Quality & Quantity (2026) 60:18853–18887
https://doi.org/10.1007/s11135-026-02916-6

Workers' perceptions of the economic impact of generative AI on sustainable economic development: evidence from ensemble tree models and explainable machine learning

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Received: 3 March 2026 / Accepted: 11 June 2026 / Published online: 18 June 2026
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Abstract
Generative artificial intelligence (GenAI) is transforming society, including its economic foundations. This study examines the drivers and barriers shaping perceptions of GenAI's influence on sustainable economic development (SED) among the working population. We adopt a conceptual framework in which these perceptions are shaped by four cognitive factors: three derived from the Technology Readiness and Acceptance Model, namely technological optimism, technological insecurity, and habitual use of GenAI, and a fourth related to the perceived need for regulation. The framework also incorporates three professional and sociodemographic characteristics: entrepreneurial status, gender, and membership in digital versus non-digital generations. Using a survey from Spain, we employ an analytical approach that combines ensemble tree–based machine learning models with Shapley Additive Explanations (SHAP) to enhance interpretability and explanatory insight. Among the evaluated models, XGBoost and Bayesian Additive Regression Trees achieve the strongest predictive performance. Random Forest exhibits comparatively weaker generalization performance. SHAP analyses consistently reveal that cognitive factors related to technology perceptions and habit in GenAI use play a central role in shaping evaluations of its contribution to sustainable economic development, whereas entrepreneurial status and generational cohort exert a secondary influence. Gender, however, shows greater explanatory relevance than perceptions regarding the need for regulation and reveals a pronounced gender gap in GenAI acceptance, with women exhibiting systematically less favorable perceptions than men. Although entrepreneurship exerts a relatively small effect, entrepreneurs tend to hold more favorable views regarding GenAI's role in fostering sustainable economic development. Overall, the findings demonstrate that ensemble-based machine learning models, combined with SHAP, provide a powerful and transparent framework for explaining perceptions of GenAI's contribution to SED.

Keywords Generative artificial intelligence · Sustainable economic development · Technology acceptance · Ensemble tree methods · Shapley additive explanations · Gender gap · Entrepreneurship

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1 Introduction

The emergence of generative artificial intelligence (GenAI) marks a turning point in contemporary digital transformation. The development and deployment of systems based on foundation models accelerated markedly during the 2020–2022 period, and their rapid social and organizational diffusion (Feuerriegel et al. 2024) has positioned GenAI as a general-purpose technology with the capacity to reshape productive processes, work routines, and business models (Polak and Anshari 2024). From an economic perspective, GenAI enables the partial automation of cognitive tasks and the creation of new knowledge-intensive services (Chatterji et al. 2025) while also reconfiguring value chains in sectors such as manufacturing (Tamvada et al. 2022) and digital agriculture (Alobid and Szűcs 2025). However, these productivity gains coexist with perceived risks related to loss of employment, bias, privacy concerns, and the increasing dominance of major corporations over technological resources (Fraisl 2024).

These transformations are particularly relevant when examined through the lens of the Sustainable Development Goals (SDGs), which emphasize that sustainable economic development (SED) does not rely solely on growth, but also on employment quality, industrial innovation, and the resilience of productive systems (United Nations 2015). The development and use of GenAI are directly related to SDG 8 (Decent Work and Economic Growth) and SDG 9 (Industry, Innovation, and Infrastructure), as these goals explicitly incorporate productivity, employment, and technological change (United Nations Global Compact, Accenture 2024). GenAI may also affect SDGs with a strong sectoral-economic component, such as SDG 2 (Zero Hunger, sustainable agriculture) and SDG 12 (Responsible Consumption and Production), where resource efficiency, productive modernization, and process sustainability are central elements (United Nations 2015).

Analyzing the relationship between GenAI and sustainable economic development is socially relevant. The 2030 Agenda frames the SDGs as an integrated plan for "people, planet, and prosperity," linking economic progress to the reduction of vulnerabilities and broader social outcomes (United Nations 2015). From this perspective, the economic impact of GenAI is relevant insofar as it may influence the conditions that support well-being, such as employment opportunities and job quality (Zarifhonarvar 2024), access to goods and services, and the adaptive capacity of productive systems (United Nations Global Compact, Accenture 2024). In addition, the literature on well-being suggests that advances in economic dimensions, captured by SDG-related indicators, are associated with evaluations of human well-being (Iriarte and Musikanski 2019), reinforcing the relevance of studying emerging technologies through their perceived contribution to sustainable development. Prior research also shows a robust and significant relationship between societal happiness and economic development (Behera et al. 2024; Celik et al. 2025).

Against this background, this study focuses on analyzing the drivers of the Spanish working population's perception of the impact of GenAI on sustainable economic development (SED). This impact is conceptualized as a subjective evaluation of the potential contribution of GenAI to SED, encompassing domains such as the labor market, industry, economy, and agriculture. The analysis was based on microdata from the Spanish Social Perception of Artificial Intelligence Survey (Centro de Investigaciones Sociológicas 2025), which provides detailed information on knowledge, use, and attitudes toward GenAI among

the Spanish population, including perceptions of benefits and risks, as well as a strong societal preference for regulation.

Judgments of the economic impact of GenAI are structured along two tiers. The first tier is based on theoretical approaches to innovation acceptance and adoption of information systems, including extensions from Technology Readiness (TR) (Parasuraman 2000; Parasuraman and Colby 2015) and the Technology Acceptance Model (TAM) (Davis 1989), the so-called Technology Readiness and Acceptance Model (TRAM) (Lin et al. 2007). In addition, sociodemographic characteristics such as entrepreneurial orientation, gender, and generational cohort are incorporated because they capture differences in exposure, perceived opportunities, and evaluative frameworks.

This study pursues three research objectives:

RO1: Develop a conceptual framework capable of explaining and predicting perceptions of the impact of GenAI.
RO2: Determine the direction and relative importance of the associations between attitudinal and sociodemographic variables and perceptions of GenAI's impact on sustainable economic development.
RO3: Examine whether the influence of gender and entrepreneurship operates autonomously or interacts with cognitive variables in shaping evaluations of GenAI.

The theoretical contribution of this study lies in adapting a simplified TRAM framework to the specific context of GenAI. In particular, we introduce regulation as an additional cognitive-institutional belief, arguing that evaluations of GenAI are shaped not only by optimism and insecurity, but also by perceptions about the need for oversight, accountability, and governance (Zhou et al. 2024). We also extend the sociodemographic dimension of the model by differentiating younger digital generations and occupational roles, since GenAI may be interpreted differently depending on individuals' familiarity with digital tools and their position in the labor market (Abaddi 2024). Finally, we conceptualize the outcome as a specific attitudinal subdimension, namely the perceived contribution of GenAI to sustainable economic development, rather than as a general attitude toward technology. In terms of the outcome, we consider the perception that GenAI contributes to sustainable economic development, as this can be understood as a relevant dimension of attitudes toward a technology, which is a classic outcome in studies of behavior (Ajzen 1991) and technology acceptance (Davis 1989). Taken together, these elements provide a more context-sensitive theoretical account of how people evaluate GenAI's socioeconomic implications.

From a methodological standpoint, this study adopts an explainable machine learning (XAI) approach with a dual objective: to model perceptions of GenAI's impact on SED, and to derive interpretations useful for public policy design and intervention strategies. Specifically, four ensemble methods were implemented: Gradient Boosting Machine (GBM) (Friedman 2001), Random Forest (RF) (Breiman 2001), Bayesian Additive Regression Trees (BART) (Chipman et al. 2010), and Extreme Gradient Boosting (XGBoost) (Chen and Guestrin 2016)—designed to maximize predictive performance. These models were combined with Shapley Additive Explanations (SHAP) (Lundberg and Lee 2017) to provide interpretability for the final model (Maqbool and Qureshi 2026). Ensemble methods allow for the capture of non-linear relationships and complex interactions without imposing restrictive a priori assumptions on the functional form, which is particularly useful in studies

of technology acceptance (Andrés-Sánchez et al. 2026a). SHAP techniques, through variable importance measures and local and global explanations, help translate model predictions into actionable insights.

The remainder of this paper is structured as follows. Section 2 presents the proposed theoretical framework to explain the perceptions of GenAI's impact on sustainable economic development. This is followed by a description of the data and the analytical techniques used to address the research objectives. The subsequent section presents the results, which are discussed in the light of the theoretical framework. Finally, the article concludes with the main findings, highlighting the key takeaways and their theoretical and practical implications.

2 Theoretical foundations

2.1 Conceptual framework

The outcome of the model is the perception that GenAI contributes positively to SED (SEDP) in domains such as the labor market, industry, and agriculture. Ultimately, this outcome must be contextualized within the concept of attitude, understood as an individual's overall evaluation of whether a given action is desirable or beneficial (Ajzen 1991). In this sense, perceptions of GenAI's economic impact reflect the extent to which its use is considered a good idea, meaningful advance, or positive contribution in economic terms. In several technology acceptance frameworks, attitude is primarily grounded in perceived usefulness (Davis 1989; Taylor and Todd 1995), defined as the extent to which individuals perceive that using a technology improves their task performance (Davis 1989). Accordingly, a positive evaluation of GenAI's economic impact can be interpreted as an extension of perceived usefulness from the individual level to a more aggregated and societal assessment.

Figure 1 shows that the outcome is explained by two sets of variables. The first set comprises behavioral variables, including technological optimism, technological insecurity, habitual use of GenAI, and perceived need for regulation, which are based on TRAM. Technological optimism and insecurity are fixed dispositions that shape the way people interact and engage with technological advances (Parasuraman 2000). These underlying orientations shape the way individuals interpret central features of the technology, including the benefits it offers over existing alternatives, the effort required to use it, and its fit with their needs, values, or prior practices, which in turn affect both adoption decisions and economic evaluations (Rogers 2003).

The second group of variables is sociodemographic in nature and includes employment status (entrepreneur vs. salaried worker), as well as gender and age. Entrepreneurs' perspectives on GenAI as a potential game changer in the labor market are likely to differ from those of salaried employees given their different exposure to opportunities and risks associated with automation and innovation (Abaddi 2024). Gender is included because of the temporal stability of gender differences in tech adoption (Oudshoorn et al. 2004) that could be intensified in the GenAI setting (Borwein et al. 2024). With respect to age, previous research has identified generational differences in technology adoption, suggesting that digital-native cohorts, particularly Generations Y and Z, tend to show a greater propensity to adopt new information technologies than older digital-immigrant cohorts (Hoffmann et al. 2014).

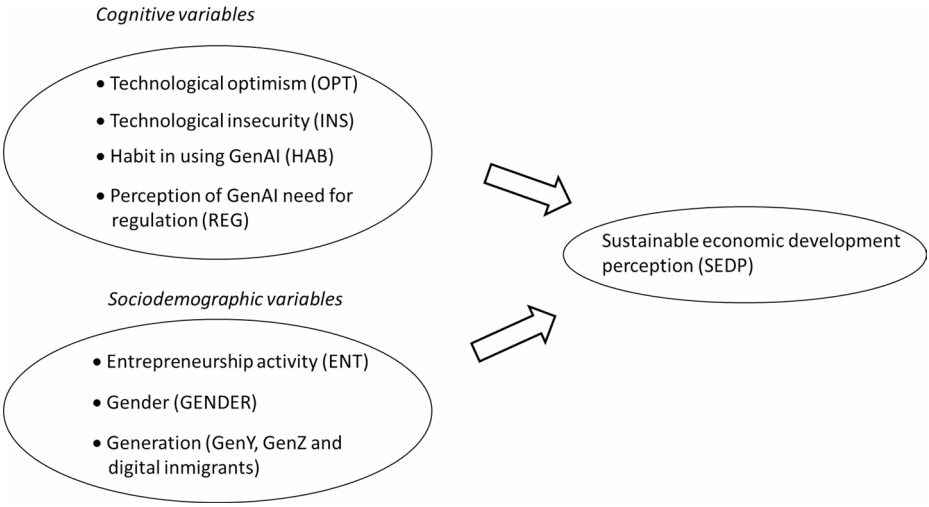


Fig. 1 Conceptual model used in this paper

Although regression-based approaches, such as structural equation modeling (SEM), remain the dominant methodology for analyzing the acceptance of blockchain-based applications (Souto-Romero et al. 2025), recent years have seen a growing incorporation of machine learning (ML) techniques in studies of technology adoption. The increasing emphasis on predictive analytics in information systems and consumer behavior research has accelerated the integration of ML methods into traditional technology acceptance frameworks (Andrés-Sánchez et al. 2026a).

Within this context, a growing, although still limited, body of literature has applied various ML techniques, including tree-based ensemble methods such as RF and XGBoost, artificial neural networks, word embedding algorithms and support vector machines, to predict behavioral intention or actual technology use (Maqbool and Qureshi 2026). Applications include robo-advisors (Chung et al. 2023), mobile learning (Almaiah et al. 2021), shared autonomous vehicle adoption (Guo et al. 2025), AI-supported accounting practices (Cuc et al. 2025), fintech-related behaviors (Abbas et al. 2025), blockchain adoption (Andrés-Sánchez et al. 2026a), using laptops to serve customers (Dey and Jenamani 2025), and the use of GenAI (Pérez-PorTable et al. 2026).

Regarding model interpretability, previous studies in marketing and economics have employed different approaches to assess variable importance. Early research relied mainly on impurity-based importance measures (e.g., the Gini index or variance reduction) and sensitivity analyses, particularly in neural network models. More recent work has incorporated advanced explainable artificial intelligence (XAI) techniques, such as Shapley Additive Explanations (SHAP), which allow for a more detailed decomposition of each predictor's contribution to the model outcome and provide both local and global interpretability (Andrés-Sánchez et al. 2026a; Razaghzadeh Bidgoli et al. 2024; Pérez-Portabella et al. 2025; Wang 2026).

Because ensemble models empirically identify existing non-linear links and interactions among variables without requiring the explicit formulation of mediation or moderation hypotheses, the hypothesis development in this paper assesses the global effects of these

factors on perceptions of GenAI's contribution to sustainable economic development, without explicitly hypothesizing interaction effects among predictors.

2.2 Influence of cognitive factors on the perceived economic impact of generative artificial intelligence

From the perspective of technology readiness, technological optimism (OPT) can be defined as the belief that technology provides greater control, efficiency, flexibility, and quality of life. This disposition operates like an internal stimulus that encourages individuals to adopt technological innovations (Parasuraman 2000; Parasuraman and Colby 2015). DOI theory complements this view by explaining how psychological predispositions translate into differentiated evaluations of technological attributes. Specifically, individuals with a positive technological orientation tend to perceive greater relative advantage, lower complexity, and higher compatibility, thus exhibiting profiles closer to those of early adopters (Rogers 2003), which also applies to GenAI (Al-kfairy 2024).

By contrast, technological insecurity (INS) can be understood as an individual's distrust of technology and concerns with respect to its dependability, safety, technical robustness, and potential displacement of human roles (Parasuraman 2000). This construct acts as a cognitive obstacle to technology adoption, even when functional advantages are evident. Consequently, people who experience greater uncertainty are more likely to postpone use or position themselves among late adopters or laggards (Rogers 2003).

Both OPT and INS have been integrated into widely used technology adoption frameworks. This applies to TAM and TRAM (Lin et al. 2007). In this model, both constructs are linked to usage intention, mainly mediated by perceived ease of use and perceived usefulness (Blut and Wang 2020). Consistently, TAM3 showed that positive predispositions toward technology, such as playfulness, directly increase perceived ease of use and, through it, perceived usefulness, whereas negative predispositions, such as technology anxiety, negatively affect these perceptions via the same mediating mechanism (Venkatesh and Bala 2008).

Empirical evidence indicates that technology readiness constructs, particularly OPT, significantly influence attitudes across multiple technological innovations (Blut and Wang 2020). This link has been reported in the acceptance of artificial intelligence in settings such as primary care (Chalutz 2023) or library/information services (Tunmibi 2023). In the economic domain, optimism has been shown to stimulate sustainable economic development by encouraging investment decisions and productive risk-taking (Puri and Robinson 2007), whereas uncertainty and perceptions of potential negative consequences tend to discourage such behavior (Lensink et al. 1999).

Accordingly, the following hypotheses are proposed:

H1: *Higher technological optimism is linked with a more positive evaluation of GenAI's influence on sustainable economic development.*

H2: *Higher technological insecurity is linked with a more negative evaluation of GenAI's influence on sustainable economic development.*

Another variable frequently identified as relevant to technology acceptance is habitual use (Venkatesh et al. 2012). In this study, habit is operationalized as the habitual use of GenAI (HAB), understood as the tendency to perform a behavior automatically as a result of learning and repetition. The repeated use of a technology is linked to the consolidation of perceptions, such as usefulness, ease of use, and perceived value over time (Venkatesh et al. 2012). In this sense, the habitual use of GenAI can be interpreted as an enabler in the formation of more favorable economic perceptions, as it reinforces learning processes, perceived control, and experience-based evaluations.

Social cognitive theory posits that behavioral repetition increases self-efficacy and strengthens outcome expectations (Bandura 2001), which in this context translates into the belief that using GenAI may enable the achievement of desirable economic outcomes. Direct experience with functional applications, such as task automation, decision support, or efficiency improvements, can facilitate evaluations of GenAI's economic impact based not only on abstract considerations, but also on observable benefits in individuals' own work performance or immediate environment (Zarifhonarvar 2024).

DOI theory also explains why the more frequent use of GenAI tends to improve evaluations of its economic attributes. Repeated adoption of an innovation reduces perceived complexity, increases relative advantage, and enhances result observability, factors that accelerate diffusion and reinforce value attribution to the technology (Rogers 2003). Prior research has shown that habit plays a particularly important role in shaping positive evaluations of GenAI (Biloš and Budimir 2024; Bahadur et al. 2024; Grassini et al. 2024). Accordingly, we propose the following hypothesis:

H3: *Greater use of GenAI is linked with a more positive evaluation of its influence on sustainable economic development.*

The perceived need for the regulation of GenAI (REG) is rooted in the broader normative and societal challenges raised by this technology, including the risks it may pose for legal accountability, social welfare, and ethical governance. As its use expands, debates have increasingly focused on threats related to personal data protection, the spread of unreliable or manipulated information, cybersecurity vulnerabilities, and biased algorithmic outcomes (Zhou et al. 2024). In addition, a significant proportion of organizations acknowledge that the implementation of their AI-driven initiatives has been delayed by uncertainty regarding the internal functioning of AI systems (KPMG International 2023).

Simultaneously, growing social and political pressure exists to establish regulatory frameworks that ensure transparency, fairness, data protection, and respect for human rights (Mahmoud et al. 2025). Economic research has shown that regulatory policies and governance quality significantly influence countries' economic performance such that inadequate or insecure regulatory frameworks may hinder competitiveness and growth (Nicoletti and Scarpetta 2003). Thus, a higher perceived need for the regulation of GenAI can be interpreted as the belief that existing institutional frameworks are insufficient, which is likely to constrain economic and entrepreneurial development. Accordingly, we propose the following hypothesis:

H4: *Perceiving a greater need for the regulation of GenAI is linked with a negative evaluation of its influence on sustainable economic development.*

2.3 The role of entrepreneurial disposition and sociodemographic factors on perceptions of GenAI's impact on economic development

GenAI profoundly transforms value-creation processes, work organization, and competitive dynamics in markets. For labor market agents with entrepreneurial status (ENT), GenAI enables business development by facilitating the creation of entrepreneurial ideas and helping transform them into more structured business plans with greater speed and efficiency (Abaddi 2024). In addition, it reduces market-entry constraints by enabling the launch of projects with lower initial capital requirements, leaner organizational structures, and shorter development timelines (Fernandes et al. 2024).

GenAI also represents a particularly valuable tool for aligning business strategy with the SDGs and SED. By acting as a translation mechanism between a global, abstract, and normative agenda and firms' operational realities, it facilitates the identification of the most relevant strategic objectives according to a firm's activity (Ponnock 2025). Following this prioritization, GenAI enables the transformation of these objectives into concrete strategic and operational actions that can be integrated into business planning processes (Fonseca et al. 2024).

Beyond its role in opportunity recognition, planning, and efficiency, GenAI may also influence entrepreneurial decision-making through behavioral mechanisms. Recent review evidence suggests that judgments involving AI-based systems are shaped not only by functional evaluations, but also by cognitive frames and heuristics such as overconfidence, social proof, loss aversion, and attention-related effects. In entrepreneurial settings, these mechanisms may affect how opportunities and risks are interpreted under uncertainty (Şeker et al. 2025).

GenAI may strengthen managerial decision-making by converting extensive and heterogeneous data into analytically useful information that supports strategic planning (Spaniol and Rowland 2023). By processing information quickly and systematically, these tools can help firms detect emerging market patterns, reduce uncertainty in decision contexts, improve cost allocation, and manage organizational complexity more effectively (Biloslavo et al. 2024). In addition, GenAI can assume routine administrative and monitoring tasks, allowing managers and employees to redirect time and effort toward activities with greater strategic value (Ponnock 2025). Accordingly, we formulate the following hypothesis:

H5: *Entrepreneurs tend to have a more positive perception of the influence of GenAI on sustainable economic development than non-entrepreneurs do.*

Gender (GENDER) has repeatedly been shown to be a relevant variable in understanding the acceptance of technological innovations. While many men often relate to technology as a space for exploration, experimentation, and play, many women tend to view it primarily as a tool for accomplishing specific tasks (Turkle 2005). Moreover, many technologies have frequently reflected male-centered assumptions in both their design and commercialization, emphasizing priorities such as control, competitiveness, and technical efficiency while giving less attention to relational, caring, and collaborative dimensions (Oudshoorn et al. 2004).

Among the challenges posed by GenAI, gender gaps in its use and adoption are particularly relevant as they cut across several of the issues noted above. Men often exhibit a

greater degree of use and confidence in these tools, particularly in workplace and technically oriented settings, while women tend to show greater sensitivity to ethical implications and to perceive greater levels of risk (Otis et al. 2024). Thus, GenAI may reinforce gender inequality through two interconnected mechanisms: women's limited presence in the teams and institutions that design AI systems, and the embedding of gendered assumptions into the algorithms and applications through which these systems operate (Borwein et al. 2024). Such embedded biases can produce unequal or discriminatory effects in domains where algorithmic systems increasingly shape outcomes, including recruitment, targeted advertising, and automated decision processes (Graño 2024).

The gender-related finding can be further contextualized from a behavioral perspective. Recent review work on AI-related decision-making suggests that judgments about AI-based systems are shaped not only by functional evaluations, but also by cognitive frames, risk perceptions, and decision heuristics, including overconfidence, social proof, loss aversion, and attention-related effects (Şeker et al. 2025). More direct evidence on gender differences in AI adoption also points in the same direction: women tend to report higher AI anxiety and, at the same time, lower positive attitudes toward AI, lower perceived knowledge, and lower levels of use than men (Russo et al. 2025). This interpretation is further reinforced by evidence of a sizeable gender gap in actual GenAI adoption. Using survey data, Aldasoro et al. (2024) report that around 50% of men versus 37% of women had used generative AI tools, and show that this difference is only partly explained by demographic factors, privacy concerns, or trust, while self-assessed knowledge plays a particularly important role (Aldasoro et al. 2024). Taken together, these findings suggest that the gender effect observed in our study may reflect not only a sociodemographic difference per se, but also unequal trajectories of familiarity, confidence, and risk framing in relation to GenAI (Russo et al. 2025).

GenAI may also generate different effects on productivity. In the academic domain, Tang et al. (2025), using a sample of more than 680,000 SSRN preprint observations (2022–2023), found that following the release of ChatGPT, the productivity of male researchers increased by 6.4% more than that of female researchers, significantly widening the gender gap.

Furthermore, GenAI has disproportionate implications for occupations heavily reliant on interpersonal communication, including administrative work, customer support, standardized content creation, and certain educational functions, which are highly feminized. As a result, GenAI may amplify gender-based labor inequalities if not accompanied by adequate reskilling and professional adaptation policies (UNESCO, International Research Centre on Artificial Intelligence 2024). Consequently, women tend to be more concerned about work-related threats induced by GenAI, such as job replacement or salary reductions, while also associating GenAI with fewer potential benefits (Borwein et al. 2024; Aldasoro et al. 2024). Thus, it is proposed:

H6: *Women tend to have a more negative perception of the influence of GenAI on sustainable economic development than men do.*

Generational cohort is relevant because individuals socialized in different technological environments tend to develop distinct cognitive orientations, motivational patterns, and modes of engagement with information technologies (Akçayır et al. 2016; Chan and Lee 2023). In this regard, digitally native cohorts, usually identified as millennials and zoomers,

are generally more responsive to cues related to usability, social diffusion, and perceived convenience, whereas older cohorts, such as Generation X and baby boomers, tend to assess technological adoption through a more evaluative lens, weighing possible risks and benefits more deliberately (Hoffmann et al. 2014).

Age-related differences are also evident in the way GenAI is perceived and trusted. Younger users, whose everyday practices have been shaped by early and continuous exposure to digital environments, are more likely to interpret GenAI as a useful and dependable resource. By contrast, older adults tend to approach these tools with greater caution and skepticism (Kozak and Fel 2024). However, digital-native cohorts should not be treated as homogeneous. Generation Z appears to be more strongly driven by intrinsic motivation and more responsive to motivational stimuli, while Generation Y more often relies on internalized forms of obligation or self-pressure (Mahmoud et al. 2025). Based on this, we propose the following hypothesis:

H7: *Individuals of Generation Z and Y evaluate the influence of GenAI on sustainable economic development more positively than individuals from earlier generations.*

3 Survey and methods

3.1 Data collection and sample

This research is based on data from the survey (Centro de Investigaciones Sociológicas 2025). The sampling procedure combined the random selection of landline telephones and mobile phones, and respondents were selected using quota sampling by gender and age. Stratification was constructed by crossing territorial units, comprising the 17 autonomous communities and the two autonomous cities, with municipality size, grouped into seven population-based categories. A total of 1131 municipalities across 50 Spanish provinces were included. Fieldwork took place in February 2025.

The final analytical sample included individuals who indicated knowledge of GenAI and belonged to the active population, as defined in Instituto Nacional and de Estadística (2011). This selection led to N = 2432 and the following sociodemographic characteristics:

- *Gender*. Men 1044 and women 1,388.
- *Age.* 28 years or younger (Generation Z): 237; between 29 and 44 years (Generation Y): 957; 45 years or older (Generation X and older cohorts): 1238.
- *Nationality*. Spanish: 2259; Spanish and other nationality: 93; other nationality: 80.
- *Employment status.* Salaried employees: 1988; self-employed professionals or business owners (with or without employees): 426; members of cooperatives: 18.
- *Monthly household income.* Up to €900: 49; €901–2400: 752; €2401–3000: 420; €3001–4500: 636; €4501–6000: 287; above €6000: 214; no response: 74.

3.2 Measurement procedure and data preparation

The items assessed in this research were obtained from the survey (Centro de Investigaciones Sociológicas 2025). Table 1 details the questions used to operationalize the dependent

Table 1 Items and factors in the empirical analysis

Variable	Scale	Data preprocessing (scores)
Outcome		
Perceived impact of GenAI on Sustainable Economic Development (SEDP)		
SEDP1 = Labor market (SDG 8) SEDP2 = Industry (SDG 9) SEDP3 = Agriculture (SDGs 1, 2, 8, 9, 12) SEDP4 = Economy (SDG 8)	3-point scale: 1 = more problems 2 = equal gains and problems 3 = more gains	Composite score derived from the standardized values of the leading component identified through principal component analysis (PCA) and empirical coherence assessed through Cronbach's alpha and average variance extracted (AVE)
Input variables		
Cognitive variables		
Technological optimism (OPT): Indicate the extent to which you agree with the following consequences of technological innovations: OPT1 = Progress OPT2 = Wealth OPT3 = Efficiency OPT4 = Well-being	10-point Likert scale: 1 = total disagreement 10 = total agreement	Composite score derived from the standardized values of the leading component identified through PCA and validated through Cronbach's alpha and AVE
Technological insecurity (INS): Indicate the extent to which you agree with the following consequences of technological innovations: INS1 = Dehumanization INS2 = Social inequality INS3 = Uncertainty INS4 = Loss of autonomy INS5 = Loss of human control	10-point Likert scale: 1 = completely disagree 10 = completely agree	Composite score derived from the standardized values of the leading component identified through PCA and validated through Cronbach's alpha and AVE
Habit (HAB): Frequency of interaction with GenAI systems: HAB1: ChatGPT, HAB2: Gemini HAB3: Microsoft Copilot HAB4: Perplexity HAB5: Other	Ordinal scale: 0 = Never 1 = Once 2 = Several times a year 3 = Several times a month 4 = Several times a week 5 = Every day	Composite score calculated as the standardized score of the maximum observed frequency among HAB1, HAB2, …, HAB5
Regulation (REG): Indicate your level of agreement with the following statements: REG1 = The design and training of AI systems should be subject to regulation REG2 = Companies and organizations should be required to disclose when AI is used instead of human agents REG3 = The use of AI should be regulated REG4 = AI represents a potential threat to intellectual property rights REG5 = Establishing stricter ethical standards and legal safeguards for AI is one of the major challenges currently facing society	5-point Likert scale: 1 = completely disagree 3 = neutral 5 = completely agree	Composite score derived from the standardized values of the leading component identified through PCA and validated through Cronbach's alpha and AVE
Entrepreneurial inclination		

Table 1 (continued)

Variable	Scale	Data preprocessing (scores)
Entrepreneur status (ENT) Entrepreneurs vs. non-entrepreneurs	0 = Salaried employees 1 = Entrepreneurs, including self-employed professionals, business owners, and members of cooperatives	Same as above
Sociodemographic variables		
Gender (GENDER)	0 = Men 1 = Women	Same as above
Generation	Digital immigrants (Generation X and older cohorts) as baseline	Two dummy variables were included to capture generational effects: GENZ, coded as 1 for Zoomers and 0 otherwise, and GENY, coded as 1 for Millennials and 0 otherwise

and explanatory variables, explains how these items were preprocessed and converted into composite indicators, and reports the checks conducted to assess the robustness of the measurement procedure (Greco et al. 2019; Nardo et al. 2005).

3.2.1 Measurement of variables

With regard to perceptions of sustainable economic development (SEDP), the items considered for its measurement are the labor market, industry, agriculture, and the overall economy. Economic development is commonly understood as a process of structural transformation across interconnected sectors rather than isolated domains (Rodrik 2007). Accordingly, their selection is grounded in the view of sustainable economic development as a systemic and multidimensional phenomenon (Brundtland 1987), as reflected in the well-known Sustainable Development Goals proposed by the United Nations (United Nations 2030). From this perspective, the selected items capture relevant dimensions through which individuals may perceive the broader economic implications of GenAI.

Positive impacts on the labor market and industry are central to sustainable economic development, as they support job creation, productivity improvements, and the expansion of emerging activities such as the circular economy, thereby contributing to decent work (Accenture 2024). This transition also depends on the development of green skills through vocational training, which can enhance labor productivity while supporting a just transition (Commission et al. 2025). In addition, the Industry 5.0 paradigm reinforces this process by placing workers' well-being at the center and using technology to promote prosperity within planetary boundaries (Andrés-Sánchez et al. 2026b).

Likewise, the modernization of agriculture through agrotech and foodtech is essential for food security, as it enables higher productivity with fewer resources and more efficient use of water and energy (United Nations 2030). These improvements can also strengthen sectoral competitiveness, reduce poverty, and increase resilience to climate change (OECD 2020). Taken together, these sectoral transformations contribute to an economy that pro-

gressively decouples development from environmental degradation, consistent with evidence that environmental sustainability investment can foster long-term labor productivity (Petreski et al. 2024).

It should be noted that SEDP is not intended to represent a strictly reflective psychological scale, but rather a composite indicator designed to summarize a broader perceived economic evaluation of GenAI across several interconnected domains. This approach is consistent with common practice in economics, public policy, and development research, where complex multidimensional phenomena are frequently captured through composite indicators built from distinct but related components (Greco et al. 2019; Nardo et al. 2005). We are dealing with an index that the literature often describes as formative, in contrast to reflective ones (Diamantopoulos and Winklhofer 2001). Well-known examples include the Human Development Index, which combines health, education, and income dimensions (United Nations Development Programme 2025), as well as SDG-based monitoring frameworks and broader sustainability indices, which routinely aggregate heterogeneous dimensions in order to provide an analytically useful summary of a more general phenomenon (United Nations 2030). In this context, the relevant requirement is not perfect homogeneity among components, but a sound conceptual justification that the selected dimensions contribute to a broader and substantively coherent evaluative construct.

The selection of items for OPT and INS from Centro de Investigaciones Sociológicas (2025) is grounded in their alignment with the Technology Readiness and Acceptance Model (TRAM), which conceptualizes these dimensions as core predispositions shaping individuals' attitudes toward technology. In this study, OPT and INS are operationalized using the available survey items that capture respondents' general positive or negative beliefs about technology, thus reflecting structural dispositions rather than context-specific evaluations (Parasuraman 2000).

HAB is likewise informed by this perspective, as it captures the extent to which interaction with generative AI tools becomes routinized through repeated use. In this study, however, HAB is not intended to capture habit in the strict psychological sense of full automaticity, but rather a more observable pattern of habitual use, understood as routinized and recurrent engagement with GenAI tools. In line with this logic, HAB is constructed from the frequency of use across several general-purpose GenAI tools included in the survey, thereby approximating the degree of behavioral regularity and familiarity with the technology. From this perspective, frequent use of at least one GenAI application may already reflect a stable and consolidated relationship with the technology, even if such use is not distributed across multiple tools. This is also consistent with technology readiness approaches, which link enduring predispositions toward technology to actual patterns of use and engagement (Parasuraman and Colby 2015).

Finally, REG is derived from multiple survey items related to respondents' perceptions of AI governance. These items reflect key dimensions such as control, accountability, transparency, and ethical oversight, which are widely identified as central societal demands in the context of artificial intelligence (Zhou et al. 2024). These operationalizations ensure that the selected variables are both theoretically grounded and consistent with the empirical constraints of the survey instrument.

Regarding the entrepreneur–non-entrepreneur dichotomy (ENT), entrepreneurship is defined as self-employment, following the most commonly used definition in empirical research, largely because of greater data availability and comparability (Bjuggren et al.

2012). Under this definition, entrepreneurs are individuals who work for themselves without an employment dependency relationship, including both self-employed workers and firm owner-managers (González-Sánchez et al. 2020). As shown in Table 1, this category includes self-employed professionals, business owners (with and without employees), and members of cooperatives.

The gender variable was binary (0 = male, 1 = female). Generation Z (GENZ) included individuals born in 1997 or later, corresponding to a maximum age of 28 years at the time of the survey. Generation Y, or the millennial cohort (GENY), includes individuals born between 1981 and 1996, corresponding to ages between 29 and 44 years. Finally, Generation X and earlier cohorts included individuals born no later than 1980, corresponding to those aged 45 years or above when the survey was conducted (Pew Research Center 2019).

3.2.2 Calculating scores of multiple item factors

Table 1 indicates that the indicators corresponding to the outcome variable, SEDP, and the explanatory variables OPT, INS, and REG were quantified with the help of principal component analysis (PCA). This procedure allows the common information of each group of questions to be summarized into an individual composite score, decreasing dimensionality while preserving the main empirical pattern within the set of items. In the case of SEDP, these diagnostics are not intended to demonstrate reflective measurement validity, but rather to provide descriptive evidence of empirical coherence among the components included in the composite indicator (Nardo et al. 2005). Although the four items refer to distinct sectoral domains, our aim is not to model sector-specific expectations separately, but to construct a broader composite evaluation of GenAI's perceived macroeconomic contribution. The PCA and reliability diagnostics are therefore used as descriptive evidence of empirical coherence among the selected components.

Table 2 shows that the composite indicators are robust. In all cases, the Cronbach's alpha exceeds the 0.7 threshold, indicating adequate internal consistency. Factor loadings are above 0.5, Bartlett's test rejects the hypothesis that the correlation matrix of items in every set is the identity matrix, and the Kaiser–Meyer–Olkin (KMO) measure is above 0.7. These results support the empirical coherence of the composite indicators employed. However, particularly for SEDP, they should be interpreted as descriptive diagnostics of aggregation suitability (Nardo et al. 2005).

In contrast, HAB was operationalized using the maximum reported frequency of use across the GenAI tools considered, rather than a simple or weighted average. This decision reflects the distinction between intensity and breadth of use. A maximum-based indicator

Table 2 Measures of goodness of composite variable construction with PCA

	Cronbach α	AVE (%)	Loadings	Bartlett's test	KMO
SEDP	0.710	53.9	0.715–0.730	1755 ($p<0.001$)	0.714 (0.698–0.731)
OPT	0.742	56.5	0.715–0.801	2051 ($p<0.001$)	0.79 (0.785–0.803)
INS	0.736	51.3	0.614–0.746	2240 ($p<0.001$)	0.817 (0.755–0.989)
REG	0.816	58.2	0.635–0.833	3223 ($p<0.001$)	0.76 (0.726–0.803)

AVE stands for average variance extracted, and KMO denotes the Kaiser–Meyer–Olkin measure

captures routinized and recurrent engagement with at least one GenAI tool, which may be sufficient for habitual use to emerge. By contrast, an average-based measure would mainly reflect breadth of engagement across several tools and could underestimate individuals who rely intensively on a single dominant application. Accordingly, the HAB indicator follows a non-compensatory "at least one" logic, consistent with an extreme Ordered Weighted Average criterion, in which limited use of some tools does not offset frequent use of another (Fullér 1996). This operationalization better captures habitual use intensity, whereas the mean-based alternative is retained as a robustness check reflecting breadth of multi-tool engagement.

3.3 Data analysis

Once the data preparation process had been completed, the empirical assessment proceeded in four sequential stages designed to address the three research questions.

Step 1. Train–test split.

An 80/20 random split was applied to the dataset, with stratification used to retain the original proportions of gender and entrepreneur/non-entrepreneur status in both subsamples. The 20% holdout sample was not involved in either model estimation or hyperparameter optimization, ensuring that out-of-sample performance was evaluated on data that had remained fully unseen during the modelling process. This step was implemented using the rsample and dplyr packages in R (version 4.4.2).

Step 2. Hyperparameter tuning via cross-validation.

The hyperparameters of four tree-based ensemble methods—GBM, RF, Bayesian Additive Regression Trees (BART), and XGBoost—were tuned exclusively on the training set (80%) using fivefold cross-validation. Table 3 summarizes the procedure.

For GBM, 48 candidate configurations were evaluated by varying the number of trees (100, 200, 400, and 800), interaction depth (1 and 2), learning rate (shrinkage = 0.03, 0.05, and 0.1), and bag fraction (0.5 and 0.7). For RF, 48 candidate configurations were explored by combining the number of trees (500, 800, 1,000, and 1,200), the number of candidate

Table 3 Hyperparameter tuning design for the candidate machine learning models and predictive evaluation

Model	Tuned hyperparameters	Grid explored	No. of combinations	Selection criterion
GBM	Number of trees; interaction depth; learning rate; bag fraction	Number of trees: 100, 200, 400, 800; interaction depth: 1, 2; shrinkage: 0.03, 0.05, 0.1; bag fraction: 0.5, 0.7	48	Lowest mean CV-RMSE
RF	Number of trees; mtry; minimum node size	Trees: 500, 800, 1,000, and 1,200; mtry: 3–6; node size: 2, 5, 10	48	Lowest mean CV-RMSE
BART	Number of trees; regularization (k); expected tree depth; split probability	Trees: 50, 100, 200; k: 1, 2, 3, 4; power: 1.5, 2.0; base: 0.75, 0.95	48	Lowest mean CV-RMSE
XGBoost	nrounds; max_depth; eta; subsample; colsample_bytree	nrounds: 100, 200; depth: 3, 5, 7; eta: 0.05, 0.1; subsample: 0.7, 0.8; colsample_bytree: 0.6, 0.8	48	Lowest mean CV-RMSE

Hyperparameters were tuned on the training set using fivefold cross-validation. The best-tuned specification obtained for each model is reported in Table 4. Final model comparison was subsequently conducted on the isolated holdout test set using a bootstrap-based predictive assessment with 5000 replications

variables at each split (mtry = 3, 4, 5, and 6), and the minimum terminal node size (2, 5, and 10). In the case of BART, 48 candidate configurations were examined by varying the number of trees (50, 100, and 200), the regularization parameter k (1, 2, 3, and 4), the expected tree depth (power = 1.5 and 2.0), and the split probability (base = 0.75 and 0.95). For XGBoost, 48 candidate configurations were explored by combining the number of boosting iterations (100 and 200), maximum tree depth (3, 5, and 7), learning rate (0.05 and 0.1), subsampling rate (0.7 and 0.8), and column subsampling rate (colsample_bytree = 0.6 and 0.8). In all cases, the optimal model was selected based on the lowest mean RMSE obtained across the cross-validation folds.

Hyperparameter tuning was performed using the rsample, gbm, ranger, dbarts, and xgboost packages in R (version 4.4.2). In addition, the in-sample performance of all tuned models was evaluated on the training subset using the root mean squared error (RMSE), mean absolute error (MAE), and coefficient of determination (R^2).

Step 3. Model comparison and final model selection.

Once the best-performing specification of each ensemble method (GBM, RF, BART, and XGBoost) had been identified, the models were compared on the previously isolated holdout test set using a bootstrap-based predictive assessment with 5,000 replications, as described in Table 3. In each replication, RMSE, MAE, and Q^2 were recalculated. Predictive performance was assessed using RMSE, MAE, and Stone–Geisser's Q^2, and the model showing the most favorable and stable out-of-sample performance across these criteria was selected as the final model. This selected model was then used to analyze the importance of the explanatory variables using SHAP values.

The bootstrap-based predictive comparison was implemented using the Metrics and rsample packages in R (version 4.4.2).

Step 4. Variable importance analysis using SHAP (global and SEDP-specific levels).

Before estimating SHAP values, a bivariate correlation matrix was examined for the dependent variable and the main predictors, as well as among the predictors themselves. This preliminary diagnostic was used to assess whether correlations between explanatory variables could partially obscure the relative importance of some predictors in the subsequent interpretability analysis. Although such correlations do not prevent the estimation of the selected ensemble model, they may affect how variable importance is distributed across correlated features.

With the final model selected, SHAP values were estimated for the full sample to measure the relevance of every predictor to the predicted values. Global variable importance was measured as the mean absolute SHAP value (mean |SHAP|) and visualized using beeswarm plots, which simultaneously convey the magnitude, direction, and dispersion of each variable's impact on the outcome.

As a robustness check, we conducted two additional analyses to assess the stability of the findings with respect to both the economic indicator used to measure the outcome and the operationalization of habit:

a) The best-performing model was estimated separately for each economic component of SEDP (SEDP1, SEDP2, SEDP3, and SEDP4), and the resulting mean |SHAP| values were compared with those obtained for the composite SEDP indicator.
b) HAB was alternatively measured as the mean frequency of use across GenAI tools. Under this specification, HAB reflects breadth of engagement across tools more than

routinized use intensity. The best-performing machine learning model was then re-estimated for SEDP using this alternative measure, and the results were compared to assess the extent to which the substantive findings remained stable.

Subsequently, heterogeneity in explanatory importance was examined across different levels of the outcome variable (SEDP). The sample was divided into four groups defined by the quartiles of SEDP (Q1–Q4, using the 25th, 50th, and 75th percentile cutoffs), and the mean |SHAP| value was computed for each variable within each quartile. This procedure enabled a comparison of how the relative relevance of predictors varied between lower and higher levels of the perceived economic impact of GenAI.

In addition, the interaction structure between the main cognitive determinants, gender, and entrepreneurial status was examined using SHAP dependence plots incorporating interaction effects. These plots allow the identification of potential moderating patterns and help distinguish between primarily additive contributions and heterogeneity patterns across the range of the explanatory variables. To complement this visual assessment, a between-group comparison of mean |SHAP| values was conducted to evaluate whether gender and entrepreneurial status were associated with meaningful changes in the explanatory importance of the main cognitive predictors. Differences across groups were interpreted as analytical evidence of heterogeneity in predictor relevance, consistent with a potential moderating role in the configuration of SEDP.

The analysis of variable importance using SHAP values, both globally and by SEDP quartiles, was conducted using the fastshap, ggplot2, dplyr, and tidyr packages in R (version 4.4.2).

4 Results

4.1 Fit and predictive performance assessment

Table 4 shows that, during the fine-tuning phase using cross-validation, the four ensemble methods exhibit very similar RMSE values. It is also noteworthy that XGBoost achieves a slightly lower mean RMSE and, additionally, the lowest standard deviation, indicating a more stable performance during cross-validation. RF performs worst in this phase.

By contrast, it is striking that RF displays a substantially superior in-sample fit compared to the other methods, whereas XGBoost clearly outperforms GBM and BART, exhibiting lower RMSE and MAE values and a higher R^2. GBM and BART show virtually equivalent levels of fit, whereas XGBoost can capture a larger proportion of explained variance without reaching the extreme degree of in-sample overfitting observed in RF.

The results in Table 5 suggest that according to the mean RMSE, the ranking of the models is XGBoost > BART > GBM > RF, identifying XGBoost as the method with the lowest mean squared error. The mean Q^2 followed the same ranking as RMSE. This ordering is slightly nuanced when considering MAE, as BART exhibits the lowest mean absolute error, whereas GBM and XGBoost exhibit nearly identical MAE values. Thus, while RF consistently performs the worst from a predictive standpoint, the results indicate that XGBoost delivers the best overall performance, albeit very close to that of BART.

Table 4 Training-phase results for the ensemble methods

Model	Best hyperparameters	RMSE CV (mean ± SD)	RMSE train	MAE train	R^2 train
GBM	n.trees = 200; interaction.depth = 1; shrinkage = 0.05; bag fraction = 0.5	0.830 ± 0.033	0.804	0.643	0.344
Random Forest	num.trees = 800; mtry = 3; min. node.size = 10	0.840 ± 0.025	0.526	0.418	0.777
BART	ntree = 200; k = 3; power = 2.0; base = 0.95	0.823 ± 0.024	0.802	0.643	0.348
XGBoost	nrounds = 100; max_depth = 3; eta = 0.05; subsample = 0.8; colsample_bytree = 0.6	0.825 ± 0.013	0.776	0.622	0.396

RMSE = Root mean squared error, MAE = Mean absolute error, CV = cross-validation, "train" indicates that the measures have been obtained with the best hyperparameter configuration in the overall train sample

Table 5 Bootstrap results for predictive assessment

Model	RMSE	MAE	Q^2
GBM	0.8326	0.6604	0.3471
Random Forest	0.8393	0.6710	0.3363
BART	0.8293	0.6593	0.3533
XGBoost	0.8286	0.6607	0.3578

RMSE is the mean root mean squared error, MAE = mean absolute error, and Q^2 is the Stone–Geisser measure

Table 6 Pairwise tests of mean RMSE differences across models on the predictive subsample

Model 1	Model 2	RMSE (Model 1)	RMSE (Model 2)	Δ RMSE	t-value	*p*-value	Cohen's d
GBM	RF	0.8326	0.8393	−0.0067	−12.31	< 0.001	−0.17
GBM	BART	0.8326	0.8293	0.0033	5.99	< 0.001	0.08
GBM	XGBoost	0.8326	0.8286	0.004	7.44	< 0.001	0.11
RF	BART	0.8393	0.8293	0.01	18.69	< 0.001	0.26
RF	XGBoost	0.8393	0.8286	0.0107	20.14	< 0.001	0.28
BART	XGBoost	0.8293	0.8286	0.0007	1.26	0.208	0.02

Tables 6, 7, and 8 present pairwise model comparisons based on the bootstrap-based predictive assessment for RMSE, MAE, and Q^2, respectively. These results allow the assessment of not only the average model ranking but also the statistical significance and magnitude of predictive differences.

In terms of the RMSE, the ranking observed in Table 5 is largely supported by the inferential comparisons in Table 6. Differences between models were statistically significant in most contrasts, with effect sizes (Cohen's d) ranging from small to moderate. The only notable exception was the comparison between BART and XGBoost, for which the slight RMSE advantage of XGBoost was not statistically significant.

Table 7 Pairwise tests of mean MAE differences across models on the predictive subsample

Model 1	Model 2	MAE (Model 1)	MAE (Model 2)	ΔMAE	t-value	*p*-value	Cohen's d
GBM	RF	0.6604	0.6710	−0.0105	−22.72	<0.001	−0.32
GBM	BART	0.6604	0.6593	0.0012	2.51	0.012	0.04
GBM	XGBoost	0.6604	0.6607	−0.0003	−0.62	0.536	−0.01
RF	BART	0.6710	0.6593	0.0117	25.75	<0.001	0.36
RF	XGBoost	0.6710	0.6607	0.0103	22.71	<0.001	0.32
BART	XGBoost	0.6593	0.6607	−0.0014	−3.18	0.001	−0.05

Table 8 Pairwise tests of mean Q^2 differences across models on the predictive subsample

Model 1	Model 2	Q^2 (Model 1)	Q^2 (Model 2)	ΔQ^2	t-value	*p*-value	Cohen's d
GBM	RF	0.3471	0.3363	0.0108	15.82	<0.001	0.22
GBM	BART	0.3471	0.3533	−0.0061	−8.90	<0.001	−0.13
GBM	XGBoost	0.3471	0.3578	−0.0107	−15.62	<0.001	−0.22
RF	BART	0.3363	0.3533	−0.0170	−24.96	<0.001	−0.35
RF	XGBoost	0.3363	0.3578	−0.0215	−31.46	<0.001	−0.45
BART	XGBoost	0.3533	0.3578	−0.0045	−6.63	<0.001	−0.09

Table 7 reveals a different pattern for MAE. BART significantly outperforms the other methods, with effect sizes that are modest when compared with GBM and XGBoost, but moderate when compared with RF. By contrast, the comparison between GBM and XGBoost did not show statistically significant differences. Table 8 shows that Q^2 confirms a clear hierarchy consistent with RMSE: XGBoost significantly outperforms the remaining models, with effect sizes ranging from moderate to relatively large, particularly in comparison with RF.

A consistent finding across all three metrics is that RF systematically ranks as the worst-performing model, exhibiting statistically significant differences relative to the other methods, and the largest effect sizes in most comparisons. This pattern suggests that during the fine-tuning phase, RF suffered from overfitting under conventional tuning procedures.

To assess whether the relatively poor predictive performance of RF was driven by an insufficiently explored hyperparameter space, we substantially expanded the original tuning grid. The initial RF specification evaluated 48 hyperparameter combinations, whereas the extended search considered 144 configurations. With fivefold cross-validation, this increased the number of model fits from 180 to 720. In addition, the expanded grid incorporated more restrictive configurations—such as lower mtry values and larger terminal node sizes—aimed at enhancing model regularization and generalization. Importantly, while the original tuning design was broadly comparable across methods, this additional exercise gave RF a comparatively more favorable and computationally intensive tuning treatment than the other algorithms. This expanded RF search should therefore be interpreted as a diagnostic robustness exercise rather than as a fully symmetric re-tuning of all candidate models. Despite this more exhaustive and RF-favoring search, the gains in predictive performance were only marginal. The best expanded RF specification (num.trees = 800, mtry = 2, min.node.size = 25) achieved a cross-validated RMSE of 0.831 (SD = 0.026), with final test-sample performance of RMSE = 0.838, MAE = 0.668, and $R^2 = 0.346$. Although

the expanded search yielded a more regularized and somewhat more stable RF model, its predictive performance remained below that of XGBoost, GBM, and BART.

These findings suggest that the comparatively weaker predictive performance of RF cannot be attributed solely to a narrow tuning grid, but rather reflects differences in the intrinsic regularization and learning mechanisms of the algorithms considered.

Therefore, the results indicated that XGBoost provided the best aggregate predictive performance, combining superior RMSE and Q^2 values relative to the other models. For this reason, although the differences between XGBoost and BART are generally small, XGBoost was selected as the final model for subsequent SHAP-based variable importance analysis.

To assess the robustness of the results, HAB was alternatively operationalized as the mean frequency of use across GenAI tools, introducing a compensatory aggregation structure. We then re-estimated the best-performing model (XGBoost) with this alternative specification. The results remained consistent in terms of optimal hyperparameters, predictive performance, and model stability ($R^2 \approx 0.36$ in the test sample). However, this operationalization attenuates the explanatory power of usage-related variables, as averaging dilutes the effect of intensive use of a single tool. This finding reinforces the conceptual appropriateness of the maximum-based (OWA) indicator, which better captures the non-compensatory and intensity-driven nature of habitual behavior.

4.2 Shapley additive explanations assessment

4.2.1 Main results

Prior to the SHAP-based interpretability analysis, a bivariate correlation matrix was examined to assess whether correlations among predictors could partially mask the relative importance of some variables. Table 9 shows that the observed correlations were generally low to moderate, with no evidence of severe collinearity among the explanatory variables. The highest associations between predictors were found for INS–REG (r=0.371), HAB–REG (r=−0.309), and GENZ–GENY (r=−0.265), suggesting some shared variance but not a level of overlap likely to invalidate the interpretation of variable importance. Therefore, the correlation structure does not indicate that any predictor should be systematically obscured in the subsequent SHAP analysis, although importance patterns were interpreted with caution where moderate associations were present. This also suggests that the slightly negative sign of GENZ and GENY is unlikely to be explained by problematic shared variance with

Table 9 Pearson's correlation matrix between variables

	SEDP	OPT	INS	HAB	REG	ENT	GENDER	GENZ	GENY
SEDP	1	0.398	−0.305	0.38	−0.303	0.06	−0.191	0.026	0.02
OPT	0.398	1	−0.084	0.223	−0.179	−0.007	−0.023	0.051	0.033
INS	−0.305	−0.084	1	−0.189	0.371	−0.063	0.175	−0.049	−0.01
HAB	0.38	0.223	−0.189	1	−0.309	−0.007	−0.136	0.169	0.128
REG	−0.303	−0.179	0.371	−0.309	1	−0.046	0.209	−0.145	−0.057
ENT	0.06	−0.007	−0.063	−0.007	−0.046	1	−0.07	−0.058	−0.052
GENDER	−0.191	−0.023	0.175	−0.136	0.209	−0.07	1	−0.013	−0.02
GENZ	0.026	0.051	−0.049	0.169	−0.145	−0.058	−0.013	1	−0.265
GENY	0.02	0.033	−0.01	0.128	−0.057	−0.052	−0.02	−0.265	1

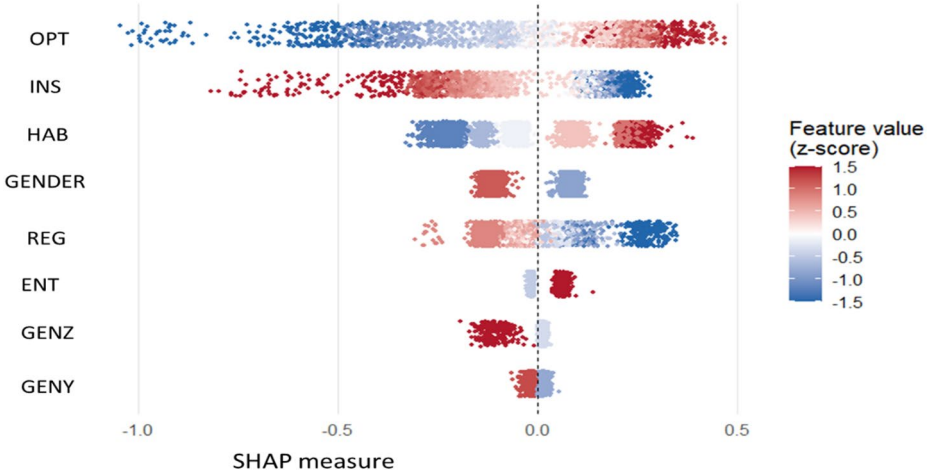


Fig. 2 SHAP beeswarm plot of variables contributing to SEDP evaluation

Table 10 Mean |SHAP| scores of factors in the whole sample and by SEDP quartiles

Variable	Overall sample	1st quartile	2nd quartile	3rd quartile	4th quartile
OPT	0.224	0.280	0.208	0.190	0.216
INS	0.181	0.214	0.174	0.169	0.168
HAB	0.181	0.182	0.172	0.176	0.193
GENDER	0.097	0.100	0.097	0.098	0.091
REG	0.085	0.082	0.072	0.082	0.104
ENT	0.022	0.021	0.021	0.022	0.024
GENZ	0.021	0.016	0.022	0.024	0.021
GENY	0.013	0.016	0.014	0.012	0.011

the main cognitive predictors, and is better interpreted as a weak residual association with limited substantive relevance.

The SHAP beeswarm plot in Fig. 2 shows that SEDP evaluations are primarily explained by three cognitive variables (OPT, INS, and HAB), which account for most of the predictive impact and display clear directional patterns. The stronger explanatory role of the cognitive factors across the full sample is also evident in Table 10.

The results of SHAP analysis indicate that OPT is the most influential predictor and exhibits a monotonically positive pattern; greater values of perceived benefits are often linked with more favorable evaluations, and smaller scores are associated with negative contributions. HAB displays a similarly increasing pattern, although with a smaller magnitude, suggesting that greater experience and familiarity with GenAI are linked to more favorable perceptions of its economic contribution. By contrast, INS shows a predominantly negative relationship, such that more critical or restrictive perceptions are consistently associated with lower SEDP values. Among the cognitive factors, REG is the least important and, as expected, its relationship with SEDP is negative.

Among the non-cognitive variables, gender emerged as the most relevant sociodemographic factor, even exceeding REG in importance. The beeswarm plot indicates that being

female is associated with less favorable evaluations of GenAI. Entrepreneurial status shows a positive but weaker effect than gender, suggesting that entrepreneurial orientation may predispose individuals to slightly more favorable perceptions of GenAI's economic potential, albeit with clear secondary importance. Finally, generational variables (GENZ and GENY) exhibit very limited contributions concentrated around zero. Notably, their effects are weak and opposite in sign to expectations because belonging to younger generations is associated with a slightly more negative contribution to the perceived economic impact of GenAI.

Taken together, these findings suggest that perceptions of GenAI's contribution to sustainable economic development are more closely related to OPT and HAB than to demographic background. In substantive terms, this implies that more favorable evaluations of GenAI's contribution to SED are grounded mainly in perceptions of productivity, usefulness, and familiarity, whereas less favorable evaluations are shaped more strongly by distrust and perceived risks. Thus, perceptions of GenAI's economic implications appear to depend less on individuals' demographic or occupational characteristics than on how they cognitively frame the technology and how intensively they have incorporated it into their routines.

Table 10 reveals a relatively stable structure across outcome levels. In all quartiles, the level of OPT remains the most influential factor, indicating that differences in SEDP, even at the most favorable levels, are largely driven by general expectations regarding the benefits of GenAI.

INS and HAB exhibited similar levels of importance in the lower SEDP quartiles, with a slight predominance of INS in the first quartile. This pattern suggests that rejection or skepticism toward GenAI is driven primarily by concerns and resistance rather than by a lack of experience or use. As acceptance increases, the hierarchy between these two factors gradually reverses. In the higher quartiles, HAB becomes more relevant than INS, indicating that among individuals who evaluate GenAI positively, familiarity and habitual use are strongly associated with favorable assessments. This shift suggests that more favorable evaluations of GenAI's economic contribution are associated not only with abstract beliefs, but also with accumulated use-based experience. This explanation is theoretically consistent with the hypotheses proposed and with TRAM, according to which repeated use reinforces familiarity and more favorable evaluations of technology (Parasuraman and Colby 2015). However, given the cross-sectional nature of the data, this relationship should not be interpreted in strictly causal terms, as reverse causality remains plausible; that is, individuals with more positive perceptions of GenAI may also be more likely to use it more frequently due to having a more favorable attitude toward this behavior (Ajzen 1991).

This quartile pattern has an important economic implication. Among respondents with less favorable evaluations, skepticism toward GenAI is linked mainly with insecurity-related concerns, suggesting that resistance is rooted in perceived threats and uncertainty. By contrast, among those with more favorable evaluations, habitual use becomes relatively more important, indicating that positive economic perceptions are increasingly associated with repeated exposure and practical familiarity.

It is also observed that, as INS loses relevance across higher quartiles, REG gains importance, at least in the upper SEDP quartile. Regarding sociodemographic factors, gender consistently shows the strongest association across all quartiles. This pattern indicates that gender differences in the economic evaluation of GenAI are both persistent and structural.

Table 11 Mean |SHAP| scores of factors in the whole sample across the sector-specific components of SEDP

Variable	SEDP1	SEDP2	SEDP3	SEDP4
OPT	0.164	0.158	0.140	0.199
INS	0.184	0.155	0.077	0.119
HAB	0.148	0.123	0.146	0.157
GENDER	0.064	0.034	0.094	0.054
REG	0.081	0.052	0.049	0.110
ENT	0.026	0.005	0.007	0.016
GENZ	0.016	0.010	0.046	0.007
GENY	0.016	0.015	0.008	0.010

Table 12 Pearson's correlation matrix between the composite SEDP indicator and its four component items

Outcome	SEDP	SEDP1	SEDP2	SEDP3	SEDP4
SEDP	1				
SEDP1	0.969	1			
SEDP2	0.968	0.985	1		
SEDP3	0.891	0.782	0.783	1	
SEDP4	0.951	0.908	0.913	0.851	1

Finally, ENT showed consistently higher relevance than GENY, while its relevance was very similar to that of GENZ.

In the first robustness analysis, the final XGBoost model was re-estimated separately for SEDP1, SEDP2, SEDP3, and SEDP4, and the corresponding mean |SHAP| values are reported in Table 11. Table 12 presents the Pearson correlations among the mean |SHAP| rankings obtained for the composite economic indicator (SEDP) and its sector-specific components. Table 11 shows that the explanatory structures are not identical across all outcomes. For instance, in the labor-market dimension, INS is more important than OPT, whereas in the agriculture dimension it plays a comparatively modest role. However, the correlations between SEDP and the partial indicators are very high, generally around 0.90 or above, and correlations among the sector-specific indicators are also high. Agriculture shows the lowest alignment with the other dimensions, although even in this case the lowest correlations, observed with SEDP1 and SEDP2, are still close to 0.80. Taken together, these results suggest that the different SEDP components are sufficiently aligned to support the use of the composite indicator as a summary measure of a broader perceived economic evaluation.

We also conducted an additional SHAP analysis using an alternative compensatory, mean-based operationalization of HAB. The results confirm that OPT remains the most influential predictor (mean |SHAP|=0.2189). However, an important difference emerges in the relative importance of HAB and INS. Under the original maximum-based (OWA) specification, both variables displayed broadly similar levels of importance, whereas the mean-based specification increases the relative contribution of HAB (Mean |SHAP|=0.1928), placing it above INS (mean |SHAP|=0.1689). This suggests that, although overall model fit remains stable, a compensatory aggregation changes the substantive interpretation of the explanatory structure. More specifically, the mean-based specification gives greater weight to breadth of multi-tool engagement, whereas the maximum-based indicator is better aligned with the intensity of routinized use through at least one dominant tool. In this sense, the two operationalizations capture related but not identical aspects of user behavior. Accordingly, these results support the use of the maximum-based (OWA) indicator as the

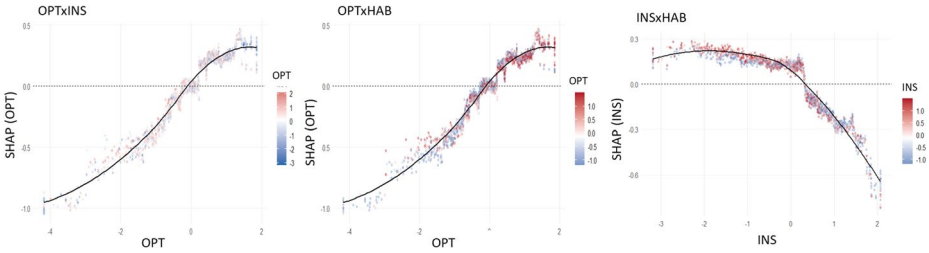


Fig. 3 SHAP dependence plots of optimism, insecurity and habit

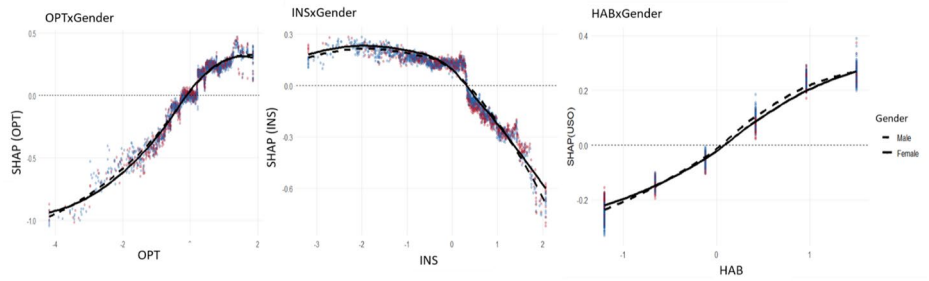


Fig. 4 SHAP dependence plots of optimism, insecurity and habit with gender. *Note*: The dashed line represents the trend for males, and the solid line represents the trend for females

main non-compensatory operationalization of habitual use intensity, while the mean-based version is better interpreted as reflecting breadth of engagement across tools.

4.2.2 Findings on the interaction of the main cognitive factors, gender, and entrepreneurship

Regarding OPT × INS, Fig. 3 suggests that the positive and increasing effects of OPT are moderately attenuated when INS has high values, particularly at medium and high levels of OPT. This indicates that elevated perceptions of INS reduce the extent to which perceived benefits translate into a positive economic evaluation without reversing the direction of the effect. Figure 3 also shows a moderately positive interaction between OPT and HAB, concentrated at medium and high OPT levels, where higher levels of habitual use slightly reinforce the positive impact of perceived technological benefits. In contrast, INS × HAB shows that the negative and non-linear effects of INS are strong and dominant beyond a threshold and are barely mitigated by HAB. Even at high levels of habitual use, SHAP contributions associated with high INS remain clearly negative.

Figure 4 shows that OPT, INS, and HAB maintain clear and structural relationships with the economic evaluation of GenAI—positive and increasing for OPT and HAB, and nonlinear relationships with a threshold effect for INS, which do not vary substantially by gender. The functional forms and intensities of these effects were very similar for men and women, although not identical. In particular, at medium and high levels of OPT and HAB, men tended to exhibit slightly higher SHAP values, whereas at lower levels, women displayed marginally higher contributions for equivalent OPT/HAB values.

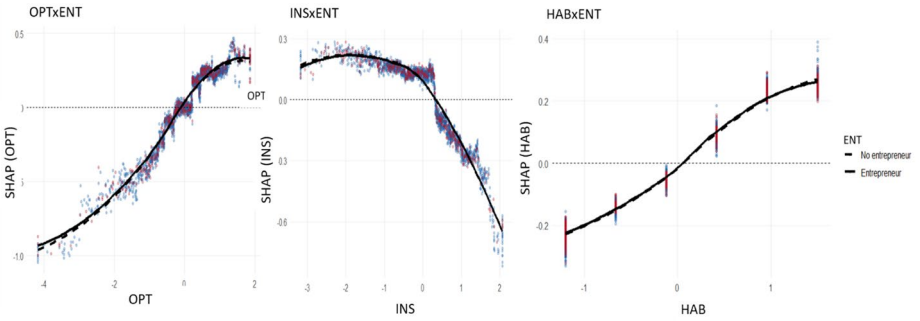


Fig. 5 SHAP dependence plots of optimism, insecurity and habit with entrepreneurship. *Note*: The dashed line represents the trend for non-entrepreneurs, while the solid line represents the trend for entrepreneurs

Table 13 Group differences in Mean |SHAP| values by gender and entrepreneurial status

	Mean|SHAP| non-entrepreneurs vs entrepreneurs				Mean|SHAP| males vs females			
	ENT = 0	ENT = 1	Diff	Cohen's d	GENDER = 0	GENDER = 1	Diff	Cohen's d
OPT	0.2369	0.2549	−0.0181	−0.0930	0.2476	0.2303	0.0173	0.0891
INS	0.1834	0.1838	−0.0004	−0.0039	0.1785	0.1902	−0.0117	−0.1142
HAB	0.2058	0.2148	−0.0090	−0.1058	0.2097	0.2045	0.0052	0.0603

ENT = 0 for non-entrepreneurs and ENT = 1 for entrepreneurs; GENDER = 0 for males and GENDER = 1 for females. Diff. denotes the difference in Mean |SHAP| between groups

Overall, this indicates that the gender effect on SEDP is essentially direct, although limited and localized interaction effects with the main psychological determinants can be detected. For INS, women exhibited higher SHAP values at the most extreme levels of this factor, whereas men did so at intermediate levels. This suggests the presence of a weak and localized moderating effect of sex, dependent on the cognitive range considered, rather than a structural change in the functional relationship between OPT, INS, HAB, and SEDP.

Figure 5 shows that the economic evaluation of GenAI is structured similarly for entrepreneurs and non-entrepreneurs with respect to OPT, INS, and HAB. Nevertheless, a weak moderating effect of entrepreneurial status was observed for OPT, concentrated at non-intermediate levels, indicating that entrepreneurs exhibit slightly higher SHAP contributions at comparable levels of OPT. Taken together, these results suggest that both GENDER and ENT operate mainly as direct effects.

Table 13 allows us to examine whether the observed SHAP differences associated with gender and entrepreneurial status implied substantively meaningful differences in the explanatory importance of the remaining predictors. To do so, we compared the Mean |SHAP| values across groups and calculated both unpaired mean-difference tests and effect sizes. Following conventional criteria, effect sizes below 0.20 were interpreted as practically negligible, even when statistically significant. The results show that, although some subgroup differences in Mean |SHAP| values are observable, all associated effect sizes are trivial or close to zero. Therefore, the explanatory importance of OPT, INS, and HAB appears to be highly stable across gender and entrepreneurial status, with no evidence of substantively meaningful heterogeneity.

5 Discussion

5.1 General remarks

This paper examined the determinants of the perception of the impact of generative artificial intelligence (GenAI) on sustainable economic development (SEDP) among the Spanish working population by combining tree-based ensemble models with explainable machine-learning techniques. The results allow several clear conclusions to be drawn with respect to the three research objectives (RO1–RO3) and provide relevant theoretical and practical implications.

With regard to RO1, which aimed to develop a conceptual framework capable of explaining and predicting perceptions of GenAI's economic impact, the results confirm the suitability of an approach based on cognitive factors, complemented by sociodemographic factors including entrepreneurial status. The predictive performance achieved by the ensemble models, particularly XGBoost and BART, with Q^2 values above 25%, indicates a moderate predictive capacity, supporting the adequacy of the proposed approach (Hair et al. 2019).

Regarding RO2, which focuses on identifying the direction and relative importance of the determinants of the perceived economic impact of GenAI, the results were particularly conclusive. Cognitive variables clearly dominate the explanatory structure, with technological optimism and habitual use acting as the main positive correlates and technological insecurity as the main negative correlates, whereas sociodemographic factors play a clearly secondary role.

From a TRAM-based perspective, this pattern is theoretically meaningful because the variables with the greatest explanatory relevance are precisely the most proximal cognitive predispositions toward technology. In particular, technological optimism and technological insecurity reflect positive and negative readiness orientations, while habitual use captures the routinized engagement through which interaction with GenAI becomes more familiar and stable. In this sense, the machine-learning results do not replace the theoretical framework, but help clarify which components of the proposed model are more strongly associated with perceived economic evaluations in the specific context of GenAI.

The greater importance of technological optimism (OPT) and habitual use (HAB) relative to technological insecurity (INS) and the perceived need for regulation (REG) indicates that positive cognitive factors show stronger associations than inhibitory ones in this context. This result is consistent with the Technology Readiness Index literature, which shows that drivers tend to exert stronger and more consistent effects than inhibitors in explaining the acceptance and use of emerging technologies (Blut and Wang 2020).

Although age or membership in so-called digital generations has often been identified as a key factor in technology acceptance (Akçayır et al. 2016; Chan and Lee 2023), it is noteworthy that in this study, entrepreneurial (ENT) status and gender (GENDER) exhibit greater explanatory power for evaluations of GenAI's economic impact.

From a behavioral perspective, the limited relevance of belonging to a digital generation can be interpreted by distinguishing between technology adoption and the evaluation of its broader economic implications. While prior literature consistently shows that younger cohorts tend to exhibit higher levels of technology adoption, this does not necessarily translate into more favorable assessments of GenAI's contribution to sustainable economic development. Greater familiarity with digital technologies may also be associated with a

more critical or nuanced understanding of their potential risks, particularly in domains such as labor market disruption and economic uncertainty. Thus, the weak explanatory power of generational variables in the SHAP analysis suggests that generational membership, by itself, is a relatively coarse descriptor of economic perceptions in this context.

This result also helps refine the role of sociodemographic variables within the proposed framework. While generational membership is often treated as a proxy for digital familiarity, the present findings suggest that such cohort-based differences are comparatively distal and less informative once cognitive predispositions and routinized use are taken into account. By contrast, the greater explanatory relevance of gender suggests that evaluations of GenAI's economic implications may be more closely related to differences in confidence, perceived risks, and patterns of exposure and engagement than to broad age-based differences in digital socialization.

Beyond the relative ranking of predictors, the results suggest a broader interpretive pattern: perceptions of GenAI's contribution to SED are shaped less by stable sociodemographic attributes and more by cognitive-experiential orientations toward the technology. In this sense, evaluations of GenAI appear to depend primarily on how individuals frame technological change (optimism versus insecurity) and on whether interaction with the technology has become sufficiently recurrent to normalize its presence in everyday practice. This is theoretically relevant because, unlike more specific or purely utilitarian technologies, GenAI functions as a general-purpose and symbolically charged technology, whose perceived economic implications are filtered through broad attitudes toward innovation and accumulated experience of use.

Finally, with respect to RO3, the results show that GENDER and ENT status appear to operate mainly as direct associations rather than as strong moderators of cognitive factors. Interactions identified through SHAP between these variables are generally small and localized, suggesting that gender and entrepreneurial differences operate more as structural shifts in how economic impact is evaluated than as substantial changes in how the underlying cognitive relationships are structured. This finding partially contrasts with classical models, such as UTAUT (Venkatesh et al. 2012, 2003), where gender and other contextual factors are primarily conceptualized as moderators. In contrast, the exploratory machine-learning approach adopted in this study suggests that these variables act, in practice, as additional factors with direct explanatory relevance for the outcome.

5.2 Theoretical implications

This paper underscores the need to select ensemble methods in light of the trade-off between predictive performance and generalization. Although XGBoost and BART exhibit very similar average performance, their differences relative to RF are substantial, particularly in out-of-sample prediction. The strong overfitting observed in RF underscores that excellent in-sample fit does not necessarily translate into strong explanatory capacity or predictive accuracy in real-world settings, an issue that is especially relevant in perception and attitude studies characterized by high individual heterogeneity. In other technology acceptance studies and datasets, alternative methods such as RF have outperformed other ensemble approaches (Andrés-Sánchez et al. 2026a, 2026c; Bezerra et al. 2025).

The results further underline the usefulness of SHAP not only for ranking predictors, but also for opening the black box of the model in a more nuanced way. By jointly examin-

ing beeswarm visualizations, subgroup patterns across outcome quartiles, and interaction effects, it becomes possible to move beyond average importance and identify how specific combinations of perceptions, attitudes, and prior experiences are associated with different predicted levels of the outcome (Lundberg et al. 2020). This approach is particularly useful in complementing traditional technology acceptance frameworks by empirically revealing non-linear patterns, threshold effects, and asymmetries that are rarely captured by conventional parametric models.

From a conceptual standpoint, the results reinforce the central role of technological optimism as an extension of perceived usefulness toward a more socially grounded economic evaluation. The evidence suggests that perceptions of GenAI's impact on SED do not result solely from rational calculation of productivity or employment effects but are deeply rooted in general dispositions toward technological progress. Similarly, the relevance of habit aligns with social cognitive theory (Bandura 2001) and UTAUT2 (Venkatesh et al. 2012), showing that repeated experiences with technology have a strong link with positive evaluations that transcend the individual level and extend to the broader economy.

Likewise, our results show how a data-driven machine-learning approach can complement, rather than replace, a theory-guided interpretation. In the present case, the SHAP-based results make it possible to identify which elements of the TRAM-inspired framework remain most relevant when perceptions concern not only individual technology use, but also its contribution to economic progress. This is especially relevant for variables such as gender and generational cohort, whose role in conventional acceptance models is often treated in broad sociodemographic terms, but which here appear to differ in their actual explanatory relevance.

5.3 Practical and policy implications

This research suggests clear and actionable implications. First, given that technological optimism shows the strongest positive association with evaluations of SED, public policy and communication strategies should focus on making tangible benefits visible, particularly in terms of productivity, job quality, innovation, and sustainability.

Second, the role of habitual use suggests that encouraging hands-on experience and experiential learning is essential for improving societal perceptions of GenAI. Digital literacy programs, workplace training, and access to GenAI tools in professional settings can contribute not only to skill development but also to the consolidation of favorable judgments grounded in direct experience. This approach is especially relevant for population groups that already display a positive predisposition, as habits act as a cumulative reinforcement mechanism.

By contrast, technological insecurity emerges as the most relevant psychological barrier in associative terms, even in the presence of high optimism or frequent use. This finding highlights the need for policies aimed at reducing perceived risks through clear regulatory frameworks, transparency in GenAI system functioning, and effective safeguards related to privacy, bias, and labor protection. Regulation should therefore be framed not as an obstacle to economic development but as an enabling condition that reduces uncertainty and facilitates broader and more trustworthy adoption.

The analysis also revealed a persistent gender gap in the economic evaluations of GenAI, posing a specific challenge for inclusive adoption. Policies aimed at narrowing this gap

should combine actions at multiple levels: targeted training for women in advanced digital skills, greater visibility of female role models in AI development and use, and a systematic assessment of GenAI's differential impacts on feminized sectors and occupations. Reducing this gap is not only a matter of equity, but also a prerequisite for maximizing GenAI's economic and social potential.

Finally, although entrepreneurship shows a positive association with the perceived economic impact of GenAI, its effect remains moderate, suggesting that many entrepreneurs have not fully recognized the strategic advantages of these tools. In this context, targeted awareness and GenAI literacy initiatives for entrepreneurs are needed, focusing on opportunity identification, strategic planning, uncertainty management, and alignment with sustainability objectives. The effective integration of GenAI into the entrepreneurial ecosystem can serve as an additional driver for sustainable economic development.

6 Conclusions

6.1 Principal takeaways

By combining a technology acceptance–based theoretical framework with advanced machine learning and interpretability techniques, the findings lead to several key conclusions regarding the factors shaping the perceived economic impact of GenAI. First, the results robustly show that cognitive factors far outweigh sociodemographic variables in explaining these perceptions. Technological optimism emerged as the factor with the strongest link with positive economic evaluations of GenAI, followed by habitual use, while the results for technological insecurity support its role as a consistent barrier.

The findings suggest that technology adoption drivers are more strongly associated with the outcome than barriers, in line with the technology readiness literature. This result is particularly meaningful for emerging technologies, such as GenAI, where perceived efficiency and value creation potential outweigh concerns related to risks or regulatory needs. Moreover, the fact that habitual use exceeds perceived regulatory necessity highlights the central role of direct experience in shaping economic evaluation.

Although sociodemographic variables have lower explanatory power, gender and entrepreneurial status stand out as the relevant factors. The persistence of a gender gap across all outcome levels and the positive, albeit moderate, effect of entrepreneurship suggest that these characteristics function as structural shifts in economic evaluation rather than as simple contextual moderators. Overall, these findings provide empirical evidence that complements and nuances classical technology acceptance models, highlighting the added value of exploratory machine learning approaches in capturing complex and heterogeneous relationships.

6.2 Limitations and future research

Although the paper offers relevant insights, its findings should be interpreted in light of certain limitations, which also point to opportunities for further studies. First, the assessment relies on a cross-sectional survey, which precludes strict causal inferences between the determinants examined and perceptions of the economic impact of GenAI. Although

machine learning methods capture complex and non-linear patterns, longitudinal studies are needed to analyze how optimism, insecurity, and habitual use evolve as technology matures and adoption spreads.

From a theoretical perspective, the observed pattern is consistent with TRAM, according to which repeated use of a technology reinforces familiarity and reduces perceived uncertainty, thereby being associated with more favorable evaluations. However, given the cross-sectional nature of the data, these findings should not be interpreted in strictly causal terms. Reverse causality remains plausible, as individuals with more positive perceptions of GenAI in terms of its economic and sustainability implications may also be more likely to develop more favorable attitudes toward it (i.e., to consider it a good idea) and to use it more frequently, in line with theories such as the Theory of Planned Behavior (Ajzen 1991). Accordingly, future research based on longitudinal data would be needed to assess whether a self-reinforcing loop exists between use and perception. In this sense, the relationship between habitual use and perceived impact is better understood as potentially mutually reinforcing rather than strictly unidirectional, and the present results should therefore be interpreted as reflecting a behavioral alignment between use and perception rather than a definitive causal effect.

This study focuses on subjective perceptions of economic impact, which, while central to understanding technology acceptance, do not necessarily translate directly into observed behaviors or objective economic outcomes. Future research could combine perceptual measures with indicators of actual use, productivity, or economic performance to assess the consistency between expectations and realized effects of GenAI.

A further methodological limitation concerns the measurement structure of SEDP. Although the study conceptualizes SEDP as a composite indicator rather than as a strictly reflective psychological scale, alternative factor structures or confirmatory measurement models were not formally tested. Future research could examine whether the perceived economic impact of GenAI is better represented as a single composite index, as several sector-specific dimensions, or through alternative formative-reflective specifications.

Although the analysis includes relevant sociodemographic variables such as gender, age, and entrepreneurial status, other potentially influential dimensions, such as specific digital skills, sector of activity, or organizational context, are not explicitly considered. Incorporating these factors would allow for a more refined understanding of the underlying mechanisms and deeper exploration of the observed heterogeneity.

Even though the use of ensemble methods and SHAP provides robustness and transparency, the comparison is limited to a specific set of algorithms and configurations. Future research could expand this approach by incorporating additional explainable models or combining machine learning with confirmatory approaches such as structural equation modeling to formally test theoretical hypotheses derived from exploratory results.

Finally, the analysis was conducted within a specific geographical and temporal context, characterized by rapid GenAI diffusion. Given the dynamic nature of these technologies and the influence of regulatory, cultural, and economic frameworks, replication across countries and time periods would be particularly valuable for assessing result stability and contributing to a more generalizable understanding of the factors shaping economic perceptions and the acceptance of GenAI.

Author contributions J.d.A.S. and T.T.C. have contributed equally to the paper. Both participated in the conception, writing of the paper, performing the calculations, and revision of the paper in equal proportions.

Funding Open Access funding provided thanks to the CRUE-CSIC agreement with Springer Nature. Funding was provided by Telefonica and the Telefonica Chair on Smart Cities of the Universitat Rovira i Virgili and Universitat de Barcelona (project number 42.DB.00.18.00), 42.DB.00.18.00.

Data availability The raw data supporting the paper is freely available at https://www.cis.es/es/detalle-ficha-estudio?origen=estudio&codEstudio=3495. Accessed 7 May 2025.

Declarations

Conflict of Interest The authors declare no competing interests.

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