contrast, AI inventors in nations with lower levels of indulgence are more compliant with regulations, as restraint is prominent in these societies, which suppress the gratification of needs and enforce strict social norms (Hofstede, 2011). Following the above logic, AI inventors in indulgent societies will likely navigate information processing and regulatory constraints more effectively.

In sum, we propose that the negative impact of the GDPR announcement on AI innovation is weaker in countries with higher levels of indulgence, as AI inventors in these societies are better equipped to handle information processing challenges due to their strong preference for freedom over restrictions.

Hypothesis 7 *The negative impact of the GDPR announcement on AI innovation is weaker in GDPR-affected countries with higher levels of indulgence than in GDPR-affected countries with lower levels of indulgence.*

Methods

Data and sample

We built our dataset by relying on a variety of sources, including the patent database of the U.S. Patent and Trademark Office (USPTO) (Hall et al., 2001), the Hofstede model of national culture (Hofstede, 1980, 1984, 2001), the GLOBE's cultural practices (House et al., 2004), the Fraser Institute's Economic Freedom of the World index (Gwartney et al., 2019), the Freedom House political rights index, the Human Development Index, and the World Bank Open Data platform (see Online Appendix Table I).

To construct our sample, we considered the following criteria: First, we considered data availability, as the coverage of national culture variables is naturally limited. For instance, while Hofstede's national culture variables cover approximately 70 countries, several countries (e.g., Costa Rica, Iceland, Ukraine, Qatar, and Saudi Arabia) had to be dropped because they did not have complete scores for all six cultural dimensions. Second, we did not include countries without AI patenting during the analysis period. Third, based on the CNIL (2018) classification of global privacy laws, several non-European Union countries with stringent privacy protections equivalent to the GDPR – such as Argentina, Israel, Japan, New Zealand, South Korea, and Switzerland – were excluded from the main analysis. This is because these countries do not fit into the categories of either GDPR-affected or GDPR-unaffected countries, as they do not have GDPR but possess stringent privacy regulations. All remaining non-EU member states, which CNIL (2018) assessed as having privacy laws less stringent than the GDPR, were included in the control group (see Online Appendix Table II: GDPR-unaffected countries/territories).

For our analysis, we used a balanced panel dataset with 960 country-year observations of 48 countries from 2000 to 2019. To maintain consistency and balance in comparing AI patenting activity before and after the GDPR announcement in 2011 (EDPS, 2024), we covered the period from 2000 to 2019. We tried a shorter pre-treatment period (2006–2010) to test the robustness of the results, finding them consistent, as reported in Online Appendix Table XIII. Based on country-level panel data, our analysis ensures cross-country comparability and consistency with our theory, which focuses on explaining the joint effects of formal institutions and national culture on AI innovation. We analyzed this dataset using the difference-in-differences (DID) method to estimate the causal effect of the treatment or intervention, i.e., the announcement of the GDPR.

Variables

Dependent variable

AI innovation was measured using AI patents identified from the AIPD dataset (Giczy et al., 2021), which employs machine learning to analyze USPTO patent texts and citations. Our sample includes 559,962 AI patents across 48 countries from 2000 to 2019 (see Online Appendix Tables II, III, and IV). The dependent variable is the AI patent count per country and year. We also used alternative dependent variables – AI publications and AI companies – both of which yield consistent results, as shown in the robustness checks.

Independent variables

Because our analysis is grounded in the DID method, we categorize our sample into control and treatment groups. The treatment group consists of European member-state countries. Before the GDPR, these countries had various data privacy laws (Malgieri, 2019). However, the GDPR aimed to harmonize data protection regulations across the EU, providing a single set of rules applicable to all member states (Goddard, 2017; Hoofnagle et al., 2019). GDPR is directly applicable across all EU member states without the need for national legislation to implement it. Hence, despite some leeway in implementing the GDPR for each EU member state, the privacy protection laws between different EU countries are largely aligned due to the GDPR. Thus, our first independent variable, i.e., GDPR-affected countries, is coded as one if a country is part of the EU and 0 otherwise.

However, it is important to note that non-EU countries have also implemented privacy laws, though their stringency varies considerably. According to CNIL (2018)[4], several non-European countries have privacy protection laws as stringent as GDPR (i.e., deemed adequate). Hence, we exclude these countries[5] (Argentina, Israel, Japan, New Zealand, South Korea, and Switzerland) from the control group to avoid confounding issues.

Our second independent variable, i.e., GDPR announcement, takes one if the sample data is from 2011 onwards and 0 otherwise[6]. We designate the year of the GDPR announcement in 2011 as the commencement of the treatment period (EDPS, 2024). This choice is based on the widely recognized tendency of both organizations and individual actors to respond to significant policy shifts upon announcement, initiating the process of adapting to new institutional environments rather than waiting until the policies are officially implemented (Bomfim, 2003; Pastor & Veronesi, 2012). Indeed, 2011 marks the effective resumption of the EU's privacy regulation project, which was initiated in 1995 but had seen little substantive action until then (EDPS, 2024). Given the considerable time span between 1995 and 2011, the GDPR announcement in 2011 came as a surprising and significant event for AI inventors (Aridor et al., 2020; Ferracane et al., 2020; Jia et al., 2021). Moreover, as we are theorizing about how the supply side (i.e., inventors) responds to a new regulation rather than how the demand side (i.e., the general public) perceives GDPR, it makes sense to use the announcement year. Often, the general public does not pay much attention to a new law until it is implemented and impacts their lives.

Moderating variables

We used Hofstede's (1980, 1984, 2001) six cultural dimensions – individualism, masculinity, uncertainty avoidance, power distance, long-term orientation, and indulgence – which are widely applied in IB and innovation studies (Graafland & Noorderhaven, 2020; Shane, 1993) to capture national values and preferences. These dimensions range from 0 to 100, with higher scores indicating greater individualism, masculinity, uncertainty avoidance, power distance, long-term orientation, and indulgence. Because these cultural values are considered relatively stable over time (Hofstede, 1980, 1984, 2001), we treat the six moderating variables as time-invariant in our analysis. Further, we used the GLOBE's cultural practices scores (House et al., 2004) for a robustness test.

Control variables

We incorporated a wide range of control variables. Using the cumulative numbers of AI prior patents, we controlled for past AI patenting levels of countries to acknowledge the self-reinforcing mechanisms of technologies (e.g., countries with larger prior knowledge bases can produce more AI innovations) (Furman et al., 2002). We controlled for GDP growth rate (annual %) because a rapidly growing economy attracts inventors to fund and develop new technologies and markets related to AI (Yoon et al., 2024). We controlled for the Economic Freedom of the World index (Gwartney et al., 2019), as greater economic freedom is expected to foster AI innovation by providing market incentives for inventors (Boudreaux et al., 2019; Graafland & Noorderhaven, 2020). Because R&D is one of the driving forces behind AI innovation and patenting activities, we controlled for gross domestic expenditures on R&D, expressed as a percentage of GDP, and the number of researchers per million involved in R&D (Yoon et al., 2024). Investing in education is a precondition for a new and emerging technology such as AI to be widely adopted and diffused (Gao et al., 2017; Moore et al., 2021), so we controlled for gross domestic expenditures on education, expressed as a percentage of GDP. We controlled for the focal country's Freedom House political rights index, which is based on questions reflecting the country's free and fair elections, political competition, and the autonomy of all citizens (Gao et al., 2017). We assume that higher political rights will offset corruption and stimulate economic growth, which will promote AI innovation. The political rights index takes values from 1 to 7, with 1 denoting the lowest level of political rights in the focal country and 7 the highest level. As the large populations of specific countries, such as India and China, may amplify the number of AI patents, we controlled for the population size (Gao et al., 2017). We distinguished whether a country is developed since developed countries are more likely to be more innovative. This binary variable takes one if the focal country is considered one of the highest development countries according to the World Bank's classification and 0 otherwise (Moore et al., 2021). We also controlled for the focal country's yearly corporate tax rate (Mukherjee et al., 2017), as high tax rates disincentivize AI inventors from engaging in innovation activities. Moreover, because AI innovation capabilities are more likely to develop in countries with strong high-tech industries, we controlled for the proportion of medium-high and high-tech (MHT) industry value added to the total value added of manufacturing in the focal country for a given year (Wenjuan et al., 2023).

We used the natural logarithm on several control variables, including cumulative AI innovation, number of researchers in R&D, and population size, to facilitate interpretation of their estimates and mitigate their high skewness,

[4] https://www.cnil.fr/en/data-protection-around-the-world.

[5] https://commission.europa.eu/law/law-topic/data-protection/international-dimension-data-protection/adequacy-decisions_en#latest.

[6] We also conducted the analysis using alternative years, 2016 and 2018, and found that our difference-in-differences effect holds.

and lagged them by 1 year to better ascertain their effects on the dependent variable over time and to account for potential reverse causality (Furman et al., 2002).

Finally, we included year dummies to account for changes over time. We did not incorporate country dummies into our models, as they would capture all effects of time-invariant variables, including national culture variables. Instead, we included region dummies – North America, Latin America and the Caribbean, Europe, Asia, and Oceania – to account for geographic heterogeneity and employed a random effects model for our main analysis. However, to address potential unobserved heterogeneities across countries, we also tested the robustness of our results using a fixed-effects Poisson model.

Empirical methods

To test Hypothesis 1, we used the DID to estimate the difference in AI innovation rates between GDPR-affected and unaffected countries from 2011 onwards, relative to the difference in patenting rates between the two groups before 2011. Thus, we estimate the following equation (1):

$$\begin{aligned}\ln\left(\mathrm{AIinnovation_{it}}\right) &= \alpha + \beta_1 \mathrm{GDPRannouncement}_t \\ &+ \beta_2 \mathrm{GDPR\ affected\ countries}_i \\ &+ \beta_{12} \mathrm{GDPR\ announcement}_t x \mathrm{GDPR\ affected\ countries}_i \\ &+ \delta H_{ji} + \theta C_{it} + \mu \mathrm{Year}_t + \gamma \mathrm{Region}_i + \varepsilon_{it}\end{aligned} \tag{1}$$

where $AIinnovation_{it}$ is the number of AI patents in country i in year t, H_{ji} is the set of *time-invariant* Hofstede cultural measures (j = 1,..,6); C_{it} is the set of control variables. $Year_t$ and $Region_i$ control, respectively, for heterogeneities over time and across cultural groups and ε_{it} is the random error term. β_{12} is the key coefficient of interest, which captures the difference in patenting rates between treatment and control groups from 2011 onwards relative to the difference in patenting rates between treatment and control groups before 2011.

In Hypotheses 2 to 7, we test whether the differential in AI innovation rates between GDPR-affected and unaffected countries before and after the announcement of GDPR in 2011 might be contingent on national culture (individualism-collectivism, masculinity-femininity, uncertainty avoidance, power distance, long-term orientation, and indulgence) by estimating the following equation (2):

$$\begin{aligned}&\ln\left(\mathrm{AIinnovation}_{it}\right) \\ &= \alpha + \beta_1 \mathrm{GDPR\ announcement}_t \\ &\quad + \beta_2 \mathrm{GDPR\ affected\ countries}_i \\ &\quad + \beta_{12} \mathrm{GDPR\ announcement}_t x \mathrm{GDPR\ affected\ countries}_i \\ &\quad + \delta_{j1} \mathrm{GDPR\ announcement}_t x H_{ji} \\ &\quad + \delta_{j2} \mathrm{GDPR\ affected\ countries}_i x H_{ji} \\ &\quad + \delta_{j12} \mathrm{GDPR\ announcement}_t x\ \mathrm{GDPR\ affected\ countries}_i x H_{ji} \\ &\quad + \theta X_{it} + \mu \mathrm{Year}_t + \gamma \mathrm{Region}_i + \varepsilon_{it}\end{aligned} \tag{2}$$

In Equation (2), δ_{j12} (j = 1,..,6) are the coefficients of interest since they capture the DID in AI patenting trends between GDPR-unaffected and affected countries contingent on the national cultural dimensions' levels (individualism, masculinity, uncertainty avoidance, power distance, long-term orientation, and indulgence).

Since our dependent variable is a count variable, we used the panel Poisson model because it is better suited to a highly skewed distribution than a panel linear regression model that relies on a normal distribution (Hausman et al., 1984). Moreover, we employed a random-effect Poisson specification to test our hypotheses and a fixed-effects Poisson specification to conduct robustness checks.

Results

Parallel trends assumption

Before testing our hypotheses with the DID model, we test the assumption of parallel trends in the pre-treatment data (absence of divergence in trends) between the treatment and control groups before the GDPR announcement. We conducted a lead/lag treatment effect analysis every year to check the pre-GDPR announcement differences in AI innovation between GDPR-affected and -unaffected countries in the focal year relative to differences in AI innovation between the two groups in the previous year. Figure 1 depicts these yearly DIDs using a random effects Poisson specification, including the complete set of interactions between the EU states dummy and each year dummy, the Hofstede cultural variables, and the control variables. Figure 1 indicates no pre-existing differential trend between the GDPR-affected and -unaffected countries in the number of AI patents per year from 2003 to 2010 (the confidence intervals of the estimated DIDs include zero). However, it shows a significant differential trend in AI innovation over the years between the two groups after the GDPR announcement in 2011, except in 2012. This observation substantiates the absence of a differential pre-trend before the GDPR announcement, satisfying the DID analysis's fundamental assumption.

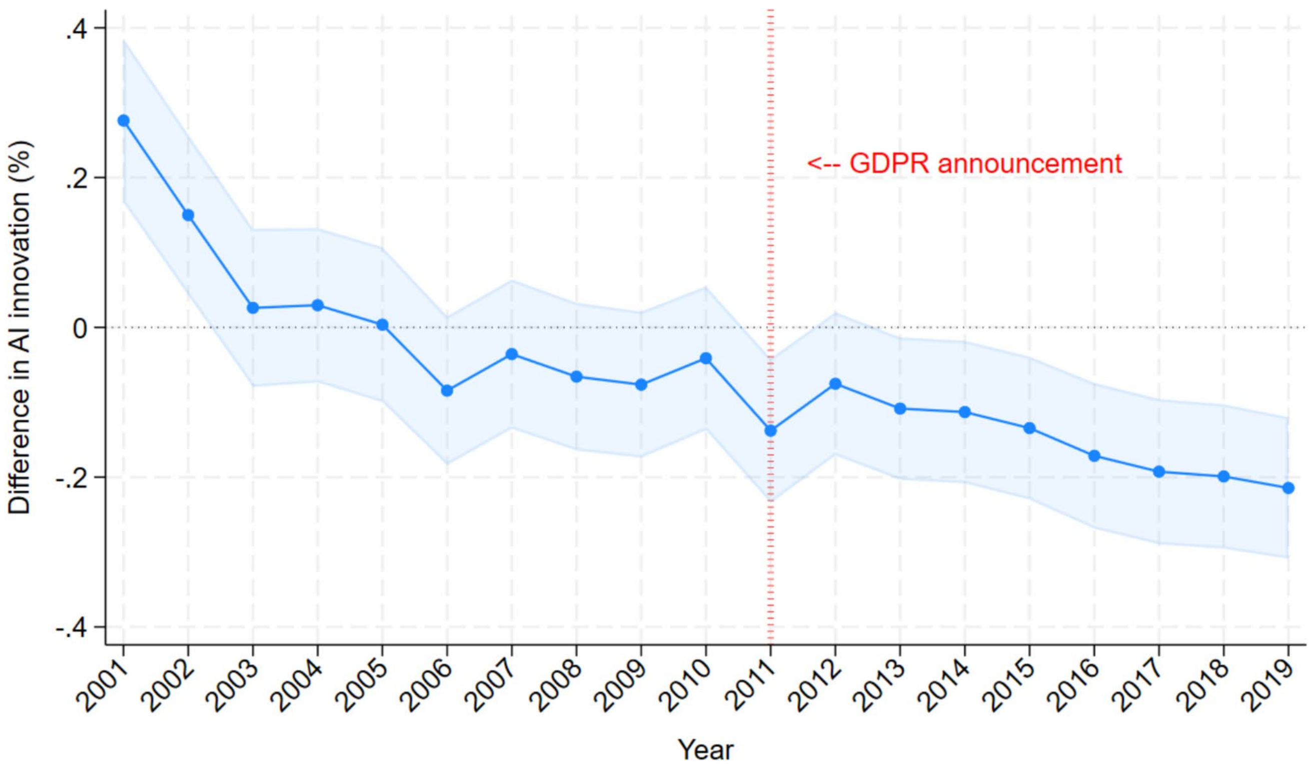

Fig. 1 Parallel trend test: estimated DID in AI patenting rates between GDPR-affected and GDPR-unaffected Countries. The figure shows the estimated difference in AI-logged patenting rates between GDPR-affected and unaffected countries, relative to their difference in the previous year, with 95% confidence intervals

Tests of hypotheses

We report the descriptive statistics and bivariate correlations in Table 1. Regarding multi-collinearity concerns, the mean variance inflation factor (VIF) score is well below the acceptable threshold of 10.

Table 2 reports the results of the random effects Poisson regressions, including estimated coefficients and *p* values. Model 1 tests the effects of the GDPR announcement on AI innovation in GDPR-affected countries relative to GDPR-unaffected countries. Models 2 to 7 test the moderating effects of national culture on the relationship between the privacy protection law announcement and AI innovation in GDPR-affected countries relative to GDPR-unaffected countries. The Wald measure indicates an overall fit significance for each model ($p \approx 0.000$), confirming that the models are acceptable for interpretation.

Hypothesis 1 posits that GDPR-affected countries will underperform in AI innovation compared to GDPR-unaffected countries following the GDPR announcement. The estimated β12 ($p \approx 0.000$) in model 1 indicates that, on average, GDPR-affected countries produce 10.8% fewer AI patents per year after 2011 compared to GDPR-unaffected countries, relative to the difference in AI patents between the two groups prior to 2010. This result provides support for Hypothesis 1.

Hypothesis 2 predicts that higher levels of individualism enable GDPR-affected countries to reduce their underperformance in AI innovation relative to GDPR-unaffected countries after the GDPR announcement. The estimated β_{12} ($p \approx 0.000$) in model 2 of Table 2 indicates a significant and negative DID of about 72% in AI patents between GDPR-affected countries and -unaffected countries when the level of individualism is low. However, the positive and statistically significant three-way interaction term ($\delta_{112} = 0.008$, $p \approx 0.000$) in model 2 suggests that this underperformance is mitigated in GDPR-affected countries with higher levels of individualism. Specifically, a ten-unit increase in the individualism score will, on average, reduce the annual gap in AI innovation between the two groups by 8%, favoring the GDPR-affected countries. Panel A of Fig. 2 shows that the difference in AI innovation rates between GDPR-affected and unaffected countries is negative when the level of individualism is low. However, the gap in AI innovation between the two groups is reduced at higher levels of individualism and even turns statistically not significant when the individualism score approaches 90. Therefore, Hypothesis 2 is supported.

Table 1 Descriptive statistics and pairwise correlations

Variables	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1 Yearly AI innovation	552.8	3115.6	1.000																			
2 GDPR announcement	0.450	0.498	0.091	1.000																		
3 GDPR-affected countries	0.511	0.500	−0.132	0.000	1.000																	
4 Individualism	46.28	24.04	0.273	0.000	0.513	1.000																
5 Masculinity	48.30	17.66	0.120	0.000	−0.169	0.074	1.000															
6 Uncertainty avoidance	65.13	22.85	−0.133	0.000	0.287	−0.118	−0.010	1.000														
7 Power distance	59.32	20.48	−0.141	0.000	−0.488	−0.690	0.064	0.212	1.000													
8 Long-term orientation	49.98	21.40	−0.124	0.000	0.224	0.041	−0.107	−0.038	0.011	1.000												
9 Indulgence	46.23	21.57	0.136	0.000	−0.132	0.188	0.157	−0.094	−0.227	−0.534	1.000											
10 Cumulative AI innovation[a,b]	4.365	2.714	0.438	0.435	0.054	0.523	0.181	−0.245	−0.320	0.122	0.200	1.000										
11 GDP growth[b]	3.094	3.403	−0.038	−0.049	−0.275	−0.234	0.041	−0.213	0.226	0.095	−0.159	−0.094	1.000									
12 Economic freedom[b]	6.919	1.812	0.116	0.217	0.200	0.289	−0.046	−0.130	−0.274	0.084	0.031	0.529	0.095	1.000								
13 R&D expenditure[b]	1.186	0.864	0.270	0.178	0.325	0.537	−0.083	−0.195	−0.552	0.261	0.209	0.720	−0.159	0.531	1.000							
14 Researchers in R&D[a,b]	6.914	1.982	0.110	0.251	0.348	0.397	−0.131	−0.047	−0.341	0.161	−0.001	0.567	−0.000	0.673	0.671	1.000						
15 Education expenditure[b]	4.435	1.617	0.139	0.146	0.228	0.344	−0.197	−0.046	−0.357	0.017	0.278	0.472	−0.077	0.667	0.644	0.695	1.000					
16 Political rights[b]	2.291	1.840	−0.083	0.021	−0.643	−0.586	0.095	−0.273	0.514	0.001	−0.206	−0.206	0.294	−0.292	−0.380	−0.243	−0.339	1.000				
17 Population size[a,b]	17.03	1.649	0.233	0.020	−0.565	−0.160	0.337	−0.122	0.361	−0.084	−0.027	0.232	0.185	−0.197	−0.184	−0.296	−0.200	0.419	1.000			
18 Developed country	0.617	0.486	0.116	0.000	0.630	0.627	−0.101	−0.019	−0.666	0.167	0.108	0.324	−0.275	0.376	0.579	0.445	0.361	−0.662	−0.564	1.000		
19 MHT value added[b]	36.17	12.55	0.141	0.103	0.033	0.257	0.267	−0.454	−0.138	0.093	0.197	0.428	−0.004	0.173	0.433	0.177	0.109	0.008	0.127	0.162	1.000	
20 Tax rate[b]	15.67	9.451	0.302	0.060	0.559	0.645	−0.119	0.028	−0.485	−0.064	0.165	0.317	−0.228	0.279	0.435	0.352	0.326	−0.578	−0.363	0.526	0.110	1.000

[a] Logarithm transformed; [b]1 year lagged. $N = 960$ observations. Correlations with absolute values of 0.065 or above are significant at $p < 0.05$. All tests are two–tailed

Hypothesis 3 predicts that higher levels of masculinity enable GDPR-affected countries to mitigate their underperformance in AI innovation compared to GDPR-unaffected countries after the GDPR announcement. The significant estimated β_{12} ($p \approx 0.000$) in model 3 of Table 2 suggests a negative DID of about 24% in AI patents between the two groups after the GDPR announcement when masculinity is low. However, the negative DID between the two groups decreases when the level of masculinity increases (δ_{212} = 0.003, $p = 0.034$). Specifically, a ten-unit increase in the masculinity score will, on average, reduce the annual gap in AI innovation between the two groups by 3%, favoring the GDPR-affected countries. Panel B of Fig. 2 shows that after the GDPR announcement, the AI innovation gap between affected and unaffected countries diminishes at low masculinity levels and becomes statistically not significant around a score of seventy. These findings support Hypothesis 3.

Hypothesis 4 proposes that higher levels of uncertainty avoidance increase the divergence in AI innovation between GDPR-affected and –unaffected countries after the GDPR announcement. The non-significant estimated β_{12} ($p = 0.247$) of model 4 in Table 2 shows no difference in AI innovation between GDPR-affected and -unaffected countries due to the GDPR announcement when the level of uncertainty avoidance is low. However, the DID in AI innovation between the two groups becomes more negative as the uncertainty avoidance level increases (δ_{312} = -0.003, $p = 0.002$). Specifically, a ten-unit increase in the uncertainty avoidance score will, on average, create a 3% annual gap in AI innovation between the two groups, favoring the GDPR-unaffected countries following the GDPR announcement. Panel C of Fig. 2 clearly illustrates this finding by showing the underperformance in AI innovation of GDPR-affected relative to GDPR-unaffected countries after the GDPR announcement, when the uncertainty avoidance scores exceed forty. Therefore, Hypothesis 4 is supported.

Hypothesis 5 proposes that higher levels of power distance will magnify the negative impact of GDPR on AI innovation in GDPR-affected countries relative to GDPR-affected countries. The estimated positive and significant β_{12} ($p \approx 0.000$) in model 5 of Table 2 indicates a positive DID in AI patents of 51% in favor of the GDPR-affected countries with lower power distance over their counterparts after the GDPR announcement. However, the negative and statistically significant three-way interaction term in model 5 ($\delta_{412} = -0.013$, $p \approx 0.000$) suggests that the positive DID decreases as the power distance level increases. Specifically, a ten-unit rise in the power distance score will, on average, reduce the annual relative difference in AI innovation between the two groups by 13%, favoring the GDPR-unaffected countries. Panel D of Fig. 2 shows that, following the GDPR announcement, GDPR-affected countries with higher levels of power distance tend to lose this relative advantage versus GDPR-unaffected countries and produce fewer AI innovation for power distance scores above 50. Therefore, Hypothesis 5 is supported.

Hypothesis 6 tests whether the negative impact of the GDPR announcement on AI innovation is more pronounced in GDPR-affected countries with higher levels of long-term orientation than in GDPR-affected countries with lower levels of long-term orientation by referring to GDPR-unaffected countries. The estimated positive and significant β_{12} ($p \approx 0.000$) in model 6 indicates a substantial gap of about 55% in AI patents in favor of short-term oriented GDPR-affected countries relative to GDPR-unaffected countries after the GDPR announcement in 2011. However, this outperformance disappears in long-term oriented GDPR-affected countries, as indicated by the negative and statistically significant three-way interaction term in model 6 (δ_{512} = -0.013, $p \approx 0.000$). Specifically, a ten-unit increase in the long-term orientation score will, on average, reduce the annual relative difference in AI innovation between the two groups by 13%, favoring the GDPR-unaffected countries. As seen in panel E of Fig. 2, short-term-oriented GDPR-affected countries initially outperform GDPR-unaffected countries in AI innovation following the 2011 GDPR announcement, but this advantage reverses in more long-term-oriented GDPR-affected countries. Therefore, Hypothesis 6 is supported.

Finally, Hypothesis 7 predicts that higher levels of indulgence will reduce the divergence in AI innovation between GDPR-affected and -unaffected countries caused by the GDPR announcement. The estimated negative and significant β_{12} ($p \approx 0.000$) in model 7 suggests that GDPR-affected countries with low levels of indulgence produced approximately 103% fewer AI patents per year on average than GDPR-unaffected countries after 2011. This AI innovation disadvantage of GDPR-affected countries relative to GDPR-unaffected countries diminishes as the level of indulgence increases, as indicated by the positive and statistically significant three-way interaction term in model 7 ($\delta_{612} = 0.016$, $p \approx 0.000$). Specifically, a ten-unit increase in the indulgence score will, on average, reduce the annual relative difference in AI innovation between the two groups by 16%, favoring the GDPR-affected countries. Panel F of Fig. 2 shows that the AI innovation gap between GDPR-affected and unaffected countries, initially negative at low indulgence levels, turns positive when indulgence exceeds 50. Therefore, Hypothesis 7 is supported.

Robustness checks and additional analyses

We conducted robustness tests to validate our findings, including (1) sensitivity analysis with a fixed-effects Poisson model (Online Appendix Table III), (2) alternative

Table 2 Predicting AI innovation with random effects Poisson model

Yearly AI innovation	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
GDPR announcement (β_1)	0.469	1.178	0.434	0.533	0.153	0.544	1.624
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GDPR-affected countries (β_2)	−0.029	1.960	−0.244	0.499	−2.891	0.678	0.976
	(0.960)	(0.029)	(0.802)	(0.762)	(0.163)	(0.479)	(0.176)
GDPR announcement *x* GDPR-affected countries (β_{12})	**−0.108**	**−0.721**	**−0.236**	**0.048**	**0.506**	**0.550**	**−1.029**
	(0.000)	**(0.000)**	**(0.000)**	**(0.247)**	**(0.000)**	**(0.000)**	**(0.000)**
Individualism	−0.020	0.020	−0.022	−0.014	−0.016	−0.007	−0.017
	(0.060)	(0.286)	(0.045)	(0.149)	(0.145)	(0.543)	(0.119)
Masculinity	−0.002	0.001	−0.009	−0.000	0.000	−0.001	−0.002
	(0.783)	(0.841)	(0.611)	(0.939)	(0.993)	(0.834)	(0.787)
Uncertainty avoidance	−0.022	−0.026	−0.023	−0.015	−0.031	−0.019	−0.026
	(0.000)	(0.000)	(0.001)	(0.086)	(0.000)	(0.002)	(0.000)
Power distance	−0.003	−0.006	−0.003	0.002	−0.032	−0.000	−0.005
	(0.723)	(0.498)	(0.735)	(0.846)	(0.070)	(0.980)	(0.646)
Long-term orientation	0.017	0.023	0.017	0.016	0.020	0.025	0.020
	(0.010)	(0.000)	(0.010)	(0.005)	(0.002)	(0.009)	(0.004)
Indulgence	0.014	0.023	0.015	0.011	0.022	0.012	0.034
	(0.073)	(0.004)	(0.063)	(0.132)	(0.012)	(0.084)	(0.005)
Cumulative AI innovation[a,b]	0.531	0.460	0.533	0.538	0.426	0.464	0.417
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GDP growth[b]	−0.003	0.005	−0.004	−0.003	0.006	0.007	0.006
	(0.133)	(0.006)	(0.038)	(0.059)	(0.001)	(0.000)	(0.000)
Economic freedom[b]	−0.177	−0.126	−0.183	−0.174	−0.174	−0.109	−0.149
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R&D expenditure[b]	−0.033	−0.057	−0.046	−0.032	−0.057	0.010	−0.046
	(0.079)	(0.003)	(0.020)	(0.090)	(0.003)	(0.634)	(0.017)
Researchers in R&D[a,b]	−0.136	−0.155	−0.125	−0.135	−0.082	−0.195	−0.099
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Education expenditure[b]	0.050	0.047	0.047	0.041	0.041	0.052	0.038
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Political rights[b]	0.037	0.056	0.039	0.038	0.037	0.054	0.037
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Population size[a,b]	0.809	0.848	0.844	0.661	0.872	0.693	0.889
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Developed country	1.438	1.751	1.458	1.329	1.415	1.113	1.585
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)
MHT value added[b]	0.003	−0.001	0.003	0.003	−0.002	0.003	−0.002
	(0.054)	(0.460)	(0.020)	(0.022)	(0.180)	(0.032)	(0.232)
Tax rate[b]	0.002	0.003	0.002	0.003	0.003	0.004	0.004
	(0.048)	(0.000)	(0.018)	(0.000)	(0.000)	(0.000)	(0.000)
GDPR announcement *x* Individualism		−0.006					
		(0.000)					
GDPR-affected countries *x* Individualism		−0.058					
		(0.014)					
GDPR announcement *x* GDPR-affected countries *x* Individualism (δ_{112})		**0.008**					
		(0.000)					
GDPR announcement *x* Masculinity			0.000				
			(0.737)				
GDPR-affected countries *x* Masculinity			0.006				
			(0.749)				

Table 2 (continued)

Yearly AI innovation	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
GDPR announcement *x* GDPR-affected countries			**0.003**				
x Masculinity (δ_{212})			**(0.034)**				
GDPR announcement *x* Uncertainty avoidance				−0.001			
				(0.036)			
GDPR-affected countries *x* Uncertainty avoidance				−0.005			
				(0.753)			
GDPR announcement *x* GDPR-affected countries				**−0.003**			
x Uncertainty avoidance (δ_{312})				**(0.002)**			
GDPR announcement *x* Power distance					0.014		
					(0.000)		
GDPR-affected countries *x* Power distance					0.040		
					(0.103)		
GDPR announcement *x* GDPR-affected countries					**−0.013**		
x Power distance (δ_{412})					**(0.000)**		
GDPR announcement *x* Long-term orientation						0.006	
						(0.000)	
GDPR-affected countries *x* Long-term orientation						−0.010	
						(0.443)	
GDPR announcement *x* GDPR-affected countries						**−0.013**	
x Long-term orientation (δ_{512})						**(0.000)**	
GDPR announcement *x* Indulgence							−0.013
							(0.000)
GDPR-affected countries *x* Indulgence							−0.025
							(0.189)
GDPR announcement *x* GDPR-affected countries							**0.016**
x Indulgence (δ_{612})							**(0.000)**
Constant	−9.569	−14.601	−9.564	−8.007	−9.894	−8.793	−12.245
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	960	960	960	960	960	960	960
No. of countries	48	48	48	48	48	48	48
Log-likelihood	−4825.9	−4587.1	−4810.1	−4793.4	−4443.2	−4547.9	−4417.9
Chi2 overall model fit	147204.6	146906.8	147211.5	147259.9	146719.0	147176.8	146580.7
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

[a] Logarithm transformed; [b] 1 year lagged; *p* values in parentheses; significance tests are two-tailed.

calculations for moderating variables (Online Appendix Table IV), (3) GLOBE cultural measures (Online Appendix Table V), (4) alternative control variables (Online Appendix Table VI), (5) GDP per capita while addressing multicollinearity (Online Appendix Table VII), (6) alternative dependent variables (Online Appendix Tables VIII & IX), (7) excluding high-population and high-patent-volume countries (Online Appendix Tables X–XII), and (8) shortening the pre-treatment period (Online Appendix Table XIII).

All results, available in the Online Appendix, confirm the consistency of our findings; see the online supplementary file for details.

Discussion and conclusion

The main aim of this study is to understand the impact of privacy protection laws on the AI industry. We have developed a set of novel theoretical predictions at the intersection of comparative institutional literature and cross-cultural

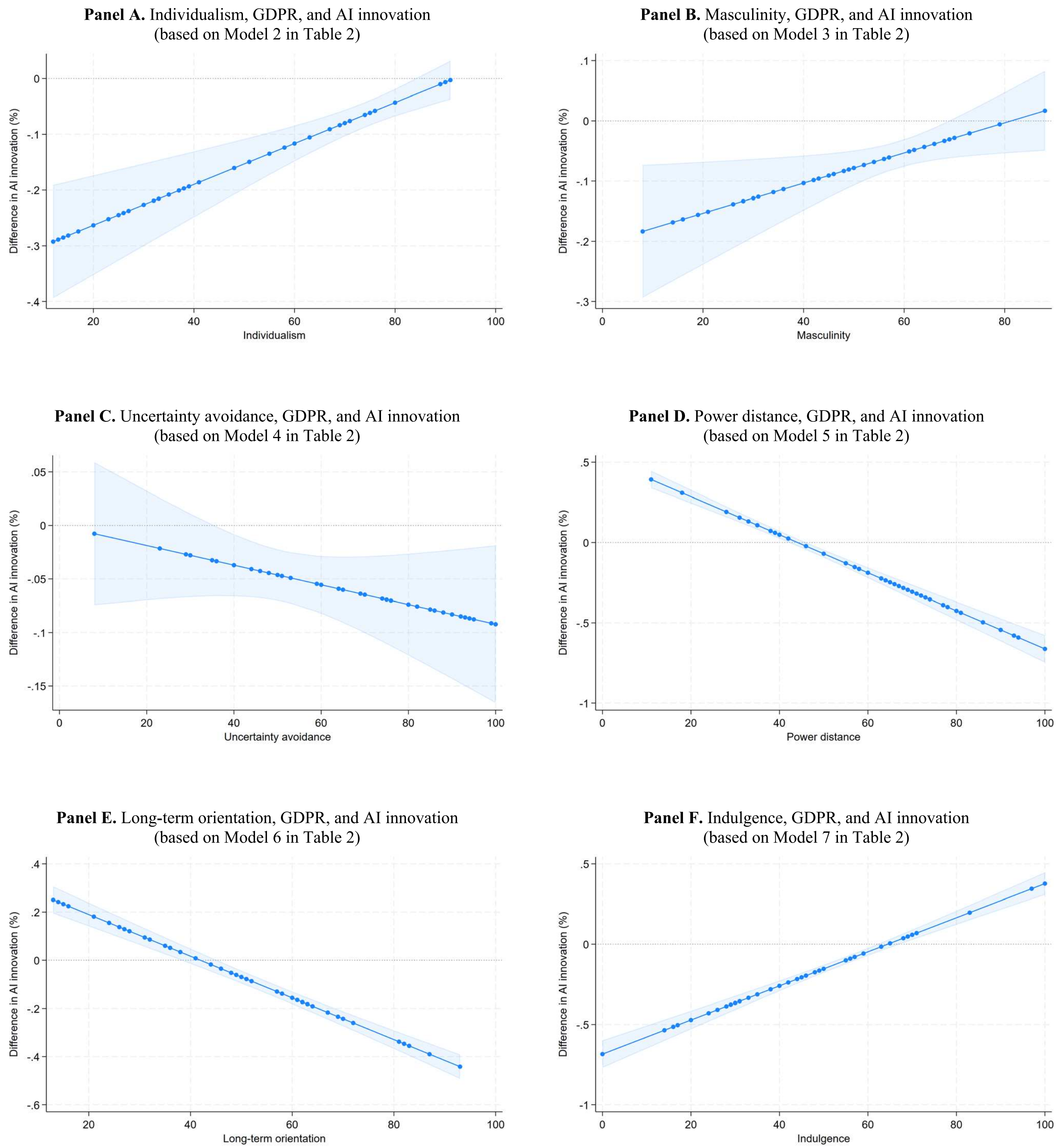

Fig. 2 Joint effects of GDPR and culture on AI innovation. All figures represent the estimated AI innovation difference (%) with 95% confidence intervals between GDPR-affected and unaffected countries after the GDPR announcement, relative to their pre-announcement difference, across the full range of Hofstede's cultural dimension scores

research to explain how the interplay of GDPR and national culture influences AI innovation rates. Our study generates insights into how inventors and entrepreneurs in countries with stringent privacy protection laws can consider their national culture dimensions to design their AI innovation activities. Our findings reveal that GDPR-affected countries saw a decline in AI patenting post-announcement compared to unaffected countries. However, this negative effect is weaker in countries with high individualism, masculinity, and indulgence, while uncertainty avoidance, power distance, and long-term orientation exacerbate it.

Theoretical contributions and implications

Our theoretical framework and empirical findings generate several contributions and implications. First, we contribute to the IB literature on information processing (e.g., Dawar et al., 1996; Luo, 2022) by teasing out the mechanisms whereby stringent privacy protection laws can provide a disincentive for innovation while theorizing how inventors process information differently depending on their cultural values. Although prior literature has firmly established that economic freedom, political freedom, and institutional quality drive the emergence of new technologies (e.g., Boudreaux et al., 2019; Nyström, 2008; Yoon et al., 2024), it largely overlooks the information processing implications of privacy protection laws and cultural values. Our study explicitly considers the role of privacy protection laws in hampering inventors' information processing abilities to engage in AI innovation and how cultural values condition this core information processing mechanism.

Second, our study contributes to transaction cost economics (Williamson, 1985, 2000) by examining how stringent privacy protection increases transaction costs and disincentivizes innovation. At the same time, we relax the assumptions of rational self-interested behavior, profit maximization, and bounded rationality (Campbell, 2004; North, 1990) by suggesting that the cultural values of inventors can enhance or detract from the effects of data protection policies on innovation. In doing so, we not only consider how formal institutions (i.e., privacy protection laws) can restrain inventors' access to and use of private data (e.g., administrative burdens to receive consent) but also account for the role of national cultural values and practices in alleviating the compromise of inventors' information processing abilities in GDPR-affected countries.

More broadly, our study contributes to the IB literature in the areas of data privacy laws, cultural studies, and innovation (e.g., Dawar et al., 1996; Luo, 2022) by examining how the interplay between formal institutions and cultural factors impacts AI innovation. In so doing, the paper focuses on a particularly timely and relevant issue, offering a new perspective on the academic debate about data capitalism and surveillance (West, 2019). By showing how national culture differentially moderates the relationship between privacy protection laws and AI innovation, our study emphasizes the importance of considering different cultural dimensions to navigate information processing challenges for inventors in countries with stringent privacy protection laws.

Managerial and policy implications

Our findings offer strategic insights for managers seeking to maximize AI innovation. EU countries with low uncertainty avoidance, low power distance, and short-term orientation (e.g., Denmark, Ireland, Portugal) are less constrained by GDPR, making them attractive for AI ventures. Similarly, countries with high individualism, masculinity, and indulgence (e.g., Netherlands, Denmark, Ireland) foster resilient innovation environments. Managers can leverage these cultural dimensions to position AI initiatives in regions that minimize regulatory constraints and enhance innovation potential.

Furthermore, our findings suggest that policymakers need to consider the advantages and disadvantages of stringent data protection regulations. On the one hand, such regulations are essential to protect their population from potential business opportunism and malfeasance. On the other hand, such regulations can disincentivize innovation relative to countries with less stringent regulations, which can be a key driver of economic growth. Indeed, Draghi's report on The Future of European Competitiveness raises concerns about GDPR's potential to hinder the EU's digital ambitions (Draghi, 2024a). Specifically, his Financial Times article notes that GDPR-related costs have reduced the profits of small European tech firms by up to 12%, reinforcing these concerns (Draghi, 2024b). Therefore, policymakers must carefully weigh the benefits of stringent data protection regulations against their potential economic drawbacks. While such regulations are crucial for safeguarding consumers from business opportunism and misconduct, they may also create barriers to innovation and competitiveness.

Moreover, we suggest that policymakers should consider their national culture when regulating emerging technologies. Our analysis shows that in GDPR-affected countries, individualism, masculinity, and indulgence ease regulatory burdens on inventors, while uncertainty avoidance, power distance, and long-term orientation exacerbate them (Dau et al., 2022). To support AI innovation, countries with high uncertainty avoidance (e.g., Belgium, Portugal, Greece), power distance (e.g., Croatia, Romania, Slovenia), and long-term orientation (e.g., Belgium, Germany, Lithuania) should provide more support for AI inventors. Likewise, countries with low individualism (e.g., Portugal, Slovenia, Romania), masculinity (e.g., Norway, Netherlands, Denmark), and indulgence (e.g., Lithuania, Estonia, Bulgaria) should reduce regulatory constraints on AI innovation.

Limitations and research agenda

Our study provides opportunities for future research. First, while patent count is one of the most widely used measures of innovation (Furman et al., 2002; Hall et al., 2001;

Yoon et al., 2024), it may not fully capture patent quality or the knowledge search behaviors of AI inventors. Future studies using patent citation data could explore how formal regulations and national culture configurations influence these innovative processes. Second, our study captures aggregate AI innovation at the national level but does not account for firms' geographically diversified responses to GDPR. Future research could explore how GDPR shapes firms' global R&D strategies across different cultural contexts. Despite this limitation, our approach retains all patent applicants, whereas firm-level data would exclude many firms, particularly nascent ones without financial records. Third, our study paves the way for research on privacy protection laws. Future work could examine how GDPR and/or national culture influence profitability, internationalization, entrepreneurship, and even non-market strategy. Finally, there is no consensus on defining national culture. Some view it as an informal institution shaping societal norms (Bennett & Nikolaev, 2021; Holmes et al. 2013), while others distinguish it from broader informal institutions, encompassing social rules and norms (Helmke & Levitsky, 2004). Future research could clarify these distinctions to enhance our understanding of their respective roles.

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