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Key policy mechanisms supporting the University–Industry collaboration in the Danube region: case study of academic HPC centres and SMEs

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Abstract

Purpose – This paper aims to explore the key anchors of the National Innovation System shaping the nature of collaboration between academic high-performance computing centres (academic HPC centres) and small- to medium-sized enterprises (SMEs) working in the automotive and electronics sectors of the Danube region. With two main research questions, it discusses the importance of knowledge transfer and technology transfer for collaboration between University and Industry (U-I collaboration) in three groups of developmentally distinct countries: competitively advanced, competitively intermediate and competitively lagging. As main anchors of the innovation system, stable legal environment, exciting innovation policies and strong R&D funding are recognised.

Design/methodology/approach – A qualitative empirical study in 14 Danube region countries included 92 focus group participants, expert representatives of academic HPC centres and SMEs. The data were audio recorded, transcribed and analysed.

Findings – The findings show the main prerequisites of the framework conditions for efficient U-I collaboration evolve through a goal-oriented National Innovation Policy and developed and functioning legal environment supporting labour market and intellectual property (IP) protection and enforcement. Additionally, skilled people are needed to be able to operate with HPC, where it seems all the countries lack such skilled workforce. In competitively lagging countries, the high levels of brain drain exhibit strong impact to U-I collaboration.

Research limitations/implications – Research into relationships between academic HPC centres and SMEs conducted was qualitative; therefore, limitations in terms of generalisation arise from it. On the other hand, the research is promising in terms of offering the guidance for policy makers who can use the findings when delivering innovation policy mix, adjusted to developmental level of own innovation ecosystem.

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Originality/value – The study is among the pioneering work in U-I collaboration between academic HPC centres and SMEs from automotive and electronics industries in the Danube region. The research addresses the dynamics of collaboration and offers policy implications to strengthen the particular U-I collaboration.

Keywords Innovation, National Innovation System, Technology diffusion, Technology transfer, Knowledge flows, Supercomputing, HPC, University-industry collaboration, Automotive and electronics industries, Danube region

Paper type Research paper

1. Introduction

Collaboration intrigues, especially in innovation studies, where it is well established that the collaboration and knowledge exchange are the drivers of progress. With the rise of the knowledge society, knowledge economy and the importance of the global research networks (Guimón and Paunov, 2022), the processes only sped up, demanding strategic collaborations on all levels. However, one, in particular, remains for us. It is the intrigue of numerous researchers exploring the dynamics of University–Industry collaboration (U-I collaboration). U-I collaboration (from here onwards U-I collaboration) is an intriguing case of two paradigmatically distinct business models (Buehling and Geissler, 2022) that were only recently addressed through the perspectives of Entrepreneurial University or even open innovation (De Bernardi *et al.*, 2020). But most of all U-I collaboration is recently being addressed to as a mean to uplift the "*third mission*" of the universities (Nsanzumuhire and Groot, 2020). Among the factors recognised as game changers, also when addressing the U-I collaboration, there is the rapid development of ICT (Hönigsberg and Dinter, 2019) and its utility in innovation processes and competitiveness (Tarutė and Gatautis, 2014), let alone communication (Camarinha-Matos *et al.*, 2019).

In terms of the desire to re-industrialise the Danube Region countries (Besednjak Valič, 2019), the U-I collaborations are welcomed and looked for, taking into account the need of the Industry to follow the global trend of digital transformation (Guimón and Paunov, 2022) and to move towards Industry 4.0 (Crupi *et al.*, 2020). To keep up with original equipment manufacturers' (OEMs') demands (Hafner and Modic, 2020; Kurpjuweit *et al.*, 2018), small- to medium-sized enterprises (SMEs) need to keep up with new technologies, such as high-performance computing (HPC) or supercomputing. HPC services can be of help (Suklan, 2019).

The present study explores the role institutional framework and actors of the triple helix of the National Innovation System (NIS) play when framing the U-I collaboration. As research shows (Nsanzumuhire and Groot, 2020), a gap in the developing countries with the respect of the U-I collaboration exists. On that note, our research focussed on the dynamics of such collaborations within developmentally distinct groups of Danube region countries. Focus group discussions included triple helix experts and representatives on U-I collaboration within those particular countries. We conducted the research within the scope of the Danube region academic HPC centres representing the University sphere and SMEs working in the automotive industry as suppliers to OEMs as Industry representatives.

Focussing on institutional frameworks surrounding the U-I collaboration, the main research questions deriving from the given situations are the following:

RQ1. What are the key anchors of the institutional forces for establishing effective U-I collaboration for the cases of academic HPC centres and SMEs in the Danube region?

RQ2. What policy mechanisms seem most appropriate to encourage the U-I collaboration among academic HPC centres and SMEs in the Danube region?

To respond to both research questions, we adopted the inductive approach, underpinning the qualitative research process. The analysis of the focus group discussion will deliver responses to the main research questions. In providing the answers, we will rely on a case-based approach.

The authors structured the paper the following way: first, we set the research's main concepts and starting points. Description of data collection follows next, and after that, the data analysis report. The final part of the paper delivers the discussion with conclusions.

2. Institutions, National Innovation Systems and HPC in the context of University–Industry collaboration in the Danube region

2.1 Institutions and key anchors for collaboration

Sociologically, when addressing U-I collaboration, we lean on neo-institutional theory as dominating organisational studies (Alvesson and Spicer, 2019). The presented research defines institutions as formalised, regulative (example legislation) (Alvesson and Spicer, 2019). On the other hand, we describe the institutions working within the legal setting as organisations. Adopting such an approach, we believe a sharper distinction between institutions (codified agreements) and organisations (formalised groups of employees working under established rules) is needed. Having said all this, to understand further the U-I collaboration dynamics, we need to remain aware that both organisations do not operate independently of the social environment. Therefore, the NIS approach is further adopted.

2.2 Innovation systems

With full awareness of different definitions of innovation system as one "*genotype*", we focus on the concept of NIS, as several "*phenotypes*" (Modic and Rončević, 2018) among the for example also: regional innovation system, sectoral innovation system or even corporate innovation system (Granstrand and Holgersson, 2020). Having said that, we follow Freeman (1987) who defined the NIS as a network of institutions interacting, importing, modifying and diffusing new technologies. However, some institutions mentioned earlier act as organisations with established organisational fields (DiMaggio and Powell, 1983). The organisations operating within NIS can be in the public or private sector (Freeman, 1987). Following the definition of NIS, we understand innovation as a sophisticated and complex process in which different elements of the system are linked to each other, enabling the sharing of knowledge and the mutual support for innovation activities (Lundvall, 1992) but especially emerging technologies and innovations (Lundvall, 2007; Nelson, 1993). NIS is composed of the linkages and flow of information among the different actors of the system concerning the generation of ideas and the innovation process (Lundvall, 2007). Other governmental policies address the importance of NIS, and policymakers invest efforts in connecting different actors of the economy (Arranz *et al.*, 2020).

Several attempts (Kuhlmann, 2001) structure the relationships among stakeholders of NIS by demonstrating the complexity of relationships among them. The most interesting is the model by (Warnke *et al.*, 2016). The model focusses on the two main subsystems of NIS: University and Industry. Intermediary organisations interlink both subsystems. The political system and influence shape the subsystems of the demand system, the framework conditions and the existing infrastructure system (Warnke *et al.*, 2016).

Different systemic arrangements, such as configurations of stakeholders and organisations, can deliver similar levels of innovative performance. Research of the European NIS over the last ten years reveals that innovation systems show inherent complexity, which leads to a high level of complementarity among their constituent components and configuration. This result implies that successful innovation policies should be systemic, leaving little flexibility in policy design and scope (Cirillo *et al.*, 2019). However, there are specific strategic competences to be developed at the level of territorial actors (Fric *et al.*, 2023). As substantive knowledge and strategic connections are among the most relevant (ibid), the plan for the future development of NIS suggests adaptation to global trends, adaptation of NIS to country specifics and fitting entrepreneurial innovation into NIS (López-Rubio *et al.*, 2022).

However, in cases of obstructed evolution of the innovation systems, the weaknesses of markets, institutions, organisations and networks are emphasised (Carlsson and Jacobsson, 1997; Jacobsson and Bergek, 2006; Jacobsson and Johnson, 2000; Rotmans *et al.*, 2001; Unruh, 2000). A weakened system structure may lead to co-called system failure, meaning a system fails to develop or does so in a stunted fashion (Carlsson and Jacobsson, 1997). There are several levels of a system failure, while for the present discussion, we focus on system failure concerning structural components (Bergek *et al.*, 2008). To prevent system failure, proper policies need to be elaborated, strategically steered to achieve economic and societal development (Rončević and Besednjak Valič, 2022).

2.3 National Innovation Systems as a triple helix

The model of NIS (Lundvall, 1992) can also be used to explain the creation of socially relevant knowledge. To illustrate the dynamics of socioeconomic relations in knowledge creation processes between the academic, economic and governmental spheres, we will use the triple helix model (Leydesdorff and Etzkowitz, 1998, 2001; Ranga and Etzkowitz, 2013). The triple helix model spotlights a trilateral network of relations between University, Industry and public authorities with the expectation to create a novel knowledge infrastructure. This involves bringing these three subsystems together, each assuming own respective role, and establishing effective organizations at the intermediate level. We place the production and transfer of knowledge at the centre of the concept of the triple spiral as a fundamental issue that converts the three subsystems. The triple helix model also tries to illuminate and explain the dynamics of internal changes in individual social subsystems as well as changes in the relationships between them.

Having said all the above, we describe the above three types of actors within the institutional framework for further conceptualisation and analysis. All three are structured as organisations and operate within the same system, undertaking their roles. Their actions and interaction thus contribute to the innovativeness of the NIS and might, in the same manner, contribute to system failure. The actors are the following: academic HPC centres, SMEs working in the automotive and electronics industries and public authorities.

2.4 Diffusing high-performance computing in the European Union

In cases when regulation obstructs the deployment of particular technologies, promising developmental trajectories may be foreclosed (Martin *et al.*, 2019). However, the law can also provide additional incentives for innovation, leading to the creation of new technologies, products and markets and the discovery of overlooked efficiencies—see also Porter hypothesis (Porter and van der Linde, 1995). Early adopters may enjoy first-mover advantages in export markets. Regulation can foster consumer trust, increasing demand for new technologies (Martin *et al.*, 2019). The countries of the EU have started to recognise the importance of intertwinement of University and Industry (Besednjak Valič *et al.*, 2023) and include this in their innovation policy mix (Modic and Rončević, 2018).

However, the HPC remains costly infrastructure, expensive also to maintain (Sajay and Babu, 2016), and it is the cost that are seen as the major burden for SMEs when deciding to adopt HPC (Botelho Junior and O'Gorman, 2022). Additionally, it is Sakellariou *et al.* (2018) who is focussing on challenges in interplay between Industry 4.0 and HPC, especially in the context of smart manufacturing systems. The authors detect the most common challenges in the interplay between Industry (4.0) and HPC: The first arises from the environment adaption of the HPC as HPCs consumes large amounts of data and resources. As HPC systems become interconnected with manufacturing systems, they will act in line with overall systems performance. And overall systems might have other objectives but time, for example energy consumptions, network traffic etc. following this Gitler *et al.* (2020) explore different regional ecosystems in Latin America to understand the overall regional specifics.

Others studies also approach the non-technical aspects of HPC, see also Botelho Junior and O'Gorman (2022), who outline detect a range of studies focussing on HPC in the context of manufacturing innovation (Kim, 2016). Basili *et al.* (2008) detect common traits in HPC project as lack of targeted HPC training and issues related to code development. Lastly, there is a specific lack of competences detected among the SMEs, especially when it comes to accessing the HPC as it predominantly occurs through the cloud (Lu *et al.*, 2022).

2.5 Innovativeness of the Danube region

The Danube region is a joint name for numerous countries in the Danube basin. Danube river is the second longest European river and runs through a total of 10 countries. The territory of the Danube basin is, in policy terms, covered by the European Union strategy for the Danube region (EUSDR, 2022).

The EUSDR covers the area spreading from the Black Forest in Germany to the Black Sea (Romania, Moldova and partially Ukraine) (Besednjak Valič, 2019). Up to 115m people inhabit the region. The Danube region and the EUSDR cover the following EU member states: Austria, Bulgaria, Croatia, Czech Republic, Germany (regions of Baden-Wurttemberg and Bayern), Hungary, Romania, Slovakia, and Slovenia), Pre-accession countries (Bosnia and Herzegovina, Montenegro and Serbia) and neighbouring countries (Moldova and, since 2022, also whole Ukraine) (Besednjak Valič, 2019).

All the above-listed countries rank very differently according to numerous statistics and reports. We could group them into three groups for further data analysis and interpretations. We did this based on their ranking by adopting the Global Competitiveness Index (Schwab, 2018). The first group was named the group of competitively advanced countries. This group includes the countries: Germany (Baden- Württemberg), Austria, the Czech Republic and Slovenia. The second group was named the group of competitively intermediate countries. The group includes Slovakia, Hungary, Bulgaria and Romania. Lastly, the third group was called the group of competitively lagging countries. It contains countries: Serbia, Croatia, Montenegro, Ukraine, Moldova and Bosnia and Herzegovina.

To sum up, researching institutional aspects of NIS needs to distinguish the difference between institutions and organisations of NIS and should focus on the interactions of two main subsystems of NIS – University and Industry while keeping in mind the distinctive differences between NIS. Adopting a triple helix approach is necessary, especially in developing countries where public authorities' intervention will enable the framework conditions for NIS development. The process is tested further on in the case of three developmentally different groups of Danube region countries. We have researched the particularities of U-I collaboration in the case of collaboration between academic HPC centres and SMEs.

3. Methodology

We analysed the data collected within the InnoHPC (InnoHPC, 2017) project to respond to the proposed research questions. As the project was transnational, the data collection took place in 14 countries of the Danube region, mostly by different performers and with groups gathered on the local availability. The data collection period ranged from May to October 2017. We conducted fourteen focus groups, and Table 1 delivers the number of participants

No.	Group according to global competitiveness index (2018)	Country	No. of participants	Participants profiles
1	*Competitively advanced*	Austria	6	3 industry representatives 2 academic HPC representatives 1 policy maker—national level
2		Czech Republic	6	3 industry representatives 1 academic HPC representatives 2 policy maker—national level
3		Germany (Baden-Württemberg)	7	3 industry representatives 4 academic HPC representatives
4		Slovenia	15	10 industry representatives 3 academic HPC representatives 2 policy makers—national level
5	*Competitively intermediate*	Bulgaria	6	2 industry representatives 2 academic HPC representatives 2 policy makers—national level
6		Hungary	10	6 industry representatives 3 academic HPC representatives 1 policy makers—national level
7		Romania	5	2 industry representatives 1 academic HPC representatives 2 policy makers—national level
8		Slovakia	6	3 industry representatives 1 academic HPC representatives 2 policy makers—national level
9	*Competitively lagging*	Croatia	5	3 industry representatives 2 academic HPC representatives
10		Bosnia and Herzegovina	4	2 industry representatives 1 academic HPC representatives 1 policy maker—local level
11		Moldova	4	1 industry representative 1 academic HPC representative 2 policy makers—national level
12		Montenegro	3	2 industry representatives 1 academic HPC representatives
13		Serbia	10	5 industry representatives 3 academic HPC representatives 2 policy makers—national level
14		Ukraine	5	4 industry representatives 1 academic HPC representatives

Source(s): InnoHPC (2017), own grouping according to Schwab (2018)

Table 1.
Number of expert participants per focus group

for each focus group. Additionally, Table 1 displays the groupings based on Global Competitiveness Index. The data collection for Germany took place in Baden- Württemberg focussing on the dynamics of that particular region. In each of the countries, one expert focus group was conducted, with expert speakers and representatives of the triple helix (Ranga and Etzkowitz, 2013) actors from the fields of academic HPC centres, Industry and policy-making. We invited the expert speakers to the discussion based on their expertise in HPC and technology transfer.

The whole research process (Alase, 2017) followed the interpretative paradigm (Lamut and Macur, 2012; Smith and Shinebourne, 2012). Within the analysis process, the authors also introduced the phenomenological aspect (Miller *et al.*, 2018). Guba and Lincoln (2004) point out that reality is constructed by the individual, so there are different interpretations of the same problem. The individual's interpretation of the problem under study is not only conditioned by their knowledge, experience and values but also depends on the specific historical, cultural and political context (Guba and Lincoln, 2004) of the environment in which the individual operates. By leaning on an interpretative paradigm, authors put emphasis on examining subjective experiences, reflections and understandings and as well as determining what meaning is attached to research topic, from the perspective of the participants included in the study.

The authors adopted a multistage qualitative content analysis approach when analysing and interpreting the data. The data collection and analysis procedure included, first, audio recorded and transcribed data collection. To obtain good transcriptions, the authors ensured the correct meanings and opinions. Second, the transcriptions were organised and arranged into a coding table. The coding table was structured to enable the position of the same question and pertaining response within a single line. Once we arranged and transcribed the data, we conducted the first reading. In the next step, we structured the data according to the two main research questions, based on the key detected topics. The final phase included the open coding of data. Lastly, we created the paradigm model based on the open coding results. The authors contributed equally to safeguarding the process and ensuring the objectivity of the analysis.

4. Results

The interviewees belonging to the group of competitively advanced countries consider the role of public authorities as weak when it comes to using HPC for industrial purposes. National policies do not seem to promote cooperation between the academic HPC centres and Industry. Further on, interviewees of the competitively advanced countries criticise the inadequate national policies in terms of limited budgetary support for U-I collaboration in the field of HPC. Subsequently, the academic HPC centres and Industry identify EU project funding as a viable source of financing for HPC infrastructure. As a result, organisations form international links and cooperation. Interviewees from the group of competitively advanced countries criticise their national strategies for lack of vision on using HPC in R&D and U-I collaboration. However, they also highlight the presence and support of national policies for tuition fee-free public offerings of HPC training/education. The workforce skilled in HPC is crucial as interviewees identify the numerous potentials of the professional labour force. According to the interviewees, the low level of HPC skills is present even among the experts.

In order to mitigate the issues related to skills to use the HPC, the respondents detect potential in organisation of non-formal training related to the use of HPC technology. Such activity is necessary, as specific HPC-related knowledge is deficient. Both sectors face this problem—University and Industry. The interviewees of the competitively intermediate countries highlight the supportive role of the public and intermediary organisations for HPC accessibility as opposed to their counterparts from advanced countries. Public organisations provide (public) financing for HPC infrastructure and also promote cooperation between the academic HPC centres and Industry through national calls and tenders. Such type of cooperation is also encouraged by EU-funded projects. At the same time, the interviewees mention the lack of financial support from the EU. The reason for this is the industry's struggle with the administrative requirements of managing EU project documentation. Another reason for the struggle is the slowness of EU funding processes.

The strong links between University and Industry are recognised within the technology transfer offices (TTOs) services by interviewees of the competitively intermediate countries. TTOs have the potential to serve as promotors of cooperation between the academic HPC centres and industry, according to the interviewees. Interviewees agree such an approach is crucial as academic demands in competitively intermediate countries do not necessarily value the applicative research and collaboration with the industry as much as basic research.

National innovation strategies usually define the HPC as a research infrastructure and one of the key enabling technologies for innovation. Based on the opinions of the interviewees, the lack of national strategies reveals itself in weak support of industrial R&D. In industrial R&D, the experts do not recognise the HPC as a priority technology. The interviewees expressed their critique of the national innovation policies as they noted the lack of vision and goals for proper positioning the HPC technology within the industry. Apart from that, the emerging industry sectors seem to be able to establish close links between clusters of potential beneficiaries of HPC infrastructure and technology. Based on the interviewees' opinion, those emerging industry sectors do not provide support for the use of HPCs outside the established clusters. Consequently, according to interviewees, competitively intermediate countries do not exploit the potential of clusters when disseminating both innovation and knowledge linked to HPC technologies.

Public authorities of the group of competitively lagging countries express the rudimentary willingness to improve and transfer of HPC technologies. Interviewees recognise the readiness of public authorities to change legal frameworks towards supporting the use of existing HPC infrastructure. Despite the declarative supportive role of public authorities, the interviewees note that the public authorities themselves act as a critical obstacle to the exploitation of HPC technologies. Public authorities do not provide sufficient financial support in funding R&D. Moreover; the interviewees note that the public authorities do not undertake investments in HPC infrastructure. According to the interviewees, public authorities expect industry initiatives to create and support the R&D and HPC technology clusters. Based on the responses from the interviewees, in the competitively lagging countries, there is a lack of mutual understanding for HPC-related R&D within different sectors. The attitudes of public authorities and the lack of knowledge, according to interviewees, reflect in the absence of strategic documents. The interviewees also note the absence of concrete strategic measures to overcome the status quo.

Focussing on the proposed RQ1, the following response is below:

RQ1. What are the key anchors of the institutional forces for establishing effective U-I collaboration for the cases of academic HPC centres and SMEs in the Danube region?

We presented the key anchors in Table 2. As key anchors for the institutional forces, we outline the technology transfer and knowledge transfer, both depending on the levels of collaboration potentials and collaboration itself. For this purpose, stable legal environment, existing innovation policies and strong R&D funding are recognised as anchors for establishment of U-I collaborations.

The U-I collaboration in the field of HPC offers an opportunity. This opportunity, however, depends on the ability to adopt HPC as HPC is costly and skills demanding infrastructure. Both setbacks are problematic for economically less developed countries experiencing

Key themes	Institutional forces for a collaboration	Policy mechanisms
Information flow between organisations	- Opportunities from academic HPC centres - Promotion of HPC from academic HPC centres - Low awareness of benefits from the side of the Industry	- Public authorities as responsible for a systematic system for the transmission of information
Institutional cooperation	- U-I collaboration is perceived as weak - Poor knowledge transfer, low applicability to Industry - Public authorities ensure free HPC training	- Need to address the development and teaching of HPC competencies systematically - Countries with strong industrial organisations do not require assistance from the public authorities
Knowledge creation in HEI and RI	- Specific cases of high HPC level knowledge exist, especially among younger researchers - Academic HPC centres support cross-sectoral cooperation and knowledge transfer	- Support the development of new study programmes tailored more according to the HPC needs of the industrial sphere
Knowledge transfer, HPC training	- Positive attitudes towards creativity, entrepreneurship and new technologies - Industry is focussed on ICT advancements and innovation - Cooperation between academic HPC centres and Industry is seen as positive	- Senior researchers in some intermediary countries, particularly lagging countries, are not seen as competent to use and teach HPC. - The reform of academic programmes is required
Ability to use HPC	- The Industry obtained the ability and skill to use HPC in advanced countries - Industry in advanced countries owns HPC research centres. Such ownership is an obstacle to collaboration in the academic HPC sphere - Results in the exclusivity of knowledge - Industry fears data disclosure and worries about data protection in the external HPC infrastructure - Industry in competitively intermediate and competitively lagging countries frequently is not HPC ready – neither in awareness, type of products, nor skills	- In intermediate and competitively lagging countries, the industries rely upon policy support when developing and using the HPC technology - The competitively lagging countries face shadow economy and tax evasion; the level of socio-economic development is the main obstacle to HPC utilisation in Industry
HPC setbacks for SMEs	- HPC readiness of the SMEs is low for reasons like; low awareness of the usefulness of HPC, lack of adequately trained human resources, high cost of licensed software, and rental of HPC infrastructure - HPC is predominantly available through EU funding. EU-funded HPC is not open to the private sector - EU projects support international networks	- In competitively intermediate and lagging countries, the academic HPC centres focus on theoretical research - Slow transfer of HPC knowledge to Industry - EU projects demand extensive administrative work. Due to the complexity of project documentation, SMEs do not desire to consider EU project funding
Transnational collaboration	- Industrial R&D needs in competitively intermediate, and lagging countries are addressed abroad	- Weak U-I collaboration in general in competitively intermediate and lagging countries

(*continued*)

Table 2.
Key themes defining institutional forces for collaboration and policy mechanisms

Key themes	Institutional forces for a collaboration	Policy mechanisms
The competitive advantage of HPC usage	- Competitively advanced and some competitively intermediary countries demonstrate collaboration between academic HPC centres to ensure competitive advantage	- The usage of HPC varies across the Danube region - Presence of clustering in automotive and electronics sectors
National innovation policy	- Existing policies support collaboration - Need for working legal environment - Public authorities are seen as hinderers of collaboration - National innovation policy needs a vision. The lack of clear long-term goals is a weakness. The non-critical best practices imported from other cultural settings are de-motivating in competitively intermediate countries - Policies supporting innovation agents who engage in clusters and networks exist in advanced countries - Slow implementation of policies, too bureaucratic approach - Unstable national and EU funding results in low investment/funding in science - Without national support, academia in competitively lagging countries creates transnational networks due to self-initiative	- In competitively intermediate and lagging countries, provision of funding for SMEs - Request the training for HPC to be free and open - Policy needs to ensure financial support for HPC (and related IPR) and promote innovation - Too much focus on solving unemployment problems *per se* - Too slow recognition of R&D profitability in competitively intermediate and lagging countries
Role of public authorities	- Public organisations are considered an obstacle to the diffusion of technology - Lack of interest in HPC in the competitively intermediate and lagging Danube region countries - Solely declarative support to HPC application - Lack of support for U-I collaboration - Lack of support towards forming networks, especially between University and Industry, as public-private partnerships are considered fraud in some competitively intermediate countries - In competitively advanced countries, the critical decision maker in national networks is in academia, while in competitively intermediate countries, the crucial actor in the networks is Industry	- Policy that enables stable financing of HPC infrastructure is considered sufficient - Lack of legislation, including IPR protection and enforcement (especially in lagging countries) - Weak or absent Internet infrastructure in some countries - Lack of long-term vision regarding innovation and short-term and long-term goals - Slow and bureaucratic policy implementation - Lack of recognition of HPC's effectiveness in the diffusion of technology

Table 2.

(*continued*)

Key themes	Institutional forces for a collaboration	Policy mechanisms
Issue of brain drain and migration	- In competitively advanced countries, the talents are attracted by the high quality of life and high quality of academically exciting research groups, professors with HPC competencies, and established U-I collaboration through study programs and HPC usage during the study - Competitively intermediate countries can also attract talented people but have difficulties retaining them - The competitively lagging Danube region countries cannot attract or retain talented individuals from other countries, as they cannot stem their brain drain	- Competitively intermediate countries are incapable of retaining talented people due to labour market issues (legislation, taxation, and incompatibility of wages with the complexity of work) - Competitively lagging countries note underdeveloped Industry, inadequate political system and labour market together with underfinanced and low-quality academic sphere - EU migration policy and globalisation support brain drain from competitively lagging countries

Source(s): Own research results interpretation

Table 2.

problems of brain drain. The ability to use HPC is prerogative for technology transfer and knowledge transfer processes.

Lastly, in competitively advanced countries accessibility to HPC capabilities lies often within organisations, where, HPC technology helps achieving organisation's strategic goals. In contrast, in competitively intermediate and competitively lagging countries, the case HPC technology is primarily introduced via higher education institutions (HEI). Further communication and cooperation with industrial actors are hindered because of the lack of competent professionals, but also due to intellectual property rights (IPR) concerns.

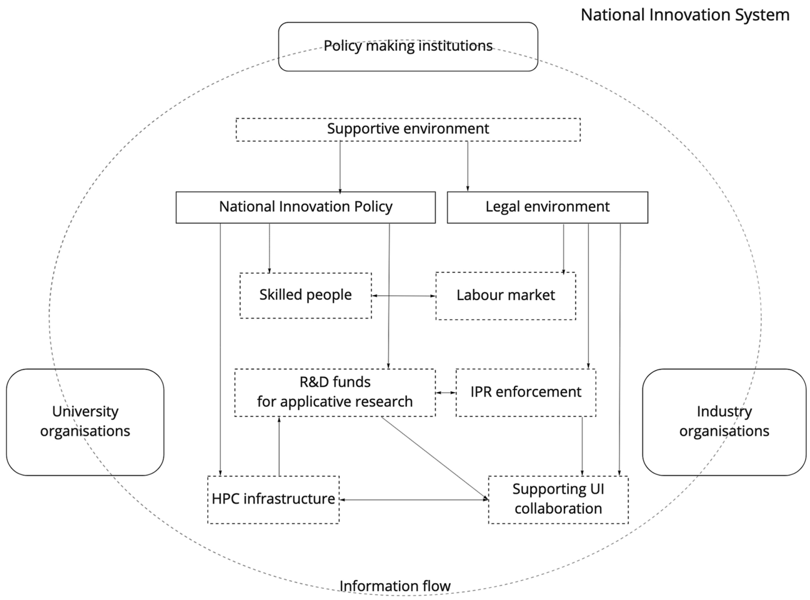
RQ2. What policy mechanisms seem most appropriate to encourage the U-I collaboration among academic HPC centres and SMEs in the Danube region?

Regarding policy mechanisms considered appropriate to address the given situations, Table 2 reveals issues on several levels. First, the public authorities must ensure the proper information flow among all triple helix actors. Second, the policies must support the demand for a skilled workforce, supporting curricula adjustments. Based on that, the policies should be set in a way to promote HPC competencies, not only among junior but also among senior staff. A stable legal environment must support for U-I collaboration and the establishment of competitive labour markets. The interviewees particularly emphasised the need to ensure the funds invested in R&D return as profits. Supported U-I applicable research can secure such returns in profits. The interviewees expect a systematic solution for providing and funding HPC infrastructure.

The below paradigm model was developed based on the analyses and responses to both research questions. The functioning NIS can play a central role through sufficient information flow among all system stakeholders. Second, a competitive National Innovation Policy that fosters technological readiness and people skills is essential. Also, the National Innovation Policy should support R&D investment to be turned into profitable products. Third, the legal environment must provide IPR enforcement and competitive labour market conditions (see Figure 1).

5. Discussion and conclusions

In a time of fierce global competition and increased transition towards new business models for numerous sectors and organisations, the U-I collaboration facilitated by public authorities



Source(s): Besednjak Valič (2022)

Figure 1. Anchoring NIS for HPC diffusion in Danube region—paradigm model

seems to remain at the heart of innovation processes. Enabling more vital collaboration is a task for numerous prosperous OECD countries (Haeussler and Colyvas, 2011). To facilitate the paradigmatic shift in research orientation, University and Industry need specific framework conditions for the collaboration to realise. Research results show that the most critical institutional anchors are two—efficient and straightforward National Innovation Strategy and a functioning legal environment. The National Innovation Strategy must focus on supporting the skilled workforce, implementing and maintaining HPC technology, and actively supporting relevant R&D research. In this context, a need for multilevel responsibility for innovation policy (as also in Modic and Rončević, 2018) is required. The practical legal environment must ensure a stimulating labour market that attracts and attain talented people and must provide the protection and enforcement of IP rights. The same conclusions can be confirmed by Viale and Campodall'Orto (2002) who are aware, together with Mali (2009), based on such legislation, that knowledge transfer is either supported or hindered. Additionally, National Innovation Strategy must support U-I collaborations in terms of equal valuation of basic and applicative research along with labour legislation enabling easier transfers of researchers from University to Industry and vice versa (Viale and Campodall'Orto, 2002).

Concerning cases of NIS failure, the results of our presented research confirmed the findings of (Bergek *et al.*, 2008). The establishment of efficient U-I collaboration between academic HPC centres and SMEs of automotive and electronics industries in the Danube region is hindered by (a) infrastructural failures, such as lack of HPC infrastructure; (b) institutional failures, such as corruption and non-functioning legislation; and (c) capabilities failures, such as lack of skilled workforce and collaboration. The findings go in line with detected barriers to U-I collaboration (Nsanzumuhire and Groot, 2020).

For the presented case of three groups of countries of the Danube region, we met two distinctions worth further exploring: (a) developmentally differentiated countries seem to have different needs when supporting U-I collaboration. Economically less developed countries rely more on public authorities and their support in the U-I collaboration endeavours. (b) In competitively lagging countries of the Danube region, a distinct pattern of rigidity in considering collaborations between academic HPC centres and SMEs was noted, especially from the side of academia. The role of mental frameworks, especially considering national/cultural characteristics in U-I collaborations, could be more important than previously considered and can be subject to further explorations of the collaboration dynamics. Additionally, following the conceptualisations of ideal types of competence model for smart territorial development (Fric *et al.*, 2023), particularly tailored policy mix can be formulated for each of the specific regional contexts.

Apart from many insightful findings, the authors are aware of the study's main limitations—results are limited to the case studies of relationships between academic HPC centres and SMEs working in automotive or electronics industries in the Danube region. However, the results still can serve as the cases of deep knowledge and guidance for future work. Apart from the sample size, another major limitation of the study is in the age of collected data. Since 2017, many world-changing events took place; however, the field of U-I collaboration within the scope of key enabling technologies (HPC included) has not changed much let alone change the main findings of the present paper.

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Microfinance's digital transformation for sustainable inclusion

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Abstract

Purpose – The purpose of this paper is to evaluate the performance of Microfinance Institutions (MFIs) offering FinTech services. This study contributes to the existing literature on microfinance digitalization, financial inclusion and sustainable development. The study also takes into consideration a behavioral perspective through the efficiency evaluation process of MFIs offering FinTech services.

Design/methodology/approach – The following study employs the Stochastic Frontier Analysis approach to estimate the operational and social efficiency scores of the 387 MFIs over the period 2005–2019. Then, it tries to consider factors influencing MFIs' efficiency and assess their effects. Hence, two separate models for operation and social efficiency introducing a set of factors, including FinTech proxies and overconfidence proxies, are tested. The first model for operational efficiency uses a random-effects estimator while the second one for social efficiency uses a fixed-effects estimator.

Findings – The results show that innovative MFIs have weaker averages of operational efficiency than non-innovative ones but higher averages of social efficiency. This was justified by the fact that innovative MFIs are more socially oriented. Further, findings of this study depict that the proxies of FinTech affect negatively the level of operational efficiency of MFIs. They also depict a negative relationship between FinTech proxies and the level of social efficiency. These results hold through robustness tests.

Originality/value – The highlight of this study is that it takes heed of the indirect effect of technological innovation on the efficiency of MFIs. It has been proved that it moderates the impact of managerial overconfidence (manifested by excessive risk-taking, viz., high levels of PAR30, LGR and NIM) on the level of both operational and social efficiencies.

Keywords Digital transformation, Financial performance, Social performance, Microfinance institutions, FinTech services

Paper type Research paper

1. Introduction

It has remained evident today that microfinance plays an important role in financial and social inclusion within the ecosystem of many developing countries (Dang and Quynh Vu, 2020). Many efforts have been maintained to guarantee the financial and consequently the social sustainability of the microfinance sector. Efforts or rather objectives such as penetrating financial markets, obtaining regulatory legitimacy and being open to institutional transformation. Far from the spotlight, microfinance institutions (MFIs) have continued to grow, serving millions of people without changing their methods (Benami and Carter, 2021). Financial services play a central role in the functioning of an economy, whether it is a country like the USA or a simple village in Africa.

However, things have started to change and the digital revolution has changed the world so profoundly that it cannot be ignored. The focus and support of the international financial

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inclusion industry have shifted sharply from credit for the poor to innovation in payment methods and delivery channels. Today, we are talking about digital finance (or financial technology, also, inclusive finance or impact finance) and its potential to reach the vulnerable and the unbanked. Many excluded people from the conventional banking system are not excluded from mobile networks and are connected to the digital world. Financial Technology (FinTech) field in the broad sense includes all companies implementing innovative solutions aimed at improving or rethinking the financial sector. The FinTech raises a real enchantment, from insurance technology; to machine learning; to payments; reverse factoring platforms; blockchain-based digital identity solutions; digital micro-pensions; credit market platforms; dematerialized loans; commerce online; artificial intelligence; etc. . . . It is a field that has three golden criteria such as energy, creativity and money trying to bring mass financial services to emerging markets. The poor are at the heart of the equation.

Digital technology could be perceived as a threat to traditional financial markets, especially for MFIs. Since these FinTech startups are creating and offering new financial services that are more cost-efficient and it has the ability to reach more poor and unbanked population. At this stage, a question arises: can this technology alone accomplish this mission? Since digital services are supposed to facilitate access for the poor, how does the dematerialized world communicate with the other world, that of cash, in which most of the poor still live? Technology is obviously part of the solution, but it is only a means. Many have anticipated that FinTech startups will destabilize traditional financial institutions, such as MFIs, but they have faced two fundamental problems: acquiring customers and raising capital. The operators of this new technology must have solid economic models and a perfect understanding of the development conditions in which we evolve, to make a real difference and change the game (Benami and Carter, 2021).

Banks and MFIs retain an essential place in the new landscape of financial services. The needs of the poor are not limited to dematerialized payments and short-term credit. They must be able to save, invest and insure their property. In many respects, MFIs are particularly well-equipped to meet these expectations. However, in our era, being all technological, they must rethink their operating methods. The profile of microfinance clients will change significantly in the coming decades: young people, perfectly mastering new technologies, increasingly educated, and living in urban areas with more defined expectations. As an example, according to the African Development Bank (AfDB), nearly 40% of Africa's population will be between 10 and 29 by 2030, and the literacy rate will have reached 80%. In total, 50% of the African population will live in cities and migratory flows, mostly intercontinental, will be increased. Therefore, better knowledge of the needs of low-income populations and a more competitive microfinance sector are already encouraging operators to innovate. They should continue to expand their product line to meet the needs of their customers and diversify their customer base. There is a real challenge for microfinance operators to place new technologies at the heart of their strategy and their operations.

Many networks, such as Microcred; international FINCA; ACTION; Opportunity international and Procredit are reinforcing their growth by relying on new technological means. ACCION, for example, has become one of the world's leading finTech investors for financial inclusion with products such as payment networks; remittances; loans to Small and Medium Enterprises, etc. . . . MFIs as well are more and more embracing financial technologies in order to enlarge their social outreach and reach more unbanked people. Microfinance banks have already implemented technologies to develop alternative distribution channels such as biometric automated teller machines (ATMs). There are MFIs that have invested in remote and digital distribution channels. In Jordan, microfinance for women moved more than 30% of its loan disbursements to client e-wallets in September 2020, and its clients made 22% of their repayments through remote payment points.

Bancamia had equipped its mobile sales agents in Colombia with a mobile application. These agents used the mobile app to enroll 270,000 clients for government grant payments and process 82% of MFI loan applications since 2019. In Peru, Caja Municipal de Ahorro y Crédito used digital channels to coordinate with clients and reschedule more than 60% of its loan portfolio (Microfinance Barometer, 2019).

Embracing this technology contributes to reducing operational costs and, therefore, allows MFIs to offer low-cost financing for their clients (Dang and Quynh Vu, 2020). According to the Consultive Group to Assist the Poor (Ignacio and Kumar, 2008), digital banking manages to lower costs for banks and financial institutions by over half by reducing operating costs. By reducing operational costs, MFIs can reduce the high-interest rates that they used to charge in order to cover micro-loans administration costs (Benami and Carter, 2021). Furthermore, the lack of reliable data about the financial and transaction history of the poor rural population is a challenge for MFIs. FinTech's embracing will provide MFIs the information about the credit worthiness of borrowers (Ye *et al.*, 2020). Finally, yet importantly, digital transformation and technology adoption will provide MFIs the opportunity to reach more unbanked population and the underserved low-income markets (Dang and Quynh Vu, 2020). Besides, and according to the Microfinance Barometer (2021), MFIs that have invested in remote and digital distribution channels were able to rely on these solutions to reach customers and continue their activities, even when the branches closed in the context of lockdown because of the Covid-19 pandemic crisis.

Academic and research studies regarding MFIs digitalization are very scares and it is mostly do the lack of sufficient data. There is a limited empirical regard to the intervention of financial technology in the microfinance mission of financial and social inclusion. This research aims to fill this gap and contribute to the existing literature on microfinance digitalization, financial inclusion and sustainable development. Toward the limited empirical studies on the financial and social efficiency evaluation of MFIs offering digital banking services. Thus, in our study, we evaluate and compare financial and social efficiency scores of FinTech offering and non-FinTech offering MFIs using the Stochastic Frontier Analysis (SFA) approach. Therefore, our research contributes to the existing literature on microfinance and digitalization and being, as far as our knowledge, the first study to evaluate the operational and social efficiency of MFIs offering mobile banking services using accounting indicators. In addition, the results of our investigation have brought some implications for practitioners, policymakers and FinTech start-ups. Our findings provide evidence for practitioners (MFI management) to improve their efficiency and expand their outreach capacity and, therefore, contribute to the development of the IMF sector. Our revealed results how MFIs have the opportunity to use digital tools to pursue their missions in an increasingly digitalized world. Digitalization offers MFIs the opportunity to reduce operational and administration charges, provide low-cost loans and reach more unbanked populations. Furthermore, our study presents a useful tool for policymakers and confirms that the existing regulation models should incorporate new particularities of digital transformation. It is necessary to review, even define the regulatory scope; license and monitor the digital transition. It is essential to give regulatory bodies the necessary means to face the challenges ahead. As for FinTech start-ups, our findings show some practical implications in the context of the opportunities for fusion projects with MFIs. In order to deal with two fundamental problems, namely, customer acquisition and capital raising and eventually paving the way for many MFIs and helping them to transform from traditional to digital. The remainder of the paper is organized into three parts. Section 2 describes the conceptual framework of the research and presents a brief review of previously published related works. Section 3 introduces the studied data and the pursued methodology. Finally, Section 4 exposes and discusses in detail the revealed results.

2. Literature review

The purpose of the present literature review is to evaluate and synthesize existing research (as provided in Table 1) and eventually conclude with a summary of the key findings and insights.

The new technological financing models have been developed outside the conventional financial system and are seen as a powerful alternative for better financial inclusion. Buchak *et al.* (2018) combined data from Home Mortgage Disclosure Act (HMDA), Fannie Mae and Freddie Mac's single-family loan performance, the Federal Housing Administration 88 (FHA) and US Census between 2007 and 2015. They found that the market share of FinTechs has passed from 3% in 2007 to 12% in 2015, providing loans to less credit-worthy borrowers. Jagtiani and Lemieux (2018) used data from both Lending Club's consumer platform and Y-14 M data reported by US banks during the period 2010–2016 to examine the impact of FinTech lending on credit accessibility of unsecured consumers. The results substantiated that FinTech lenders had a higher market share in areas that are underserved by traditional banks and where the local economy is not performing well. Likewise, Rau (2018), exploring over 3000 crowdfunding platforms, demonstrated that crowdfunding ensured borrowers had greater ease of access to the financial system.

The digital revolution has changed the world so profoundly that it cannot be ignored. The focus and support of the international financial inclusion industry have shifted from credit for the poor to innovation in payment methods and delivery channels. For MFIs to successfully turn these challenges into opportunities, they must be ready for digital transformation. MFIs have the opportunity to use digital tools to pursue their missions in an increasingly digital world. Studies on digital finance and microfinance are still very rare and often fragmented. In this context, Budampati and Raghunath (2018) study the impact of the intervention of information technology in increasing the efficiency and outreach of the microfinance industry in India. Their review shows the opportunities that IT can bring to MFIs; however, the only barrier is the resistance of the Indian rural population to embrace technological change. These conclusions are in accordance with the investigation research conducted by Saon *et al.* (2018) on the Indian MF context as well. However, the authors mention other kinds of barriers, such as inequality compared to big firms in terms of fast and efficient integration of new technologies and digitalization, pointing fingers at three important factors, i.e. regulatory framework, country-specific business climate and skills level of labor force.

A more recent research by Dang and Quynh Vu (2020), studied FinTech services and activities in the microfinance sector and recommend FinTech adoption of MFIs in Vietnam. The authors follow qualitative designed research to evaluate the microfinance sector in Vietnam and suggest instructions and recommendations for the digital transformation of the Vietnamese MFIs. In this sense of digital transformation as well, Mia (2020) empirically conducts a non-parametric investigation where she studies the determinant factors of the introduction of technological change and innovation in Bangladeshi MFIs. The author estimates the Malmquist Productivity Index to distinguish the technical change among the studied MFIs over the 2009–2014 period. The estimation results of the factors determining the technical change index highlight the importance of peer borrowing among MFIs, decentralized branches as well as the geographical location to improve the introduction of the technical innovation.

By analogy with the surveys related to the operational efficiency of banks mentioned above, we assume that the integration of FinTech services will have the same effect on the operational efficiency of MFIs. Thus, the first hypothesis will be as follows:

H1. The integration of FinTech services has a positive effect on the operational efficiency of MFIs

Author and year	Sample and period of study	Key findings
Panel A FinTechs as standalone institutions and technological change within FIs: Impact on operational efficiency		
Budampati and Raghunath (2018)	They studied the evolution of the Indian microfinance industry as well as few relevant studies about its technological transformation	- IT improves the processes of MFIs and ensures enhanced outreach more cost-efficiently - The only barrier is the resistance of the Indian rural population to embrace the technological change
Dang and Quynh Vu (2020)	The authors followed qualitative designed research to evaluate the microfinance sector in Vietnam and to study its technological transformation	- The introduction of FinTech to the microfinance industry leads to better and fast-delivered services, safer and easier access, and most importantly, lower costs. Thus, it enhances the operational efficiency of Vietnamese MFIs - Authors suggest instructions and recommendations for the digital transformation of the Vietnamese microfinance institutions
Fuster *et al.* (2019)	They analyzed FHA Neighborhood Watch Early Warning System (FHA NW) data over the period from 2015 until 2017	- Technological innovation enhanced the financial intermediation's efficiency in the US mortgage market with faster processing (nearly 20% faster than traditional lenders) - This speed does not come at the expense of higher default rates (their default rates are about 25% lower compared to those of traditional lenders) - There is no evidence about the prioritization of marginalized populations
Mia (2020)	The author selected a sample of 169 MFIs from Bangladesh over 2009–2014	The estimation results of the factors determining the technical change index highlight the importance of peer borrowing among MFIs, decentralized branches, as well as the geographical location to improve the introduction of technical innovation
Onay and Ozsoz (2012)	The sample of the survey consists of 18 Turkish banks for the period 1990–2008	The adoption of Internet banking results in important operational efficiency gains
Saon *et al.* (2018)	The paper provides theoretical assumptions	Technology integration is capable of promoting development through innovation, efficiency, and inclusion, however, the process ahead for the sector may face some challenges such as country-specific business climate and skills level of labor force
Wijesiri *et al.* (2017)	They looked at a sample of 420 MFIs operating in different geographic regions around the world for the year 2013	- Age certainly matters: older MFIs, thanks to their experience, tend to outperform younger MFIs. Thus, they are more financially efficient than younger ones, but they are relatively socially inefficient - MFIs with more assets, staff and clients are able to better achieve their financial and social goals. That is to say, larger MFIs, are more likely to have higher financial and social efficiencies - Regardless of age and size, the average efficiency scores for MFIs are low

(*continued*)

Table 1.
Referenced literature and hypotheses

Author and year	Sample and period of study	Key findings
Hypothesis 1: The integration of FinTech services has a positive effect on the operational efficiency of MFIs		
Panel B Technological change for better financial inclusion		
Buchak *et al.* (2018)	They combined data from Home Mortgage Disclosure Act (HMDA), Fannie Mae and Freddie Mac's single-family loan performance, the Federal Housing Administration 88 (FHA), and US Census between 2007 and 2015	The market share of FinTechs has passed from 3% in 2007 to 12% in 2015, providing loans to less credit-worthy borrowers
Cull *et al.* (2007)	They surveyed a sample of 124 MFIs in 49 developing countries for the 1999–2002 period	Both social and financial goals could come together except for the MFIs targeting extremely poor clients
Dorfleitner *et al.* (2019)	They conducted their research for 999 worldwide MFIs over 2012–2017	- Larger commercial MFIs are more likely to adopt mobile technology - Their social mission (depth of outreach) is weakly positively related to the provision of MFS
Ejigu (2009)	They looked at a relatively small sample of 16 Ethiopian MFIs between 2001 and 2007	There is a trade-off between social efficiency in terms of depth of outreach and financial sustainability, more precisely, operational self-sufficiency
Hermes and Lensink (2011)	They relied on a sample of 435 MFIs over the period 1997–2007, giving 1,318 total observations	MFIs with a greater depth of outreach and those with more percentage of women borrowers are less cost-efficient
Jagtiani and Lemieux (2018)	They used data from both Lending Club's consumer platform and Y-14 M data reported by US banks during the period 2010–2016	FinTech lenders had a higher market share in areas that are underserved by traditional banks and where the local economy is not performing well
Kumar and Sensarma (2017)	They examined the efficiency-outreach relation for 75 Indian MFIs over 2004–2014	- They confirmed the trade-off between cost efficiency and reaching the poorer - When it comes to empowering women, there is no such trade-off. MFIs are thereby willing to lend to women as it concomitantly helps to fulfill part of their social mission without damaging their financial sustainability
Rau (2018)	They explored over 3,000 crowdfunding platforms over the period 2005–2015	Crowdfunding ensured borrowers having greater ease of access to the financial system
Serrano-Cinca and Gutierrèz-Nieto (2014)	They based their survey on a large sample of around 1,000 worldwide MFIs between 2006 and 2010	Targeting very poor populations causes severe financial problems for MFIs
Vogeley and Lonbani (2017)	They examined 6 Indonesian MFIs over the two years 2014–2015	Employing mixed qualitative and quantitative methods, findings indicate clearly the positive impact of digital technology growth (particularly mobile money products) on social efficiency growth
Hypothesis 2: The integration of FinTech services improves the scope and scale of the outreach of MFI		
Panel C Overconfidence bias		

Table 1. (*continued*)

Author and year	Sample and period of study	Key findings
Baker *et al.* (2007)	They provided a brief review of the behavioral corporate finance literature limited to the link between corporate financing decisions and profit management	- Overconfident managers are risk-seeker - They (overconfident managers) tend to engage in more low-quality mergers and serious overinvestments - They are prone to more illusion of the control of technologies owned even if they have no knowledge about
Ben-David *et al.* (2007)	They examined the relationship between managerial overconfidence and corporate decision for a large number of US managers who provided 6901 S&P500 forecasts over the period 2001–2007	Overconfident managers tend to engage intensively in risky investments, which may result in a considerable loss of efficiency
Chen and Chen (2012)	They studied a sample composed of 64 banks with overconfident managers, 2 with neutral managers and 70 with non-overconfident managers from 2005 to 2012	Overconfident managers are more likely to take higher credit and insolvency risks
Dietzmann and Alt (2019)	They considered the 100 largest US banks between 2005 and 2015	Technological innovation moderates the risk-bearing for 95% of these banks. This is mainly thanks to novel risk management processes and improved algorithms of risk calculation
Galasso and Simcoe (2011)	They analyzed a panel of 450 large US firms between 1980 and 1994	Overconfident CEOs are more likely to opt for technological changes and to invest significant amounts for the firm's innovation strategy
Hirshleifer *et al.* (2012)	They considered a large sample of 2,577 CEOs from 1771 firms and total firm-year observations of 9,807 during the period between 1993 and 2003	Firms led by overconfident CEOs invest more in innovation
Huang *et al.* (2016)	They based their study on a sample of 4309 US firms over the 6 years between 2006 and 2012	Firms driven by overconfident managers carry a greater level of liquidity risk, which is due to the preference of overconfident managers for short-term debts
Mahdi and Boujelbène (2018)	The focused on 133 FIs (96 conventional and 37 Islamic) of the MENA region for the period 2005–2016	There is a positive relationship between managerial overconfidence and excessive risk-taking as well as cost inefficiency
Skala (2010)	They used a sample of 311 European FIs over 1997-H12008	Overconfidence brings about more risk tolerance

Hypothesis 3: The integration of FinTech services moderates the impact of managerial overconfidence on the operational efficiency of MFIs

Hypothesis 4: The integration of FinTech services moderates the impact of managerial overconfidence on the scope and scale of the outreach of MFIs

Source(s): Authors' own elaboration

Table 1.

Hermes and Lensink (2011) relied on a sample of 435 MFIs during the period over the period 1997–2007, giving 1,318 total observations. They found convincing evidence that MFIs with a greater depth of outreach and those with more percentage of women borrowers are less cost-efficient. A conclusion that Ejign (2009) has already found for a smaller sample of MFIs in Ethiopia between 2001 and 2007. This negative relation led researchers to further investigate this topic. By the same logic, Cull *et al.* (2007) surveyed a sample of 124 MFIs in 49 countries and proved that both social and financial goals could come together except for the MFIs targeting extremely poor clients. Later on, Kumar and Sensarma (2017) examined the efficiency-outreach relation for 75 Indian MFIs over 2004–2014. They confirmed the trade-off between cost efficiency and reaching the poorer. However, when it comes to empowering women, there is no such trade-off. MFIs are thereby willing to lend to women as it concomitantly helps to fulfill part of their social mission without damaging their financial sustainability. Serrano-Cinca and Gutierrèz-Nieto (2014), based on a large sample of worldwide MFIs between 2006 and 2010, proved that targeting very poor populations causes severe financial problems for the MFIs. In such cases, the solution is to focus on gaining more operational efficiency while maintaining their commitment to achieve social goals through the appropriate use of innovative communication technologies. Going further in the MFIs' efficiency debate, Vogeley and Lonbani (2017) examined the impact of digital technologies on the social efficiency of Indonesian MFIs over the two years 2014–2015 and employing mixed qualitative and quantitative methods. Findings indicate clearly the positive impact of digital technology growth (particularly mobile money products) on the social efficiency growth of almost all the MFIs in the sample. Dorfleitner *et al.* (2019) conducted their research for 999 worldwide MFIs to provide a shred of initial empirical evidence about the factors driving the introduction of Mobile Financial Services (MFS [1]). Two key findings interest us: That larger commercial MFIs are more likely to adopt mobile technology and that their social mission (depth of outreach) is weakly positively related to the provision of MFS.

H2. The integration of FinTech services improves the scope and scale of the outreach of MFI

According to Baker *et al.* (2007), the review of the behavioral corporate finance literature highlights that overconfident managers are risk-seeker and that they tend to engage in more low-quality mergers, more serious overinvestments and that they are prone to more illusion of control of technologies owned even if they have no knowledge about. Hirshleifer *et al.* (2012) found that during the period between 1993 and 2003, firms led by overconfident CEOs invest more in innovation. Galasso and Simcoe (2011) analyzed a panel of 450 large US firms between 1980 and 1994. The results showed strong empirical evidence that overconfident CEOs are more likely to opt for technological changes and to invest significant amounts in the firm's innovation strategy. Ravichandran and Zhao (2018) examined a sample of 477 firms from 1999 to 2006. They found that long-term compensations of CEOs incentivize overconfidence and risk-taking behaviors. Obviously, there is a strong interrelation between overconfidence, risk-taking, and efficiency. The starting point is to look into the credit risk in the microfinance industry. Lassoued (2017) found that the credit risk has been significantly reduced with the methodology of group lending and with a higher percentage of women served, i.e. MFIs adopting the welfarist approach (social MFIs) have lower credit risks. This conclusion confirming the creditworthiness of poor customers and efficacy of solidarity credit was based on a sample of 638 MFIs across 87 countries over the period 2005–2015. Overall, the survey proved that social orientation ensures better financial performance thanks to a lower default rate. From a behavioral perspective, the overconfidence cognitive bias of managers has been amply documented in the literature on behavioral corporate finance. Ben-David *et al.* (2007) argued that overconfidence needs to be explicitly reflected when studying managerial decision-making. They examined the relationship between managerial overconfidence and corporate decision for a large number of US managers over the period 2001–2007. The major finding of the survey is that overconfident managers tend to engage intensively in risky investments, which may result in a considerable loss of efficiency. Chen and Chen (2012) studied the effect of managerial overconfidence on banks' risk-taking for a sample composed of 64 banks with overconfident managers, 2 with neutral managers and 70 with non-overconfident managers from 2005 to 2012. They showed that overconfident managers are more likely to take higher credit and insolvency risks. Mahdi and Boujelbène (2018) proved a positive relationship between managerial overconfidence and excessive risk-taking as well as cost inefficiency of FIs (conventional and Islamic) of the MENA region for the period 2005–2016. Same results are concluded in the study conducted by Fersi and Boujelbène (2021) on MFIs. Huang *et al.* (2016) revealed that over the 6 years between 2006 and 2012, firms driven by overconfident managers carry a greater level of liquidity risk is due to the preference of overconfident managers for short-term debts. This empirical evidence was developed based on a sample of 4,309 US firms. Based on a sample of 311 European FIs over 1997-H12008, the survey of Skala (2010) showed that overconfidence brings about more risk tolerance. Dietzmann and Alt (2019) proved that technological innovation for the 100 largest US banks between 2005 and 2015 moderates the risk-bearing for 95% of these banks. This is mainly thanks to novel risk management processes and improved algorithms of risk calculation.

H3. The integration of FinTech services moderates the impact of managerial overconfidence on the operational efficiency of MFIs.

H4. The integration of FinTech services moderates the impact of managerial overconfidence on the scope and scale of the outreach of MFIs.

To close our review, we are going to take the survey of Wijesiri *et al.* (2017) that is meaningful for our study. It investigates the impact of age and size on both financial and social efficiency for a sample of 420 MFIs operating in different geographic regions around the world. The findings confirmed that age certainly matters: older MFIs, thanks to their experience, tend to outperform younger MFIs. Thus, they are more financially efficient than younger ones, but they are relatively socially inefficient. Additionally, results also revealed that MFIs with more assets, staff and more clients are able to better achieve their financial and social goals. These revealed results are in accordance with those concluded by Fersi and Boujelbène (2021), who empirically showed that larger MFIs, are more likely to have higher financial and social efficiencies. Moreover, regardless of age and size, the average efficiency scores for MFIs are low.

3. Sample, data and methodology

This section will be devoted to an exhaustive presentation of the empirical analysis framework. It details the survey's sample and data as well as models that enable the test of research hypotheses.

3.1 Sample selection

The sample taken for our study consists of 387 MFIs from various parts of the globe and with different characteristics (size, age, etc.), of which only 80 MFIs provide FinTech services. Actually, the diversity of our sample reflects the heterogeneity of MFIs and ensures better representativeness and reliability. The MFIs we consider come from 69 underdeveloped countries in South Asia, Eastern Europe and Central Asia (EECA), East Asia and Pacific (EAP), Latin America and the Caribbean (LAC), Middle East and North Africa (MENA) and Sub-Saharan Africa (SSA).

Further, to avoid small-sample associated biases, we focus our analysis on a large period between 2005 and 2019, giving total institutional yearly observations up to 5,805.

3.2 Data description

The full numerical dataset has been collected from the Mix Market portal, which is currently the largest and most reliable database collecting information on MFIs (contains more than 2000 institutions). Almost every research study related to the microfinance sector refers to the Mix Market for the collection of numerical data.

For the current survey, we are using unbalanced panel data combining both social (about outreach and impact) and financial information. From the data extracted and using FinTech proxies, we will be able to test our hypotheses. In fact, the panel or longitudinal data is a combination of cross-sectional [2] and time-series [3] data. It is simply about cross-sectional observations over several periods at regular intervals. A panel is said to be unbalanced if the subjects of the study (individuals, firms, countries, etc.) are not observed over the entire period, which is the case here.

3.3 Models and variables description

The SFA and DEA methods are the most commonly used among researchers aiming to assess the efficiency of FIs. What has been obvious in the existing literature is the absolute majority of surveys about MFIs' efficiency (to the best of our knowledge) have chosen the DEA method. Nevertheless, its weaknesses (namely, its constraint ability to discriminate inefficient DMUs as well as its great sensitivity inherent to the nature of data, the sample size and to the presence of outliers) that can be avoided with SFA have led us to opt for the latter method. The choice of the best-suited method depends on the nature of the data we have as well as the purpose of our study. According to Coelli *et al.* (2005), unlike DEA, the SFA method is appropriate for bigger samples. Further, Hjalmarsson *et al.* (1996) indicated that SFA has an undeniable advantage by ensuring accurate analysis of panel data. Hence, SFA seems to be relevant to the issue and data we had chosen.

(1) Model specification

In this context, specification is about a particular combination of inputs and outputs. In practice, the choice between varieties of possible specifications for all forms of modeling is determined by practical constraints on the data and their analysis. The SFA is no exception; however, the underlying theory is not restrictive in the view of the selection of variables nor the number of variables to be included. Thus, the existing literature, as well as rules of common sense, can serve as a reference for the specification of the model. Obviously, the higher the number of variables included; the less the model is discriminant (a greater number of DMUs are likely to be declared efficient). Therefore, it is appropriate to specify the model with a certain number of variables; so that it would be more discriminant while still allowing for a number of efficient DMUs for making comparisons between pairs. For operational efficiency, we adopted an output-oriented model with multiple inputs and a single output, which is consistent with the characteristics of SFA and in compliance with previous surveys. Namely, we will adopt exactly the same input-output selection of Khan and Shireen (2020). A rigorous selection that includes net operating income as a proxy of operational performance. According to Khan and Shireen (2020), with reference to the definition proposed by the Mix Market, it is the amount an MFI earns from its loan portfolio after the deduction of all operational expenditures. Also, it includes three inputs: total assets, operating expenses and interest expense on borrowings.

(1) Inputs: Total assets, operating expenses and interest expense on borrowings

(2) Output: Net operating income

For social efficiency, we adopted an output-oriented model but with multiple inputs and outputs. We referred to the paper of Efendic and Hadziahmetovic (2017) and that of Lebovics *et al.* (2016) for our inputs-outputs selection.

(1) Inputs: Total assets, number of employees, and financial costs

(2) Outputs: Average loan balance per borrower, number of active borrowers and percentage of female borrowers

At this stage, to complete our estimation models, we are once again facing a choice between different functional forms models: Cobb–Douglas, Translog, CES, etc. The Cobb–Douglas is usually more applied in the literature due to its accuracy and ease of use. Ideally, all the same, it should be chosen for our survey because it accommodates CRS (which is our case) and because it is better adapted for our multi-inputs and multi-outputs selection.

The selection set of factors that could substantially influence the efficiency of MFIs (with reference to the papers of Abdur Rahman and Mazlan (2014) and Khan and Shireen (2020)) as well as the underlying logic to them are well explained in Table 2.

3.3.1 Determinants of operational and social efficiencies. In order to acquire a full understanding of MFIs' operational and social efficiency, we estimate the following regression models that measure the effect of each determinant factor.

MFI specific determinants		
Portfolio At Risk (30 days)	The PAR is a universal proxy for the quality of the loan portfolio. It refers to overdue loans, and it is usually expressed as a percentage of the total loan portfolio	$PAR\,30days = \frac{Loan\ Portfolio\ with\ 30\ days\ arrears\ or\ more}{Total\ outstanding\ loan\ portfolio}$
Size	The size of an MFI is determined by the logarithm of its total assets. According to Khan and Shireen (2020), larger MFIs are more able to achieve significant economies of scale and better efficiency	
Return On Assets (ROAs)	It is an important financial indicator as it informs about the efficacy of using the available assets to generate profits	$ROA = \frac{Net\ operating\ profit\ after\ taxes}{Total\ assets}$
Capital-to-asset ratio	Usually expressed as a percentage, this ratio talks about whether the company's assets are totally financed by its capital	$CAR = \frac{Capital}{Total\ assets}$
Macroeconomic determinants		
Gross Domestic Products	A country-specific macroeconomic variable that counts only for production. The GDP of a country indicates the market value of all finished products and services produced within this country in a year	$GDPG = \frac{GDP_n - GDP_{n-1}}{GDP_{n-1}}$
Overconfidence proxies (referring to Mahdi and Boujelbène (2018))		
Loan growth	It is simply the increase in total loans of the institution, which can be generated by raising their lending (amounts and number of loans) to new customers or existing ones. In fact, loan growth has been broadly studied in the banking literature. It has been mostly associated with heightened credit risk and proved to positively affect the level of inflation	$LGR = \frac{Net\ Loan\ Portfolio_n - Net\ Loan\ Portfolio_{n-1}}{Net\ Loan\ Portfolio_{n-1}}$
Net Interest Margin (NIM)	This ratio is specific to FIs, and it shows how successful the institution is at investing its funds in comparison to the expenses incurred during a given period. It determines the difference between the amounts of interest received on loans granted and the amount of interest paid out to lenders and/or depositors relative to the assets involved to generate these earnings (also called earning assets)	$NIM = \frac{Interests\ earened - interests\ paid}{average\ invested\ assets}$

Source(s): Authors' own elaboration

Table 2. Determinants of MFIs efficiency

$$\text{Operational efficiency}_{ikt} = \alpha_0 + \alpha_1\,\text{OFSDUMMY}_i + \alpha_2\,\text{PAR30}_{ikt} + \alpha_3\,\text{LGR}_{ikt} + \alpha_4\,\text{NIM}_{ikt} + \alpha_5\,\text{SIZE}_{ikt} + \alpha_6\,\text{ROA}_{ikt} + \alpha_7\,\text{CAR}_{ikt} + \alpha_8\,\text{GDPG}_{kt} + \varepsilon_{ikt} \quad (1)$$

$$\text{Social efficiency}_{ikt} = \alpha'_0 + \alpha'_1\,\text{OFSDUMMY}_i + \alpha'_2\,\text{PAR30}_{ikt} + \alpha'_3\,\text{LGR}_{ikt} + \alpha'_4\,\text{NIM}_{ikt} + \alpha'_5\,\text{SIZE}_{ikt} + \alpha'_6\,\text{ROA}_{ikt} + \alpha'_7\,\text{CAR}_{ikt} + \alpha'_8\,\text{GDPG}_{kt} + \varepsilon'_{ikt} \quad (2)$$

To capture the effect of FinTech, we have to extend our models by including the FinTech proxies.

(1) $VTMBNOI = \frac{Value\ of\ Transactions\ via\ Mobile\ Phones}{NOI}$

(2) $VTINOI = \frac{Value\ of\ Transactions\ by\ Internet}{NOI}$

The resulting models are as follows:

$$\text{Operational efficiency}_{ikt} = \alpha_0 + \alpha_1\,\text{OFSDUMMY}_i + \alpha_2\,\text{PAR30}_{ikt} + \alpha_3\,\text{LGR}_{ikt} + \alpha_4\,\text{NIM}_{ikt} + \alpha_5\,\text{VTMBNOI}_{ikt} + \alpha_6\,\text{VTINOI}_{ikt} + \alpha_7\,\text{SIZE}_{ikt} + \alpha_8\,\text{ROA}_{ikt} + \alpha_9\,\text{CAR}_{ikt} + \alpha_{10}\,\text{GDPG}_{kt} + \varepsilon_{ikt} \quad (3)$$

$$\text{Social efficiency}_{ikt} = \alpha'_0 + \alpha'_1\,\text{OFSDUMMY}_i + \alpha'_2\,\text{PAR30}_{ikt} + \alpha'_3\,\text{LGR}_{ikt} + \alpha'_4\,\text{NIM}_{ikt} + \alpha'_5\,\text{VTMBNOI}_{ikt} + \alpha'_6\,\text{VTINOI}_{ikt} + \alpha'_7\,\text{SIZE}_{ikt} + \alpha'_8\,\text{ROA}_{ikt} + \alpha'_9\,\text{CAR}_{ikt} + \alpha'_{10}\,\text{GDPG}_{kt} + \varepsilon'_{ikt} \quad (4)$$

where i indexes MFIs $(i = 1, \ldots, 389)$, t indexes time periods $(t = 1, \ldots, 15)$ and k indexes countries $(k = 1, \ldots, 69)$

Operational efficiency$_{ikt}$: operational efficiency score of the i-th MFI from the k-th country and at the time period t (equation 5)

Social efficiency$_{ikt}$: social efficiency score of the i-th MFI from the k-th region and at the time period t (equation 6)

OFS-DUMMY$_i$: set to 1 if the MFI Offers FinTech Services and to 0 otherwise

PAR30$_{ikt}$: Portfolio At Risk of the i-th MFI at the time period t

LGR$_{ikt}$: Loan growth rate of the i-th MFI at the time period t

NIM$_{ikt}$: Net Interest Margin of the i-th MFI at the time period t

VTMBNOI$_{ikt}$: Value of Transactions via Mobile phone to the Net Operating Income of the i-th MFI at the time period t

VTINOI$_{ikt}$: Value of Transactions by the internet to the Net Operating Income of the i-th MFI at the time period t

SIZE$_{ikt}$: total assets of the i-th MFI at the time period t

ROA$_{ikt}$: Return On Assets of the i-th MFI at the time period t

CAR$_{ikt}$: Capital-to-Asset ratio of the i-th MFI at the time period t

$GDPG_{kt}$: Gross Domestic Products Growth of the k-th country at the time period t

α_n andα'n: Vectors of k unknown parameters to be estimated $(with\, n = 1, \ldots, 10)$

ε_{ikt} and ε'_{ikt}: Random errors that are deemed to be out of the MFI's control

Since we seek to propose a holistic understanding of the impact of FinTech on MFIs efficiency, we have to look at its moderating effect on managerial overconfidence as it could improve the level of efficiency.

3.3.2 FinTech moderating effect on managerial overconfidence. It has long been demonstrated that overconfidence leads managers to excessive risk-taking decisions, which deteriorates the company's efficiency. Hence, if we can prove a moderating effect of FinTech solutions on the overconfidence bias, it will be hugely beneficial.

$$\begin{aligned}\text{Operational efficiency}_{ikt} = {} & \gamma_0 + \gamma_1 \,\text{PAR30}_{ikt} + \gamma_2 \,\text{NIM}_{ikt} + \gamma_3 \,\text{LGR}_{ikt} + \gamma_4 \,\text{VTINOI}_{ikt} \\ & + \gamma_5 \,\text{VTMBNOI}_{ikt} + \gamma_6 \,\text{SIZE}_{ikt} + \gamma_7 \,\text{ROA}_{ikt} + \gamma_8 \,\text{CAR}_{ikt} \\ & + \gamma_9 \,\text{GDPG}_{kt} + \beta_1 \,(\text{PAR}_{ikt} * \text{VTINOI}_{ikt}) \\ & + \beta_2 \,(\text{PAR}_{ikt} * \text{VTMBNOI}_{ikt}) + \beta_3 \,(\text{LGR}_{ikt} * \text{VTINOI}_{ikt}) \\ & + \beta_4 \,(\text{LGR}_{ikt} * \text{VTMBNOI}_{ikt}) + \beta_5 \,(\text{NIM}_{ikt} * \text{VTINOI}_{ikt}) \\ & + \beta_6 \,(\text{NIM}_{ikt} * \text{VTMBNOI}_{ikt}) + \varepsilon_{ikt} \end{aligned} \tag{5}$$

With $\varepsilon_{ikt} = \mu_{ik} + \nu_{ikt}$

$$\begin{aligned}\text{Social efficiency}_{ikt} = {} & \gamma'_0 + \gamma'_1 \,\text{PAR30}_{ikt} + \gamma'_2 \,\text{NIM}_{ikt} + \gamma'_3 \,\text{LGR}_{ikt} + \gamma'_4 \,\text{VTINOI}_{ikt} \\ & + \gamma'_5 \,\text{VTMBNOI}_{ikt} + \gamma'_6 \,\text{SIZE}_{ikt} + \gamma'_7 \,\text{ROA}_{ikt} + \gamma'_8 \,\text{CAR}_{ikt} \\ & + \gamma'_9 \,\text{GDPG}_{kt} + \beta'_1 \,(\text{PAR}_{ikt} * \text{VTINOI}_{ikt}) \\ & + \beta'_2 \,(\text{PAR}_{ikt} * \text{VTMBNOI}_{ikt}) + \beta'_3 \,(\text{LGR}_{ikt} * \text{VTINOI}_{ikt}) \\ & + \beta'_4 \,(\text{LGR}_{ikt} * \text{VTMBNOI}_{ikt}) + \beta'_5 \,(\text{NIM}_{ikt} * \text{VTINOI}_{ikt}) \\ & + \beta'_6 \,(\text{NIM}_{ikt} * \text{VTMBNOI}_{ikt}) + \varepsilon'_{ikt} \end{aligned} \tag{6}$$

where i indexes' MFIs $(i = 1, \ldots, 389)$, t indexes time periods $(t = 1, \ldots, 15)$ and k indexes countries $(k = 1, \ldots, 69)$

Operational efficiency$_{ikt}$: operational efficiency score of the i-th MFI from the k-th country and at the time period t (equation 5).

Social efficiency$_{ikt}$: social efficiency score of the i-th MFI at the time period t (equation 6).

γ_n and $\prime_n$: Vectors of n unknown parameters to be estimated $(with\, n = 1, \ldots, 9)$

β_m and β'_m: Vectors of m unknown parameters that measure the moderating effect of FinTech on the managerial overconfidence bias and the level of risk-taking within an institution $(with\, m = 1, \ldots, 6)$

ε_{ikt} and ε'_{ikt}: Random errors that are deemed to be out of the MFI's control

Now that we have developed our empirical methodology, and before delving deep into the analyses and interpretations of the estimation findings, we must start with the overall statistical descriptions.

4. Descriptive analysis

Descriptive analysis and specification tests are the primary steps for all empirical studies. Indeed, they are crucial to extract useful information from data and prepare it for further analyses. The following will provide more information and details.

The first result to underline in the summary results table is that our dependent variables have low averages with not too high volatilities (lower than 30%), as measured by standard deviations. In fact, given that the efficiency scores are always between 0 and 1 and that the averages of operational and social efficiencies are about (0.4995) and (0.5140), respectively, they are considered low.

The FinTech proxies have the lowest averages (3.0651% for VTINOI and 6.4582% for VTMBNOI); hence, we can conclude the low adoption of FinTech services. Furthermore, the extreme values indicate a broad dispersion, which suggests that these overall averages are driven by only a few institutions. Whereas the growth of MFIs in terms of outreach measured by loan growth rates is increasing with an average of (17.308%), but also with relatively high volatility (36.0851%).

From a sustainability standpoint, the MFIs maintain an average CAR of (24.9222%); namely, three times the minimum required for all FIs, fixed at 8% in accordance with Basel principles. Besides, as it could be expected, MFIs have small sizes with a mean of log assets of (6.3947%).

Concerning their profitability, Table 3 shows an average interest income of (13.602%), as measured by the NIM, whose drawback is that it does not measure the overall profitability of an institution. It neglects the non-interest income, operating expenses and non-performing assets. To gain a more holistic vision, the ROA is satisfactory. The descriptive statistics prove that MFIs in our sample have an average ROA of (1.893%), which implies that they have good profitability. In addition, they have a tolerable risk of default with an average PAR (4.6217%).

From another standpoint, the positive high averages of NIM and LGR, which is about 17.31%, demonstrate the lack of prudence of the MFIs' managers. Finally, the table of descriptive statistics shows a GDPG average of (4.7351%) ranging between a minimum of (−27.9944%) and a maximum of (34.4662%) with a standard deviation of (3.4569%).

This analysis still with no great significance, but rather we need to assess the relationship between the different variables in our models, notably, the correlation coefficients taken in pairs. Generally, ranging between −1 and 1, a coefficient close to 1 implies a strong positive correlation; by contrast, a value close to −1 indicates a strong negative correlation. Briefly and by reference to Table A2, all correlation coefficients are low with few negative ones. Viz., for example, the operational efficiency with the social efficiency and with the FinTech

Table 3. Summary of descriptive statistics

Variable	Observations	Mean	Standard deviation	Min	Max
Operational efficiency	5,805	0.4994736	0.2794661	0.0000571	0.999532
Social efficiency	5,805	0.5140177	0.2154528	0.0004613	0.999531
VTINOI	5,805	0.0306507	1.788659	−39.42664	120.8413
VTMBNOI	5,805	0.0645823	3.050232	−44.8433	196.5598
LGR (%)	5,805	17.307974	36.08507	−148.10836	560.9784
NIM (%)	5,805	13.602005	12.771874	−130.82594	114.9199
PAR30 (%)	5,805	4.62175	9.714166	0	373.18
CAR (%)	5,805	24.922218	23.8403631	−149.79616	147.55436
ROA (%)	5,805	1.8929612	8.621921	−123.11	158.9435
SIZE	5,805	6.394725	2.636033	0	9.908261
GDPG (%)	5,805	4.735132	3.456964	−27.99444	34.46621

Source(s): Authors' own elaboration

proxies. As these coefficients highly depend on the sample size, we can use correlation tests that allow measuring the significance of the correlation [4].

Evidently, the impacts of all control and explanatory variables on the operational and social efficiencies will be fully considered hereafter, but before, it is quite important to analyze the correlation between these variables (explanatory and control). This correlation analysis will help us better understand the relevance of the selected attributes and make sure whether moderation really exists.

At first glance, we notice a positive significant correlation between VTINOI and VTMBNOI. It is as if they come as a package. Further, the directions of correlation to all control variables (captured by the signs of coefficients) are the same for both FinTech proxies. That is to say, the two proxies move in the same direction for each control variable.

The positive correlations to LGR indicate that the more MFIs offer financial services via technological channels, the more they enhance their outreach to new and current customers. However, the correlation is only significant for VTINOI, which leads us to conclude that the Internet channel is better suited and preferred for loan application processes.

Positive, weak and insignificant correlations to NIM prove that opting for a technological change slightly improves the level of NIM for MFIs. Referring to the previous statement, we can say that FinTech channels could really help to reach new customers, but maybe not at lower costs.

Similarly, the correlations to PAR30 are also positive, weak and insignificant, which means that relying more on FinTech services causes a weak deterioration of the quality of the loan portfolios. If we will presume that FinTech channels increase the ease of access to financial services (including loans) for marginalized populations, then these positive correlations could be fully explained.

For the SIZE variable, the correlations are positive and insignificant, too. They indicate that MFIs are able to benefit from technological changes to expand their activity, reach more clients and grow.

Finally, there are negative, weak and insignificant correlations to both; CAR and ROA, suggesting that MFIs offering FinTech services have lower profitability and that they rely more on current liabilities to finance their operations.

It is really worth mentioning that correlation does not mean necessarily causation especially when it is not significant.

5. Results and interpretations

This section provides the analysis and interpretation of the econometric results obtained from our models allowing us to respond to the problem posed in this thesis, which is mainly to know the impact of the integration of FinTech services within MFIs on their operational and social efficiency.

5.1 Operational and social efficiency scores

Referring to Table 4, the averages per year show that non-innovative MFIs have greater operational efficiency than those offering FinTech services for almost the whole period (12 years out of 15), which does not comply with our expectations. It is noteworthy to mention that even for the three years (2012, 2014 and 2019) when the operational efficiency of innovative MFIs exceeds that of non-innovative ones, the differences are too weak. By contrast, the differentials are sufficiently high when they are in favor of non-innovative MFIs especially, for the years 2009, 2010 and 2015. During these years, the operational efficiency of MFIs offering FinTech services dropped to its lowest levels.

Table 4.
Operational efficiency scores

	MFIs offering FinTech services							MFIs non-offering FinTech services						
	Africa	EAP	EECA	LAC	MENA	SA	Av per year	Africa	EAP	EECA	LAC	MENA	SA	Av per year
2005	0.41	0.37	0.59	0.52	0.23	0.70	0.47	0.50	0.46	0.51	0.52	0.51	0.54	0.51
2006	0.51	0.46	0.52	0.49	0.28	0.46	0.45	0.53	0.42	0.52	0.52	0.53	0.45	0.50
2007	0.59	0.49	0.53	0.47	0.20	0.50	0.46	0.64	0.44	0.40	0.55	0.52	0.55	0.52
2008	0.52	0.35	0.54	0.47	0.19	0.29	0.40	0.44	0.51	0.48	0.48	0.46	0.50	0.48
2009	0.42	0.30	0.50	0.46	0.16	0.49	0.39	0.54	0.50	0.45	0.51	0.59	0.46	0.51
2010	0.55	0.36	0.15	0.41	0.31	0.52	0.38	0.52	0.40	0.55	0.47	0.65	0.55	0.52
2011	0.51	0.44	0.56	0.41	0.49	0.49	0.48	0.51	0.38	0.49	0.49	0.60	0.46	0.49
2012	0.61	0.41	0.64	0.43	0.83	0.42	0.56	0.48	0.45	0.41	0.51	0.53	0.49	0.48
2013	0.40	0.39	0.44	0.42	0.45	0.53	0.44	0.55	0.46	0.46	0.53	0.60	0.50	0.52
2014	0.59	0.34	0.69	0.47	0.59	0.42	0.52	0.42	0.53	0.42	0.49	0.59	0.49	0.49
2015	0.42	0.38	0.46	0.42	0.36	0.52	0.43	0.52	0.52	0.50	0.43	0.61	0.45	0.51
2016	0.49	0.63	0.40	0.52	0.50	0.56	0.52	0.60	0.55	0.54	0.46	0.63	0.51	0.55
2017	0.44	0.38	0.43	0.44	0.31	0.60	0.43	0.56	0.41	0.49	0.47	0.58	0.45	0.49
2018	0.45	0.36	0.55	0.46	0.48	0.65	0.49	0.56	0.47	0.41	0.52	0.63	0.50	0.52
2019	0.60	0.60	0.59	0.60	0.59	0.59	0.60	0.59	0.59	0.59	0.60	0.60	0.57	0.59
Av by region	0.50	0.42	0.51	0.46	0.40	0.52	Av by region	0.53	0.47	0.48	0.50	0.57	0.50	

Source(s): Authors' own elaboration

It must be emphasized that the geographical distribution of our sample matters and that the significant deterioration of innovative MFIs' operational efficiency may coincide with times of disruption for the regions where the majority of innovative institutions in our sample come from. Thus, in such cases, the interpretation of the above observations must take account of the financial and economic context of these regions. For that reason, please note that the scores of efficiency by country proving the relevance of the regional distribution of MFIs are displayed and detailed in Table A1.

We know that more than 50% of innovative MFIs in our sample are from the LAC region, a very unstable region with successive wars, crises (political, diplomatic, economic, etc.) and very bad relationships between its countries having serious repercussions on all sectors. Moreover, we found that more than 30% of these institutions are in Ecuador, which is the most vulnerable and the less stable country within the region. It went through very rough times during our study period:

(1) 2008–2010, characterized by the famous global crisis of subprime added to the Andean crisis.

(2) 2015 was a year of severe recession and uncertainty.

Looking at the averages by region, we noticed that only the innovative MFIs in South Asia and the EECA regions have greater operational efficiency compared to non-innovative MFIs (not too high differentials). This can be due to the fact that both regions have great expertise in FinTech. In Asia, digital financial systems are highly developed and deeply penetrated, while Europe has a robust, innovative market with very supportive regulations.

Table 5 shows that the scores of efficiencies of both innovative and non-innovative MFIs are so close (nearly the same) with very little lead in favor of MFIs offering FinTech services, except for the year 2016. That year was marked by a superiority of traditional MFIs with a score fairly above that of innovative ones for this same year (0.55 against 0.48), which is the highest level of social efficiency for our sample throughout the entire period. Actually, the distribution of non-innovative MFIs in our sample is too geographically scattered, but still, there is a certain dominance for a few countries in terms of the number of institutions therein. Namely, Peru, Bangladesh and India. They are in the lead of the microfinance industry for the year 2016 (according to the Microfinance Barometer of 2017), and they are among the top social performers. Their mutual specificity is that they all have very high levels of poverty but also a socially engaged microfinance sector.

More importantly, the table above shows that the social efficiency of MFIs has reached significant levels (on average, 0.5) and that it has not fluctuated greatly until 2018. However, during the year 2019, the social efficiency of both innovative and non-innovative MFIs has plummeted sharply, to the lowest level since 2005. Besides, the comparison between operational and social efficiencies of both innovative and non-innovative MFIs indicates that 2019 is a key year. During that year, they both achieved their highest level of operational efficiency and their lowest level of social efficiency. As is reasonably logic to expect, the massive rise that has been known to the microfinance industry during the last years could be at the expense of its social mission if it translates into over-indebtedness or abusive recovery. In that respect, only poor people bear the adverse consequences of this growth.

The averages by region of social efficiency of innovative and non-innovative MFIs across the six regions considered in our sample prove that MFIs offering FinTech services in Africa, EAP and LAC have better social efficiency than non-innovative MFIs in these regions. In fact, this observation is not surprising at all, as we know that they have a priority shift toward social issues and that they were always able to develop or introduce novelty solutions suited to their specificities. In this case, they knew how to take advantage of the deep digital penetration, the high affordability of mobile phones and the great acceptance of technology among their populations for better social performances.

Table 5.
Social efficiency scores

	MFIs offering FinTech services							MFIs non-offering FinTech services						
	Africa	EAP	EECA	LAC	MENA	SA	Av per year	Africa	EAP	EECA	LAC	MENA	SA	Av per year
2005	0.42	0.40	0.63	0.59	0.35	0.54	0.49	0.52	0.38	0.58	0.54	0.44	0.38	0.47
2006	0.40	0.45	0.71	0.62	0.34	0.31	0.47	0.45	0.40	0.56	0.56	0.44	0.36	0.46
2007	0.48	0.43	0.80	0.63	0.36	0.22	0.49	0.51	0.40	0.60	0.56	0.46	0.39	0.49
2008	0.50	0.42	0.75	0.64	0.37	0.40	0.51	0.51	0.39	0.55	0.59	0.42	0.39	0.48
2009	0.53	0.42	0.73	0.62	0.38	0.33	0.50	0.51	0.40	0.61	0.58	0.45	0.42	0.50
2010	0.49	0.42	0.71	0.67	0.38	0.39	0.51	0.51	0.42	0.64	0.58	0.42	0.42	0.50
2011	0.53	0.50	0.73	0.67	0.40	0.34	0.53	0.50	0.44	0.68	0.59	0.52	0.43	0.53
2012	0.58	0.46	0.72	0.63	0.44	0.33	0.53	0.50	0.41	0.69	0.55	0.58	0.39	0.52
2013	0.56	0.55	0.71	0.63	0.43	0.34	0.54	0.50	0.38	0.69	0.56	0.60	0.40	0.52
2014	0.52	0.59	0.46	0.65	0.42	0.33	0.50	0.47	0.42	0.66	0.55	0.61	0.41	0.52
2015	0.52	0.60	0.48	0.62	0.43	0.33	0.50	0.51	0.47	0.63	0.56	0.56	0.42	0.53
2016	0.56	0.60	0.33	0.64	0.44	0.31	0.48	0.51	0.48	0.69	0.51	0.66	0.42	0.55
2017	0.65	0.60	0.48	0.68	0.46	0.24	0.52	0.48	0.46	0.61	0.57	0.64	0.42	0.53
2018	0.60	0.45	0.50	0.65	0.47	0.32	0.50	0.48	0.46	0.63	0.56	0.58	0.42	0.52
2019	0.42	0.42	0.42	0.42	0.42	0.38	0.45	0.42	0.42	0.42	0.41	0.42	0.42	0.42
Av by region	0.52	0.49	0.61	0.63	0.41	0.34	Av by region	0.50	0.42	0.62	0.55	0.52	0.41	

Source(s): Authors' own elaboration

It can be clearly noticed that FinTech services offering does not ensure better social and operational efficiency at once. It is as if they are mutually exclusive. For each region, where MFIs offering FinTech services have greater social efficiency compared to those that do not offer FinTech services, they have lower operational efficiency and vice versa. The only exception to that is MENA since it has very low averages of operational and social efficiency for MFIs offering FinTech services. This can be due to its lack of expertise in FinTech.

5.2 Determinants of operational and social efficiency

The specific impact of each of the explanatory variables on the operational and social efficiency of MFIs will be observed on the various regressions (Models 5 and 6), the key results of which are summarized in the following tables.

Looking at the results summed up in Table 6, the first feature to note is the insignificant impact of the NIM and the VTMBNOI variables on the0020operational efficiency of MFIs in our sample. Hence, we cannot consider their impact

The PAR30, SIZE, ROA, CAR and the OFS-DUMMY have a highly significant negative impact on the operational efficiency of MFIs (they are all significant at 1%). The negative coefficient for PAR30 is congruent with our expectations and with several anterior studies (Bassem (2012), Kulkarni (2017) and Navin and Sinha (2020)), proving that it poses a serious obstacle to the profitability and operational efficiency of MFIs. Concerning the sign of coefficient capturing the relationship between the MFIs' size and their operational efficiency, there have been mixed results. The coefficient displayed by our regression is consistent with the surveys of, e.g. Bassem (2008), Efendic and Hadziahmetovic (2017) and Johan (2019). Actually, it can be explained by the fact that larger MFIs have a vast number of clients, which makes the due diligence mission harder and, thus, a higher level of risk taken. Further, it is too hard to satisfy the specific needs of each of them individually. For the ROA and the CAR, our results contradict the majority of researchers that have proved a positive correlation of these variables with the operational efficiency of FIs. In fact, according to the results in Table 6, they have weak impacts in terms of the absolute value of coefficients but, still statistically significant for our model. An acceptable explanation for these negative relationships is that internally generated funds, as well as equity financing, can lead to more agency problems, as managers, in such instances, are willing to invest more in inefficient projects (in compliance with the agency theory).

The LGR has a positive impact on the operational efficiency of MFIs, significant at 5%. This is compliant with the results of Kwan and Eisbens (1997), indicating that moderate LGRs, up to a certain level [5], are positively related to the operational efficiency of FIs. The GDPG as a macroeconomic determinant is negatively related to the efficiency of MFIs, significant at 10%. This negative relation was confirmed in, e.g. Bolt *et al.* (2012), Combey and Togbenou (2017) and Khrawish (2011). Concerning the second proxy of FinTech, contrary to our expectations, our results reveal a negative impact, statistically significant at 10%, with an absolute value of the associated coefficient of 0.0081659 (slightly different from zero). This means that an increase of one unit in the VTINOI translates into a decrease of 0.0081659 in the score of operational efficiency of MFIs. Actually, some studies from the banking literature looked at the impact of technology investments on the financial and operational performance of banks and found a negative relationship. Khrawish and Al-Sa'di (2011), Malhotra and Singh (2009) and Willy and Obinne (2013) explained such a negative relationship by the very high expenses and costs associated with the integration and the execution of these services.

To recapitulate, the findings from Table 6 prove that the integration of mobile phone financial services does not affect the operational efficiency of MFIs. However, the integration of Internet financial services adversely affects the level of operational efficiency, which does not validate our first hypothesis.

Table 6.
Estimation results for the determinants of operational efficiency

$$\text{Operational efficiency}_{ikt} = \alpha_0 + \alpha_1\,\text{OFSDUMMY}_i + \alpha_2\,\text{PAR30}_{ikt} + \alpha_3\,\text{LGR}_{ikt} + \alpha_4\,\text{NIM}_{ikt} + \alpha_5\,\text{VTMBNOI}_{ikt} + \alpha_6\,\text{VTINOI}_{ikt} + \alpha_7\,\text{SIZE}_{ikt} + \alpha_8\,\text{ROA}_{ikt} + \alpha_9\,\text{CAR}_{ikt} + \alpha_{10}\,\text{GDPG}_{kt} + \varepsilon_{ikt} \quad (3)$$

Var	PAR	LGR	NIM	VTMBNOI	VTINOI	SIZE	ROA	CAR	GDPG	OFS-DUMM	Const
Coef	−0.027	$3.21e^{-7}$	0.0004	−0.002	−0.008	−0.014	$-1.89e^{-7}$	$-2.53e^{-8}$	−0.002	−0.036	0.524
z-Statistic	−3.65***	2.03**	0.03	−1.27	−1.76*	−9.86***	−5.03***	−2.83***	−1.86*	−4.01***	3.51***
Prob	*0.000*	*0.042*	*0.975*	*0.206*	*0.079*	*0.000*	*0.000*	*0.005*	*0.063*	*0.000*	*0.000*

Note(s): The number of stars points to the level of significance (***for 1%, **for 5%, and *for 10%)
Source(s): Author's own elaboration

Table 7 shows a negative linkage between the social efficiency of MFIs and the two FinTech proxies, which is inconsistent with our expectations. However, they are statistically insignificant. Thus, these negative relationships mean nothing to our model.

The PAR30 exerts a strong positive impact on the social efficiency of MFIs (significant at 1%). Unlike its unfavorable impact on MFIs' operational efficiency, a greater level of tolerated risk implies a better focus on the poor and results in a higher financial inclusion. The variable SIZE also has a statistically significant positive impact on social efficiency, contrary to that exercised on the operational efficiency. In fact, larger MFIs are more able to keep meeting their social responsibilities, thanks to the combination of their financial expertise with ongoing investment in enhancing their understanding of the poor problems (Copestake (2007).)

Given that the growth in granted loans is a sort of manifestation of a larger scale of outreach, it is favorable for social efficiency. The above results confirm our expectations, as it shows a positive relationship between LGR and the social efficiency of MFIs. Except a weaker magnitude in terms of the absolute value of coefficients, compared to that of operational efficiency. Further, the same as for the operational efficiency, Table 7 shows a negative impact of GDPG on the social efficiency of MFIs, significant at 1%, but with a higher magnitude. Actually, the GDPG reduces the demand for MFIs' financial services, and thus, the relative importance of MFIs for financial inclusion, which harms their social and operational efficiency (Tan and Floros (2012).)

Considering the OFS-DUMMY variable, it reveals a negative significant relationship with operational efficiency and a positive significant one with social efficiency. This suggests that innovative MFIs (offering FinTech services) are more socially oriented with better social efficiency but operationally inefficient.

Briefly, we cannot decide about the impact of the integration of FinTech services within MFIs on their social efficiency due to the insignificance of coefficients associated with the FinTech proxies.

5.3 FinTech moderating effect on managerial overconfidence

Moderation denotes a change in the magnitude of the impact of an explanatory variable on the explained variable due to a third one, denoted moderator. The existence of moderation can be exhibited by the effect of the product obtained by multiplying the moderating and the independent variables (Zainuddin *et al.* (2020)).

Since the moderating variables selected for our survey are the FinTech proxies, we limit our attention to the institutions offering FinTech services. First, we will estimate our models for operational and social efficiency without neither the FinTech variables nor the moderating variables (OE base model and SE base model). Then, we re-estimate our models with these variables, which are Models **(5)** and **(6)**.

From the first part of Table 8 (on the left-hand side), the OE's base model shows a positive [6] significant impact of PAR30. This finding is contrary to the result observed in Table 6 for the whole sample with no distinction between innovative and non-innovative MFIs, which leads us to say that maybe the innovative MFIs are better at striking a balance between operational efficiency and risk. Also, this first part of the table shows a positive insignificant impact of the LGR and a negative insignificant impact of the NIM on the operational efficiency of MFIs. Whereas Model **(5)** indicates a lower and insignificant coefficient of PAR30, a positive insignificant coefficient of LGR with a lower magnitude, and a positive but insignificant coefficient of NIM.

Indeed, the interaction variables included in Model **(5)** are used to capture the moderating effect of FinTech services on the overconfidence-operational efficiency relationship. The integration of mobile phone and Internet financial services positively moderates the

Table 7.
Estimation results for the determinants of social efficiency

$$\text{Social efficiency}_{ikt} = \alpha'_0 + \alpha'_1\,\text{OFSDUMMY}_i + \alpha'_2\,\text{PAR30}_{ikt} + \alpha'_3\,\text{LGR}_{ikt} + \alpha'_4\,\text{NIM}_{ikt} + \alpha'_5\,\text{VTMBNOI}_{ikt} + \alpha'_6\,\text{VTINOI}_{ikt} + \alpha'_7\,\text{SIZE}_{ikt} + \alpha'_8\,\text{ROA}_{ikt} + \alpha'_9\,\text{CAR}_{ikt} + \alpha'_{10}\,\text{GDPG}_{kt} + \varepsilon'_{ikt} \quad (4)$$

Var	PAR	LGR	NIM	VTMBNOI	VTINOI	SIZE	ROA	CAR	GDPG	OFS-DUMM	Const
Coef	0.002	$7.68e^{-11}$	−0.0001	−0.0003	−0.0004	0.016	$6.34e^{-8}$	$4.53e^{-9}$	−0.003	0.0461	0.415
t-Statistic	3.86 ***	5.61***	−0.38	−0.21	−0.21	10.55 ***	1.60	0.48	−3.06 ***	4.86***	35.97 ***
Prob	*0.000*	*0.000*	*0.705*	*0.837*	*0.835*	*0.000*	*0.109*	*0.630*	*0.002*	*0.000*	*0.000*

Source(s): Authors' own elaboration

Table 8. Estimation results capturing the FinTech moderating effect

	Operational efficiency				Social efficiency			
	OE's base model		Model (5)		SE's base model		Model (6)	
	Coef	Prob	Coef	Prob	Coef	Prob	Coef	Prob
PAR30	0.003346**	0.049	0.000176	0.641	0.003836***	0.000	0.001437***	0.000
LGR	1.75 e^{-11}	0.639	2.50 e^{-12}	0.848	5.99 e^{-12}	0.800	7.80 e^{-11} ***	0.000
NIM	−0.000036	0.842	−0.000039	0.813	9.20 e^{-6}	0.942	−0.000099	0.567
SIZE	−0.0214***	0.000	−0.014012***	0.000	0.224515***	0.000	0.015872***	0.000
ROA	−0.002116	0.154	−1.89 e^{-7} ***	0.000	0.002113**	0.033	5.98 e^{-8}	0.132
CAR	0.000589*	0.095	−2.51 e^{-8} ***	0.005	−0.000892***	0.000	3.17 e^{-9}	0.737
VTMBNOI			−0.009650	0.270			0.005766	0.531
VTINOI			0.009224	0.550			−0.005779	0.722
PAR* VTMBNOI			0.003031*	0.054			−0.003795**	0.023
PAR* VTINOI			0.0021734*	0.051			0.000639	0.589
LGR* VTMBNOI			2.75 e^{-11} *	0.060			−4.70 e^{-11} ***	0.002
LGR* VTINOI			−2.56 e^{-11} *	0.065			8.84 e^{-12}	0.675
NIM* VTMBNOI			−0.150671**	0.041			0.140414	0.197
NIM* VTINOI			−0.142766**	0.019			0.000244	0.998
GDPG	−0.004608*	0.085	−0.001964*	0.064	−0.000135	0.941	−0.003831***	0.001
Constant	0.605508***	0.000	0.498703***	0.000	0.418121***	0.000	0.425749***	0.000

Source(s): Authors' own elaboration

PAR30-OE relationship at level 10%, which means that the level of PAR30 will become more beneficial for MFIs with increased reliance on FinTech services.

The LGR–OE relationship is positively moderated by the integration of mobile phone financial services at 10%. However, it is negatively moderated by the integration of Internet financial services at the same level, which means that the impact of LGR on OE will become less positive. They both having inverse moderating effects, but ultimately the impact of LGR on operational efficiency remained positive and insignificant.

The two FinTech proxies VTMBNOI and VTINOI, negatively moderate the NIM-OE relationship at 5%. This means that the negative effect of NIM on the OE of MFIs with more technological innovations will become more negative. Actually, a very high level of NIM can be due to a twice alternatives. Either high-interest rates charged to clients that damage their repayment abilities and thus, the level of operational efficiency because of excessive default risk, or low-interest rates offered to depositors that prevent them from allocating their funds in such institutions, hence, obliging these institutions to switch to more expensive funding sources. Anyways, these two alternatives lead to the same result (more operational inefficiency), and they are more justified for innovative MFIs as they seek to cover the exceptionally high costs of the integration of FinTech services.

From the second part of Table 8 (on the right-hand side), the SE's base model shows a positive impact of PAR30, LGR and NIM on the social efficiency of innovative MFIs. However, only the PAR30 exercises a significant impact at a 1% level. For the interaction variables, only the PAR*VTMBNOI and the LGR*VTMBNOI are significant at 5% and 1%, respectively. They are both negative, which means that the integration of FinTech services within MFIs limited the overconfidence of managers and relegated the focus on depth of outreach to the background.

The results prove that the integration of FinTech services moderates the impact of overconfidence on the level of social and operational efficiencies, which is compliant with Hypotheses 3 and 4.

5.4 Robustness check

To prove the robustness of the above results, we need to test our models with more variables that could be correlated with MFIs' operational and social efficiencies. For the current study, we assume it would be appropriate to add two control variables, which are capital structure indicators (debt to equity ratio and deposits to asset ratio) and one macroeconomic variable (inflation).

(1) Debt to Equity Ratio (DER): It is considered as a leverage ratio, and it tells the proportional relationship of total liabilities to total equity. The DER reveals the accuracy of the long-term financial policy of an institution.

$$DER = \frac{Total\ liabilities}{Total\ equity} \tag{7}$$

There is no standard rule of decision, but it is about comparing the ratio of an institution to that of others in the same sector. Generally, a high ratio (above 1) may indicate that the institution is more heavily financed through debts, which are expensive funding resources.

(1) Deposits to Assets Ratio (DAR): *"It measures the relative portion of the MFIs total assets that is funded by deposits and gives an informed analysis of the role of deposits as funding source"*.

$$DAR = \frac{Total\ deposits}{Total\ assets} \tag{8}$$

According to the surveys of Cull and C-Kunt (2011) and Muriu (2011), there is a significant positive impact of the DAR on the MFIs' sustainability, and hence, they are required to broaden their deposit offerings. Nevertheless, contrary to the evidence mentioned above, Bogan (2009) found a negative relation between DAR and operational efficiency. He suggested that this is perhaps due to the limited experience of MFIs in terms of deposit-taking activity.

(1) Inflation: As for the GDPG mentioned earlier, it is a yearly country-specific macroeconomic variable. It is the general rise in the prices of goods and services (of daily and common use or even industrial goods) leading to the destruction of purchasing power.

The resulting models are as follows:

$$\begin{aligned}\text{Operational efficiency}_{ikt} = {} & \alpha_0 + \alpha_1\,\text{OFSDUMMY}_i + \alpha_2\,\text{PAR30}_{ikt} + \alpha_3\,\text{LGR}_{ikt} + \alpha_4\,\text{NIM}_{ikt} \\ & + \alpha_5\,\text{VTMBNOI}_{ikt} + \alpha_6\,\text{VTINOI}_{ikt} + \alpha_7\,\text{SIZE}_{ikt} + \alpha_8\,\text{ROA}_{ikt} \\ & + \alpha_9\,\text{CAR}_{ikt} + \alpha_{10}\,\text{DER}_{ikt} + \alpha_{11}\,\text{DAR}_{ikt} + \alpha_{12}\,\text{GDPG}_{kt} \\ & + \alpha_{13}\,\text{INF}_{kt} + \varepsilon_{ikt}\end{aligned} \tag{9}$$

$$\begin{aligned}\text{Social efficiency}_{ikt} = {} & \alpha'_0 + \alpha'_1\,\text{OFSDUMMY}_i + \alpha'_2\,\text{PAR30}_{ikt} + \alpha'_3\,\text{LGR}_{ikt} + \alpha'_4\,\text{NIM}_{ikt} \\ & + \alpha'_5\,\text{VTMBNOI}_{ikt} + \alpha'_6\,\text{VTINOI}_{ikt} + \alpha'_7\,\text{SIZE}_{ikt} + \alpha'_8\,\text{ROA}_{ikt} \\ & + \alpha'_9\,\text{CAR}_{ikt} + \alpha'_{10}\,\text{DER}_{ikt} + \alpha'_{11}\,\text{DAR}_{ikt} + \alpha'_{12}\,\text{GDPG}_{kt} + \alpha'_{13}\,\text{INF}_{kt} \\ & + \varepsilon'_{ikt}\end{aligned} \tag{10}$$

We seek to verify whether the sign and the significance of the independent variables are preserved after extending our models.

Looking at Table 9, the results of Model **(9)** of operational efficiency indicate that for the PAR30 and VTINOI, both the sign and the significance of associated coefficients changed compared to Model **(3)**. Whereas for the NIM, CAR, GDPG and the DUMMY variable, only the level of significance changed. Thus, we can conclude that our Model **(3)** is not too significant as a whole, which the low value of R^2 already confirms. But at least the extended model leads to the same conclusion about the negative impact of the integration of FinTech services on the level of operational efficiency of MFIs. The VTINOI became positive but insignificant so we can neglect its effect. The VTMBNOI kept the same negative effect and it remained insignificant. This negative relationship can be attributed to the poor skills of MFIs in FinTech tools or to the very high costs related to the integration of FinTech services.

From Model **(10)** of social efficiency, all the included variables kept the same $\pm$ sign and the same level of significance, except the CAR which became insignificant (of course compared to Model **(4)**). Again, the robustness check confirms our conclusion about the negative impact of the integration of FinTech services on the social efficiency of MFIs.

	Operational efficiency (9) Coef	Prob	Social efficiency (10) Coef	Prob
PAR30	0.000685*	0.072	0.001443***	0.000
LGR	2.59 e^{-11} *	0.052	6.50 e^{-11} ***	0.000
NIM	0.000024	0.881	−0.000108	0.528
VTMBNOI	−0.001175	0.324	−0.000214	0.865
VTINOI	0.000386	0.849	−0.000268	0.901
SIZE	−0.012349***	0.000	0.013498***	0.000
ROA	−1.86 e^{-7} ***	0.000	5.68 e^{-8} *	0.052
CAR	−2.51 e^{-8} ***	0.005	4.68 e^{-9}	0.620
DAR	−0.000395***	0.006	0.00056***	0.000
DER	−0.000019	0.147	−0.000013	0.349
GDPG	−0.002094**	0.049	−0.003644***	0.001
INF	0.000994*	0.066	−0.000755	0.186
DUMMY	−0.804461***	0.008	0.051059***	0.000
Constant	0.586696***	0.000	0.434119***	0.000

Source(s): Authors' own elaboration

Table 9. Results of robustness check [7]

Indeed, the fact that FinTech services have not proven their promise for enhancing the social efficiency of MFIs in our sample can be due to the reluctance of customers to opt for these services or problems with the network that fails to reach the poorest in rural areas.

6. Conclusion

This study focuses on an issue of vital importance about the integration of FinTech services within MFIs. It aimed at assessing its direct impact on the level of operational and social efficiency of MFIs, as well as its moderating impact on the managerial overconfidence-efficiency relationship.

Actually, this work coincides with exceptional circumstances rendering the microfinance and FinTech industries of paramount role to play. Further, we believe that their future together will be even brighter, faster and sooner. This was a strong motivation and a great inspiration for us to choose this topic.

The chosen analysis framework touches six distinct regions with wide disparities; some are leaders of the microfinance industry, others are leaders of the FinTech industry and the majority are characterized by prevailing poverty and overpopulation. The sample we consider consists of 387 institutions coming from 69 countries, with only 80 among them offer FinTech services. Namely, we name by innovative institutions or offering FinTech services, those who provide financial services via mobile phone or via the internet. In order to verify whether the hope raised is justified, we proposed four hypotheses to be tested based on these worldwide collected data. In the first step, we estimated the scores of efficiencies by region, year and type of MFIs using the SFA_{CD} method. Our findings show that MFIs offering FinTech services are better in terms of social efficiency, but they are not that good in terms of operational efficiency compared to non-innovative ones. Though, it must be noted that whatever the type of the institution and the region where it is located, the scores of both social and operational efficiencies are weak, with averages of 0.514 and 0.499, respectively. Further, our results reveal that FinTech services' integration does not enhance the social and operational efficiency at once, which is quite clear in the correlation matrix since it displays a negative coefficient of correlation between social and operation efficiency. However, this negative relationship is still insignificant.

In a second step, and in order to have a better understanding of the scores obtained, we estimated two separate models (for operational and social efficiency), with 2 FinTech proxies, 2 overconfidence proxies, 4 control variables and 1 macroeconomic variable. The results do not support the first two hypotheses. Then, we extended them a second time to capture the moderating effect of FinTech on the impact of managerial overconfidence on the level of efficiencies. This time, the results confirm our last two hypotheses (H3 and H4).

The last step of our methodology is the robustness check by adding to the first versions of our models (before interaction variables) three more determinants of efficiency. Again, the results support our conclusion, which means that the integration of FinTech services within MFIs does not enhance either their operational or their social efficiency. Besides, the robustness check proves that MFIs offering FinTech services are socially oriented and that the negative impact of the integration of FinTech services is statistically insignificant for both the operational and social efficiency of MFIs, but of a higher magnitude in terms of the coefficients' absolute value for operational efficiency. Finally, we should mention that the descriptive statistics show that the share of transactions via FinTech services in the profit of MFIs is very weak, with an average of VTMBNOI of about 6% vs. only 3% for VTINOI. This leads us to suggest that the rate of the integration of FinTech services within MFIs in our sample is very weak, that the poor are reluctant to opt for these services or that they are not even accessible to them.

6.1 Limitations and perspectives

Although we have tried to conduct a careful study, we note certain limitations, mainly of a methodological nature. First, we encountered a number of problems with data concerning MFIs. In fact, financial and social data are hard to come by, and even the Mix Market provides data with some missing values and some outliers that we tried to eliminate. Second, the choice of the method to use has been revealed to be a daunting task and the SFA with all the advantages it proposes, has its weaknesses. Namely, that it requires the imposition of a specific functional form (production, profit or cost function), and that the inefficiency is assumed to have a half-normal (asymmetric) distribution, which is not only inflexible but also implicitly presumes that most firms are congregated near full efficiency, with a very low probability for high levels of inefficiency. Third, the values of R^2 prove the weak significance of the selected explanatory variables for our models. We should have considered the type of MFIs (whether they are NGOs, Cooperative/credit union, Private Bank, etc.), and we should have segregated between Islamic and conventional MFIs. Finally, this study does not take into consideration of the COVID-19 crisis due to a lack of data, which harms its convenience.

The follow-up to our research work should focus on the inclusion of the COVID-19 crisis period and should distinguish at least between Islamic and conventional MFIs. In addition, it could examine the motivations and perceptions of FinTech services users who are among microfinance customers by using the Technology Acceptance Model (TAM) [8] or Unified Theory of Acceptance and Use of Technology (UTAUT) [9].

Notes

1. *"MFS is broadly defined as the usage of mobile devices with the aim of accessing or utilizing a wide range of transactions, banking activities and information"* (Dorfleitner *et al.*, 2019).
2. When many individuals or firms are observed at the same point of time
3. When the same individuals or firms are observed at various points of time
4. For further details, please check Appendix
5. Depending on the size of the FIs in question
6. Zamore (2021) explained such a result by the fact that the relation between PAR30 and operational efficiency is non-linear, i.e. up to a certain level, an increase in PAR30 (decrease of loan portfolio

quality) improves the operational efficiency of MFIs. In fact, tolerance of an acceptable level of risk reduces the costs of extra efforts of a streamlined selection and monitoring of borrowers as well as costs related to collection activity.

7. To avoid overloading this study and complicating things, we limited our robustness check to only the first part of our work, i.e. the hypothesis 1 and 2 that have been initially rejected. Actually, this result was unexpected, and we need to provide further proof.
8. The TAM was first developed by Davis (1989) and is based on behavioral psychology theories (cognitive dissonance and reasoned action). It is mainly for improving the understanding of individual potential users to opt for new technologies. It presumes that the actual or intention to use technologies depends on their Perceived Usefulness (PU) and Perceived Ease Of Use (PEOU). Venkatesh and Bala (2008) propose a new synthesis with great detail of the prior literature and provide a set of prior and post-implementation interventions, which could improve the acceptance of these technologies.
9. The UTAUT was first proposed by Venkatesh *et al.* (2003) and is based on the TAM and several other theories. It introduced four main variables that are likely to influence the intention to use new technologies. Namely, expected performance, expected efforts, social influence and enabling conditions.

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Appendix

Table A1. Summary of operational and social efficiencies by type of MFIs and region

		Full sample		Sub-sample: Non offering FinTech services		Sub-sample: Offering FinTech services	
Region	Country	Operational efficiency	Social efficiency	Operational efficiency	Social efficiency	Operational efficiency	Social efficiency
Africa	Benin	0.56	0.52	0.57	0.56	0.53	0.35
	Burkina Faso	0.56	0.35	0.56	0.35		
	Cameroon	0.54	0.62	0.63	0.65	0.44	0.60
	Congo	0.50	0.67	0.50	0.67		
	Ethiopia	0.45	0.66	0.45	0.66		
	Ghana	0.59	0.43	0.57	0.43	0.67	0.50
	Kenya	0.52	0.61	0.58	0.62	0.46	0.61
	Madagascar	0.44	0.56	0.46	0.64	0.44	0.53
	Malawi	0.51	0.42	0.50	0.31	0.52	0.47
	MAli	0.56	0.42	0.56	0.42		
	Mozambique	0.46	0.74	0.46	0.74		
	Niger	0.35	0.39	0.35	0.39		
	Nigeria	0.51	0.48	0.55	0.4	0.51	0.51
	Rwanda	0.46	0.44	0.46	0.44		
	Senegal	0.55	0.47	0.55	0.47		
	South Africa	0.42	0.38	0.42	0.38		
	Tanzania	0.60	0.59	0.60	0.59		
	Togo	0.49	0.43	0.49	0.43		
	Uganda	0.52	0.49	0.52	0.48	0.52	0.52
EAP	China	0.55	0.41	0.55	0.41		
	Combodia	0.45	0.46	0.49	0.45	0.33	0.48
	Indonesia	0.48	0.32	0.48	0.32		
	Lao PDR	0.43	0.63	0.43	0.63		
	Papua new guinea	0.46	0.63	0.38	0.67	0.55	0.60
	Philippines	0.45	0.41	0.45	0.42	0.53	0.32
	Samoa	0.48	0.32	0.48	0.32		
	Timor-Leste	0.52	0.36	0.52	0.36		

(continued)

Table A1.

		Full sample		Sub-sample: Non offering FinTech services		Sub-sample: Offering FinTech services	
EECA	Armenia	0.54	0.68	0.57	0.66	0.43	0.76
	Azerbijan	0.49	0.55	0.47	0.55	0.58	0.57
	Bosnia & Herzegovina	0.39	0.75	0.39	0.75		
	Bulgaria	0.57	0.53	0.57	0.53		
	Georgia	0.38	0.73	0.34	0.73	0.43	0.73
	Kazakhstan	0.49	0.48	0.46	0.51	0.58	0.39
LAC	Brazil	0.52	0.59	0.53	0.63	0.51	0.57
	Bolivia	0.48	0.63	0.51	0.57	0.45	0.70
	Argentina	0.53	0.57	0.56	0.70	0.47	0.32
	Chile	0.47	0.60	0.45	0.70	0.50	0.40
	Colombia	0.47	0.61	0.49	0.61	0.41	0.60
	Costa-Rica	0.43	0.38	0.43	0.38		
	Dominican	0.41	0.53	0.44	0.51	0.38	0.57
	Ecuador	0.49	0.64	0.48	0.62	0.50	0.68
	El-Selvador	0.39	0.63	0.39	0.63		
	Guatemala	0.49	0.49	0.49	0.49		
	Haiti	0.55	0.53	0.61	0.51	0.43	0.56
	Honduras	0.53	0.64	0.50	0.66	0.60	0.58
	Jmaica	0.72	0.51	0.72	0.51		
	Mexico	0.53	0.49	0.54	0.45	0.44	0.43
	Nicaragua	0.53	0.56	0.53	0.56		
	Panama	0.52	0.65	0.56	0.64	0.42	0.68
	Paraguay	0.42	0.69	0.33	0.68	0.52	0.70
	Peru	0.49	0.49	0.50	0.48	0.38	0.61
	Venezuela	0.44	0.57	0.44	0.57		

(*continued*)

Table A1.

		Full sample		Sub-sample: Non offering FinTech services		Sub-sample: Offering FinTech services	
MENA	Egypt	0.62	0.49	0.62	0.49		
	Iraq	0.59	0.33	0.59	0.33		
	Jordan	0.51	0.43	0.66	0.61	0.44	0.34
	Lebanon	0.58	0.74	0.58	0.74		
	Morocco	0.51	0.66	0.51	0.66		
	Palestine	0.53	0.45	0.53	0.45		
	Syria	0.55	0.58	0.55	0.58		
	Tunisia	0.32	0.54	0.32	0.54		
	Yemen	0.63	0.55	0.63	0.55		
SA	Afghanistan	0.49	0.41	0.50	0.47	0.47	0.21
	Bangladesh	0.49	0.45	0.48	0.45	0.59	0.29
	India	0.51	0.46	0.51	0.46	0.50	0.29
	Nepal	0.53	0.29	0.53	0.29		
	Pakistan	0.49	0.46	0.49	0.47	0.51	0.41
	Sri Lanka	0.59	0.48	0.59	0.48		

Source(s): Authors' own elaboration

	O.eff	S.eff	VTINOI	VTMBNOI	LGR	NIM	PAR	Cap	ROA	SIZE	GDPG
Operational efficiency	1										
Social efficiency	−0.0026	1									
	0.8438										
VTINOI	−0.0006	0.0047	1								
	0.9663	*0.7188*									
VTMBNOI	−0.0147	0.0014	0.0690								
	0.2639	*0.9123*	*0.0000***	1							
LGR	0.0014	0.0910	0.0367		1						
	0.9153	*0.0000***	*0.0052***	0.0053							
NIM	0.0032	−0.0056	0.0004	*0.6841*	0.0075	1					
	0.8087	*0.6671*	*0.9756*	0.0006	*0.5699*						
PAR	0.0063	0.0731	0.0052	*0.9642*	−0.0063	0.0116	1				
	0.6291	*0.0000***	*0.6915*	0.0032	*0.6294*	*0.3781*					
CAP	−0.0399	0.0063	−0.0009	*0.8076*	−0.0166	0.0133	−0.0042	1			
	*0.0023***	*0.6302*	*0.9439*	−0.0011	*0.2064*	*0.3126*	*0.7499*				
ROA	−0.0530	0.0059	−0.0008	*0.9307*	−0.0137	0.0009	0.0242	0.0653	1		
	*0.0001***	*0.6532*	*0.9535*	−0.0009	*0.2967*	*0.9427*	*0.0655*	*0.0000***			
SIZE	−0.1206	0.1534	0.0169	*0.9426*	0.0127	−0.0071	0.1446	−0.0005	−0.1083	1	
	*0.0000***	*0.0000***	*0.1971*	0.0118	*0.0000***	*0.5894*	*0.0000***	*0.9671*	*0.0000***		
GDPG	−0.0283	−0.0467	−0.0050	*0.3704*	−0.0011	−0.0354	−0.1240	−0.0507	−0.0251	0.0340	1
	*0.0312**	*0.0004***	*0.7072*	−0.0068	*0.3953*	*0.0070***	*0.0000***	*0.0001***	*0.0561*	*0.0095***	

Note(s): **,*indicate values significance at 1 and 5% respectively
Source(s): Authors' own elaboration

Table A2.
Correlation matrix

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Exploring the use of gender-fair language by influencers

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Abstract

Purpose – Explore the use of Gender-Fair Language (GFL) by influencers on Instagram.

Design/methodology/approach – The clustering methodology. A digital Bag-of-Words (BoW) Method called GFL Clustering BoW Methodology to identify whether an inclusive marketing (IM) strategy can be used. Thus, this research has a methodological and practical contribution to increasing the number of marketing technology tools.

Findings – This study is original as it proposes an inclusive digital marketing strategy and contributes with methods associated with digital transfers in order to improve marketing strategies, tactics and operations for inclusive content with a data integrity approach.

Research limitations/implications – Due to the limitations of the application programming interface (API) of the social network Instagram, a limited number of text data were used, which allowed for retrieving the last 12 publications of each studied profile. In addition, it should be considered that this study only includes the Spanish language and is applied to a sample of influencers from Chile.

Practical implications – The practical contribution of this study will lead to a key finding for the definition of communication strategies in both public and private organizations.

Originality/value – The originality of this work lies in its attractive implications for nonprofit and for-profit organizations, government bodies and private enterprises in the measurement of the success of campaigns with an IM communicational strategy and to incorporate inclusive and non-sexist content for their consumers so as to contribute to society.

Keywords Inclusive language (IL), Inclusive marketing (IM), Social marketing (SM), Gender-fair language (GFL), Digital content (DC), Marketing analytics (MA), Marketing technology (MarTech), Digital methods (DMs), Digital marketing (DM), Social networks (SN), Social inclusion (SI), Social diversity (SD)

Paper type Research paper

1. Introduction

Gender Equality (GE) is a significant problem worldwide, and the current pandemic jeopardizes many achievements in health, economy, safety and welfare (UNFPA, 2020). Previous research about Gender-Fair Language (GFL) has established that language is a variable that influences the attitudes, behavior and perceptions of society (De Lemus and

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Estevan-Reina, 2021; Patev *et al.*, 2019; Heilman and Caleo, 2018; Sczesny *et al.*, 2016; Koeser *et al.*, 2015). Other studies show that GFL aims to reduce gender stereotypes and discrimination (Sczesny *et al.*, 2016; Koeser *et al.*, 2015), which is now well established. The measurement of the use of inclusive language (IL) by both Private and Governmental Influencers will assist in improving organizational policies.

The motivation of this study is to contribute to the achievement of Sustainable Development Goal Number 5, Gender Equality (GE), from Social Marketing (SM). In this context, defining DMs for the use of IL becomes relevant to the new consumption of marketing technology (MarTech), i.e. more awareness, inclusion, and a social sense of welcoming and belonging. Defining an inclusive marketing (IM) with DMs implies working with the conviction that the DM communication strategies must promote a social value that requires a change in attitude and behavior throughout society (Lin *et al.*, 2021).

Research on the use of DM and MarTech tools for Decision Support Systems are topics that have been growing in the literature (Humphrey *et al.*, 2021). Studies on the topics now reveal the benefits of using MarTech for performance management related to Customer Experience analysis. Artificial Intelligence (AI), predictive and automated learning analyses incorporate into DM (Kotler, 2021).

The questions research hypothesis as this study answers are: (1) What is the level of use of IL by the Top Instagram Influencers in Chile in 2021? (2) What words allow for determining the minimum degree of use of GFL? (3) What is the relationship between the Top Instagram Influencers in Chile in 2021 and the use of IL in DM?

The study aims to explore the use of GFL by Influencers on Instagram by proposing a Bag-of-Words (BoW) Method called GFL Clustering BoW Methodology to identify whether an IM strategy can be used. Thus, this research has a methodological and practical contribution to increasing the number of MarTech tools.

In practice, this study will help define communication strategies for DMs in public and private organizations to improve the identification of IC in social networks (SN) and can contribute to a more Inclusive Society. In addition, the study provides a methodology that supports teams creating DM by indicating which aspects of Instagram posts may generate stronger or weaker reactions from users, what being an Influencer means in terms of interactions, likes or comments per post, and what this implies in terms of engagement.

The rest of this paper is organized as follows: (2) Theoretical background, (3) Methodology, (4) Implementation of the methodology based on technological architecture, (5) Conclusions, (6) Managerial implications and (7) Limitations and potential future research directions.

2. Theoretical background

This study aims to explore the ways and degree of use of IL by Influencers in their SN (i.e. Instagram) to propose a methodology for digital content (DC) analysis as a tool that, in turn, supports SM analysis. Previous research shows how language is a mediator for the achievement of social inclusion (SI) and social diversity (Tankosić *et al.*, 2021; Piller and Takahashi, 2011). In addition, other authors have established that language is a variable that influences the attitudes, behavior and perceptions of society (De Lemus and Estevan-Reina, 2021; Patev *et al.*, 2019; Heilman and Caleo, 2018; Sczesny *et al.*, 2016; Koeser *et al.*, 2015; Koeser and Sczesny, 2014). The literature has identified a gap in the research of more complex methodologies based on SN information (Nicolas *et al.*, 2018); therefore, this study employs Text Analysis by Data Mining Algorithms (Urrutia *et al.*, 2021) to develop the GFL Clustering BoW Methodology.

2.1 GFL and social engagement (SE)

GE appears to be positively related to GFL or Gender-Inclusive Language (GIL) (Koeser *et al.*, 2015). A Web of Science (WoS) analysis shows 95 documents on the subject, with the first one on GFL, GIL and Gender-Neutral Pronouns (GNPs) published in 1993. In addition, 51% of the papers were produced in the last three years (see Figure 1).

Ample research using different experimental methodologies has confirmed the influence of linguistic forms on the access to mental representations of men and women (CEP-PIE, 2017; Stahlberg *et al.*, 2007). Sczesny *et al.* (2016) conducted a bibliographic review and highlighted the importance of implementing GFL in daily language and using it actively. Another research piece that stands out because of its number of citations is an analysis of the introduction of a third GNP in Swedish (Senden *et al.*, 2015).

Hollebeek (2011) signals that many distinct definitions exist for consumer Brand Engagement (BE). In our study, we are close to the definition of Calder *et al.* (2016), which defines BE as "a multilevel, multidimensional construct that emerges from the thoughts and feelings about one or more enrichment experiences involved in reaching a personal goal" (p. 40). Additionally, there are studies about Social Engagement (SE), such as the ones by Moezzi *et al.* (2017), which propose that SE is a way to understand, communicate and influence others. They recommend it as a data source and creative path toward SE. De Valck *et al.* (2009) believe that SN influences the behavior of its users. The SN theory points out that a human relations network can be bound to human behavior (Granovetter, 2011). Voorveld *et al.* (2018) show that social patterns in a Social Media environment enhance SE.

Commitment Measures through GFL do not appear in any consulted publications, but there are Measuring Systems in other areas. Buente *et al.* (2020) examined the SE of Betel [1] nut DC on the image-based platform through Instagram posts tagged #pugua. In retrospect, others measured SE by asking participants how likely they would like the post (through a survey) and how facial expression influenced the effects of visual sender presence.

In its most abstract form, predictive models refer to the use of mathematical tools to predict future results based on observed and assumed facts as input variables. Predicting an output includes, for example, future trends in behavior patterns (Iyer *et al.*, 2019).

Nowadays, with the extensive use of Social Media platforms, there are enormous amounts of data that are continuously generated and consumed by users, with valuable information about demographics, tastes, preferences and behaviors, which are the basis of Predictive Models (Bigsby *et al.*, 2019).

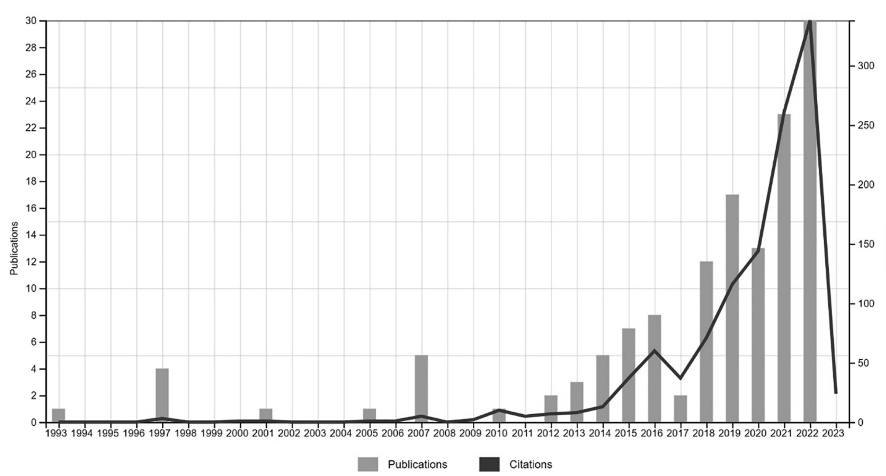


Figure 1.
Publications by year – gender-fair language (GFL)

Source(s): Web of Science (WoS), May 2022

No evidence exists in the literature about Impact Measurement when GFL is used as a DC strategy in SN regarding the SE. However, in recent years, there has been a growing number of papers about Predictive Models based on DC on Twitter – measured through retweets – specifically on sharing tweets inside one's user account. Today's retweet is the old well-known Word-of-Mouth (Ananda *et al.*, 2019). In addition, there is also a Metric to define the effectivity, popularity and influence (Nesi *et al.*, 2019; Scurlock *et al.*, 2020). Hence, knowing the motivations behind a retweet can be complex, but connecting with a Target Audience to know DC and achieve their SE.

Furthermore, a small but growing body of studies applies Predictive Models on Instagram. Some of the models are Neural Network, Convolutional Neural Network and TextCNN (Kumar and Sachdeva, 2021).

Piller and Takahashi (2011) notice that despite the SI becoming a normative framework of general politics, the ways language is used to generate SI have received little attention.

The Sentiment Analysis (SA) considers IL and GE's use levels (Koeser *et al.*, 2015). Sczesny *et al.* (2016) reviewed the literature from the time and found evidence in studies that prove that GFL is almost universal.

2.2 Sentiment analysis (SA) of Twitter data

Nagarajan and Gandhi (2019) conducted a SA with data obtained from Twitter. This study had a sample of 600 million public tweets, and they used opinion mining and automatic SA, proposed method shows a better analysis than others.

The study by Sahayak *et al.* (2015) concluded that the functions related to SN could be employed to predict the sentiment on Twitter. They found that SA for Twitter data varies in difficulty depending on the complexity of the expressions. For example, product reviews are a relatively simple field to analyze, as opposed to tweets about books, movies, art and music, from which sentiment is harder to extract.

2.3 Web data extraction systems for inline business intelligence (IBI)

Grigalis and Čenys (2013) state that nowadays, many customers do their shopping online and publicly share their user experience, opinions and purchase preferences. In most cases, users express their opinion in the form of comments or posts in forums or on SN. Customer SA is fundamental for companies to maintain a competitive advantage in delivering goods and services. Therefore, Inline Business Intelligence (IBI) solutions need access to Facebook, Twitter or any other SN to automatically identify publications about specific products, extract text, execute Natural Language Processing and understand the sentiment expressed by users.

Many big data and business intelligence (BI) software exist; the research uses tools of open access codes. One of them is the open-source Python programming language which was used to web scrape the target website (Bengfort *et al.*, 2018; Cury, 2019). Web Scraping is a technique used for automatic extraction of big data from the Internet, with many advantages: the data extracted are behavioral, the collection of datasets with millions of cases and unknown data extraction (Landers *et al.*, 2016). Another tool used was Pentaho Data Integration, business intelligence platform, which is an open-source and free tool, and its capability is world famous (Li *et al.*, 2021). It offers world-class data integration, online analytical processing (OLAP), data mining, reporting, and Extraction, Transform and Loading (ETL).

Finally, for the visualization of the results and to improve the BI process, we used Microsoft Power BI platform to create a report customized to key performance indicators (KPI) [2].

2.4 Influencers on social networks (SN)

Influencers are people who share their lives through SN and generate some degree of influence on the people who follow them called Followers (De la Piedra and Meana, 2017).

The types of influencers are as follows:

(1) Sector Specialists: They have the intuition to identify the evolutions of the sector and its different trends. They often collaborate with communication companies and organizations from different sectors.

(2) Product Specialists: They have valuable technical training for analyzing products in-depth.

(3) Niche Influencers: They have credibility with their Followers. They often advise companies.

(4) Generalist Influencers: They have Faithful Followers and write about different topics from a critical perspective. They are usually journalists or media professionals.

(5) Trend Influencers: They are specialists in their field, creative and able to revolutionize their fields to create new things.

(6) Occasional Influencers: They are high-ranking people from the cultural and political world.

(7) Reference Influencers: They hit sudden success by creating a company or brand and becoming well known.

The roles of influencers are (1) Inspiring: The Influencers need to be trusted by their Followers. To be considered, reference people in the topic, from whom there is always something new to learn. (2) Collaborator: The Influencers serve their Followers by sharing knowledge on how to stand out in the desired field. (3) Famous Star: The influencers always upload videos or photos depicting what they do at any moment. Part of their charm lies in this characteristic, as this is a way of staying close to their Followers. (4) Amplifier: The influencers are experts whom their Followers can trust. The Influencers have Faithful Followers in their DC. Potential Customers are essential to selling a product. (5) Critic: The Influencers need to know the Followers' opinions about the DC posted on the SN. For example, the purchase decisions to buy a product.

These roles in influencing another person in SN do not need to exist separately but can coexist.

3. Methodology

The GFL Clustering Methodology proposed uses a BoW of IL and non-sexist words (NSW) that we call "ILandNSW language". It may apply to Influencers of any country, not only on Instagram but any other SN like Facebook, YouTube, Twitter, TikTok or others. It has the following stages: (1) Influencer Identification, (2) Data Extraction through a Web Scraping (Landers *et al.*, 2016) code, (3) Transforming and Loading with the Pentaho Data Integration (Li *et al.*, 2021) tool, (4) Language Analysis of a Target Group using IL and NSW written by Influencers on their posts and (5) Data Visualization using the Power BI tool.

This Instagram Clustering Methodology can help

(1) To generate a Data Dictionary with a BoW of the Target Group using ILandNSW.

(2) To identify Conversation Nodes of Influencers and categorize them by the Types of Influencers.

(3) To identify whether a DC by an Influencer is complying with the ILandNSW of the Target Group.

(4) To obtain a Data Extraction process.

(5) To generate a Platform to visualize the Data Extraction process.

The following Set of Stages analyzes Instagram Influencers of any country:

Stage 1: Identifying and Selecting the Influencer Target Group.

Stage 2: Generating a GFL BoW for IL and NSW used by Influencers on Instagram.

Stage 3: Identifying and Extracting Profile and Instagram Data with Web Scraping.

Stage 4: Applying an ETL process with Web Scraping.

Stage 5: Creating, writing and saving the Profile and Instagram Data.

Stage 6: Analyzing the GFL by the Influencer Target Group.

Stage 7: Visualizing the Dashboard generated on Power BI.

Scopes: Concerning the BoW, this was created before the text analysis stage and included words belonging to the Influencer Target Group ILandNSW language. This BoW may grow if new words used in the ILandNSW language studied are discovered.

Concerning the BoW, this was created before the text analysis stage and included a small group of Spanish words belonging to the Influencer Target Group ILandNSW language used in Chile. This BoW may grow if new words used in the ILandNSW language studied are discovered. Adding new lines to the Excel file that stores the BoW and also adding other languages (English, French and so on), creating a new Excel file that stores other languages. Any difficulties you may encounter when doing something similar in another language are resolved by creating a new Excel file that stores the required words in other languages.

4. Implementation of the clustering methodology based on technology architecture

In this section, the results for the application of each proposed stage are shown in detail and the implemented Web Scraping code and dashboard are presented. The results of the same allow for answering the research questions of the study.

Stage 1: Identifying and Selecting the Influencer Target Group

In this stage, www.starngage.com shows the Top Instagram Influencers by country and year. In this study, the Country is Chile and the Year is 2020.

The Target Group is the first ten Chilean Influencers. Table 1 shows the Instagram Data. The parameters considered are Instagram Influencer Name, Followers, Following, Avg. Likes, Avg. Comments, Participation Rate and Total Publication (Posts).

Among these Influencers of the Target Group are Writers, Athletes and people from Entertainment and TV, all classified as Influencers based on their Number of Followers.

As shown in Figure 2, Arturo Vidal (@kingarturo23oficial) is the Influencer with the most significant Number of Followers, with a total of approximately 14 million, corresponding to 34.8% of Total Followers. In contrast, the Influencer with the least Followers is Raquel Calderón, with around two million, corresponding to 4.14% of Total Followers.

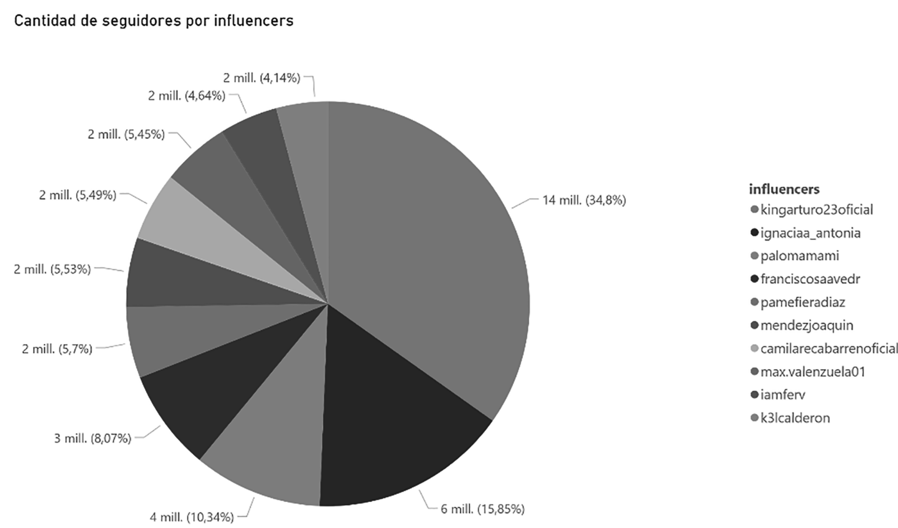
As shown in Figure 3, Accounting has 30% of the Total Followers. Three Influencers have this occupation. The occupations with the least Influencers are Lawyers, Singers and Professional Soccer Players, with one User each corresponding to 10% for each Influencer.

The Number of Followers by the Influencer and The Number of Influencers by Occupation is a Pie Chart Power BI.

Table 1.
Target group Instagram data, ten top Instagram influencers in Chile in 2020 (12/29/2020 www.starngage.com)

Instagram influencer name	Followers	Following	Avg. likes	Avg. comments	Participation rate	Total publication
@kingarturo23oficial	14,072,974	362	323,853	1,993	2.3%	1,719
@ignaciaa_antonia	6,411,946	272	618,341	8,181	9.70%	539
@palomamami	4,180,476	75	668,131	7,602	16,10%	144
@franciscosaavedr	3,264,034	4,740	6,335	134	0.10%	7,832
@pamefieradiaz	2,304,349	358	25,034	708	1.1%	1,872
@mendezjoaquin	2,236,564	3,635	39,119	1,887	1.8%	2,849
@camilarecabarrenoficial	2,219,578	1,271	71,138	357	3.2%	1,885
@max.valenzuela01	2,202,340	131	163,994	841	7.4%	31
@iamferv	1,877,563	423	331,493	5,209	17.9%	223
@k3lcalderon	1,675,004	2,089	33,778	770	2.0%	6,042

Note(s): www.starngage.com shows the Top Instagram Influencers by country and year. In this study, Chile and 2020
Source(s): Authors' elaboration



Source(s): Authors' elaboration

Figure 2.
Pie chart power BI of the number of followers by the influencer

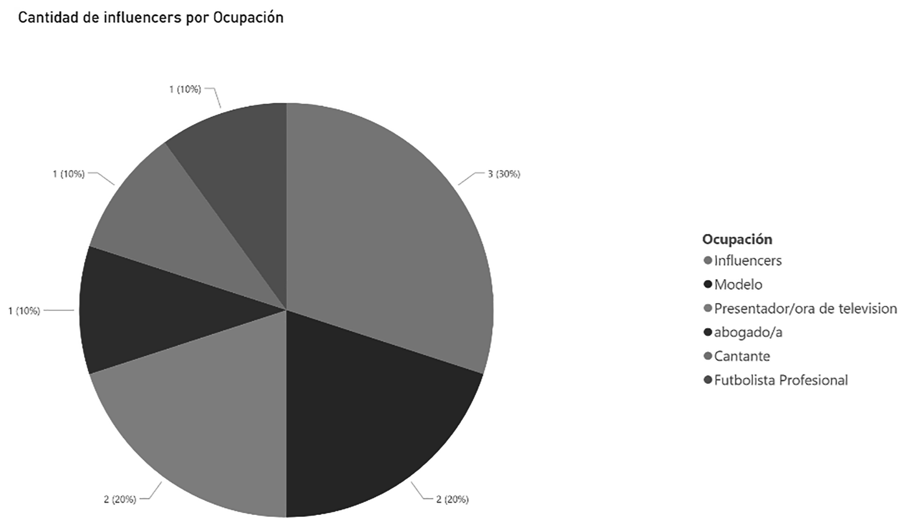
Stage 2: Generating a GFL BoW for IL and NSW used by Influencers on Instagram

In this stage, an Excel file stores the BoW that contains the IL and NSW. The column "Palabras" (Figure 4) is called "ILandNSW_words" in Stage 6.

The Identification of ILandNSW is conducted manually from Literature and comments from Instagram, Facebook and Twitter. Other sources are websites, TV and Newspapers, among others.

Stage 3: Identifying and Extracting Profile and Instagram Data with Web Scraping [3][4].

In this stage, Web Scraping will get the Instagram profile, such as the Instagram Influencer name, publication ID, publication description (what the Instagram Influencer wrote on the post), the number of comments and the number of likes per post (publications) for each Influencer of the Target Group.



Source(s): Authors' elaboration

Figure 3.
Pie chart power BI of the number of influencers by occupation

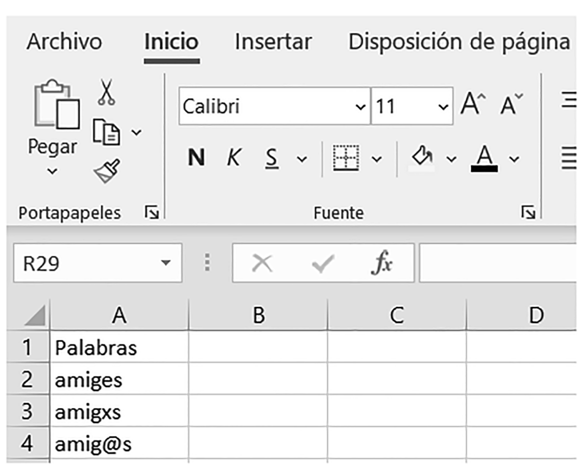
To get a public Instagram profile, a specific JSON (JavaScript Object Notation) URL [5] is implemented, see Figure 4.

The format is

profile = https://www.instagram.com/<instagram_influencer_name>/?__a=1.

In other words, to access a public influencer feed, the URL has a unique < Instagram_ influencer_name > without the parameter @ that characterizes usernames on Instagram, and the parameter?_a = 1 to read all the Instagram Influencer posts. Table 2 shows the Instagram Influencer Name and the unique JSON URL for each Influencer of the Target Group.

Stage 4: Applying an ETL process with Web Scrapping



Source(s): Authors' elaboration

Figure 4.
Excel file BoW (bag-of-words) that contains the inclusive language (IL) and Non-sexist words (NSW)

In this stage, the JSON library, REQUESTS library and CSV (Código Seguro de Verificación) library extract, transform and load the profile and Instagram data for each Influencer of the Target Group using Web Scrapping. The JSON format structure to browse the "Instagram_data_not_clean" file is shown in Figure 5.

The Python Code (Figure 6) starts with import json, import requests and import csv. The array tags contain the Instagram Influencer names (see Table 2), and the array keys contain the Instagram profile.

The Instagram profile extraction from the JSON file considers the following parameters: id (Publication ID), owner (Instagram Influencer name), edge_media_to_caption [6] (text), edge_media_to_comment [7] (count) and edge_like_by [8] (count).

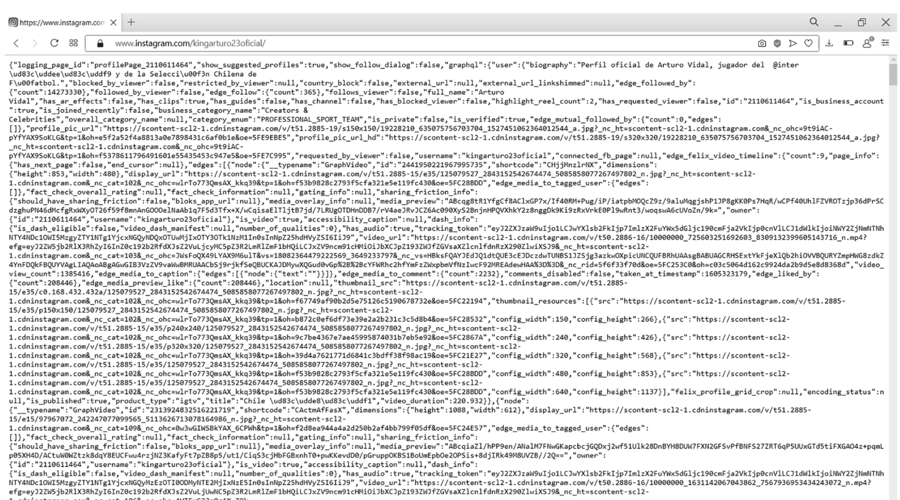
The Instagram data extraction from the JSON file considers the following parameters: "graphql", "user", "edge_owner_to_timeline_media", "edges" and "node".

The WRITER function csv.writer(Instagram_data_not_clean) [9][10] converts the Instagram data into a delimited strings chain with a write( ) method that writes on the CSV[11] called "Instagram_data_not_clean.csv". Therefore, once the file is created or opened, the function csv.writer( ) is employed to deliver a writer object that transforms user data into a delimited chain of characters.

Table 2. Instagram influencer name and JSON URL for each influencer of the target group

Instagram influencer name	JSON URL
@kingarturo23oficial	https://www.instagram.com/kingarturo23oficial /?__a = 1
@ignaciaa_antonia	https://www.instagram.com/ignaciaa_antonia /?__a = 1
@palomamami	https://www.instagram.com/palomamami /?__a = 1
@franciscosaavedr	https://www.instagram.com/franciscosaavedr /?__a = 1
@pamefieradiaz	https://www.instagram.com/pamefieradiaz /?__a = 1
@mendezjoaquin	https://www.instagram.com/mendezjoaquin /?__a = 1
@camilarecabarrenoficial	https://www.instagram.com/camilarecabarrenoficial /?__a = 1
@max.valenzuela01	https://www.instagram.com/max.valenzuela01/?__a = 1
@iamferv	https://www.instagram.com/iamferv/?__a=1
@k3lcalderon	https://www.instagram.com/k3lcalderon /?__a = 1

Source(s): Authors' elaboration



Source(s): Authors' elaboration

Figure 5. Shows the instagram influencer URL in JSON format

The function FOR for tag in tags fetches the Instagram profile and the Instagram data from the JSON file writer = csv.writer("Instagram_data_not_clean") for each Influencer of the Target Group through the array tags that sweep the tag and extract each url of Table 2, one by one through the function get_ig_page(url) to then use them in the function "fetches" through the variable ig_data_dict.

The function def get_ig_page(url, session = None) contains two parameters, "url" that returns the content of the page, and "session" [12] that calls the requests.session( ) method and calls the requests GET method session.get(url) that extracts the value of the variable "url", i.e. the content of the Influencer page, and saves it in the variable "response".

The "response.status_code" [13] method saves the value of the status in the variable "response_status_code".

In the function IF if response_status_code = = requests.codes.ok [14]. If the value of the requests status code is equal to the value of the status code, the value of the variable "url" is assigned to the variable "response"; otherwise, the value of "response" remains as None.

The function def fetches(ig_data_dict, writer) contains two parameters, "ig_data_dict" the content of the page and "writer" the JSON file [15]. This function has two IF and one FOR.

In the function IF if ig_data_dict is not None, it calls ig_data_dict.json( ) method that completes the data crawled with graphql keyword.

The requests GET method ig_data_dict.get("graphql", None), data.get("user") and user.get("edge_owner_to_timeline_media", None) extract the values of the attributes "graphql", "user" and "edge_owner_to_timeline_media", which contains an Instagram data fetch parsing, an Instagram Influencer name, and a photo or video. Those values are stored in graphql, user and posts, respectively.

```
{
    'graphql':{
        'user':{
            'edge_owner_to_timeline_media':{
                'edges':[
                    'node':{
                    }
                ]
            }
        }
    }
}
```

Note(s): It is an attribute to fetch Instagram data with queries. A query is a GraphQL Operation that retrieves specific data from the server. The most common way to browse a GraphQL API is to use GraphiQL. GraphiQL is a tool built by Facebook (pronounced "graphical") that makes it easy to explore any GraphQL API. https://hasura.io/learn/graphql/intro-graphql/graphql-queries/
It is an attribute with all the details of photos and videos posted on Instagram.
It is a node containing zero, one, or more publications (photos and videos) on Instagram

Source(s): Authors' elaboration

Figure 6.
JSON format structure ["graphql"] ["user"] ["edge_owner_to_timeline_media"] ["edges"] ["node"] to browse the "Instagram_data_not_clean" file

In the function IF if posts is not None, it calls the requests GET method posts.get("edges",None). To browse "edges", each publication for each Influencer of the Target Group (see Table 2) is contained by a different "node". The Instagram profile extraction starts once inside the "node".

To navigate the posts (publications for each Influencer of the Target Group), the function FOR for post in posts accesses the node for each post iteration.

The variables to grab are id, owner, edge_media_to_caption, edge_media_to_comment and edge_liked_by. In other words, the Publication ID, the Instagram Influencer name, the description of the photo or video posted by the Influencer on Instagram, the number of User comments per post, and the number of User likes per post for each Influencer of the Target Group (see Table 2), respectively.

Below show the Instagram profile extraction process scraping = post.get("node", None).

Instagram Scraping for Id: The function IF if keys = = "id", a variable id stores the Publication ID for each publication. The requests GET method scraping.get(keys) extracts the value of the array keys. The dumps JSON method json.dumps(keys) decodes the value and saves it in the variable id, as shown in Figure 7.

```
import json
import requests
import csv
tags=['kingarturo23oficial','ignaciaa_antonia','palomamami','franc
iscosaavedr','mendezjoaquin','camilarecabarrenoficial','pamefierad
iaz','max.valenzuela01','iamferv','k3lcalderon']
keys=['id','owner','edge_media_to_caption','edge_media_to_comment'
,'edge_liked_by']
writer = csv.writer('instagram_data_not_clean')
for tag in tags:
        url = 'https://www.instagram.com/'+ tag +'/?__a=1'
        ig_data_dict = get_ig_page(url)
        fetches(ig_data_dict, writer)

def get_ig_page(url, session=None):
    session = session or requests.session()
    response = session.get(url)
    response_status_code = response.status_code
        if response_status_code == requests.codes.ok:
        return response
    else:
        return None
def fetches(ig_data_dict, writer):

    if ig_data_dict is not None:
        ig_data_dict = ig_data_dict.json()
        graphql = ig_data_dict.get('graphql', None)
        user = graphql.get('user')
        posts = user.get('edge_owner_to_timeline_media', None)

        if posts is not None:
            posts = posts.get('edges',None)

            for post in posts:
                scraping = post.get('node', None)
```

Source(s): Authors' elaboration

Figure 7.
Python code instagram profile web scraping

Instagram Scraping for Owner: The function IF if keys = = "owner", a variable owner stores the Instagram Influencer name (see Table 2). The requests GET methods scraping.get(keys) and keys.get("instagraminfluencername") extract the values of the array keys and the Instagram Influencer name "instagraminfluencername" in the study. The dumps JSON method json.dumps(instagraminfluencername) decodes the value and saves it in the variable owner, as shown in Figure 8.

Instagram Scraping for Edge_media_to_caption: The function IF if keys = = "edge_media_to_caption", a variable edge_media_to_caption stores the description per post of photos or videos posted by the Influencer on Instagram. The requests GET methods scraping.get("edge_media_to_caption",None), edge_media_to_caption.get("edges", None), edge.get("node", None) and node.get("text") extract the value of the attributes "edge_media_to_caption", "edges", "node" and finally the description of photos or videos posted by the Influencer in the attribute "text". The dumps JSON method json.dumps(edge_media_to_caption) decodes the value and saves the value of "text" in the variable edge_media_to_caption, as shown in Figure 9.

To navigate the edges, the function FOR for edge in edges accesses the "node" for each iteration of edge up to grab "text".

Instagram Scraping for Edge_media_to_comment: The function IF if keys = = "edge_media_to_comment", a variable edge_media_to_comment stores the number of comments per post by the User of photos or videos posted by the Influencer on Instagram. The requests GET methods scraping.get("edge_media_to_comment", None) and edge_media_to_comment.get("count") extract the value of the attributes "edge_media_to_comment" and "count", and save the value of "count", i.e. the number of comments per post, in the variable edge_media_to_comment, as shown in Figure 10.

```
if keys == 'id':
   keys = scraping.get(keys)
   id = json.dumps(keys)
```

Source(s): Authors' elaboration

Figure 8. Instagram scraping for Id. Extraction of the publication ID for each publication

```
if keys == 'owner':
      keys = scraping.get(keys)
      instagraminfluencername = keys.get('instagraminfluencername')
      owner = json.dumps(instagraminfluencername)
```

Source(s): Authors' elaboration

Figure 9. Instagram scraping for owner. Extraction of the instagram influencer name

```
  if keys == 'edge_media_to_caption':
      edge_media_to_caption    =    scraping.get('edge_media_to_caption',
None)
      edges = edge_media_to_caption.get('edges', None)
      for edge in edges:
            node = edge.get('node', None)
            edge_media_to_caption = node.get('text')
            edge_media_to_caption = json.dumps(edge_media_to_caption)
```

Source(s): Authors' elaboration

Figure 10. Instagram Scraping for Edge_media_to_caption. Extraction of the description per post of photos or videos posted by the influencer on instagram

Instagram Scraping for Edge_liked_by: The function IF if keys = = "edge_liked_by", a variable edge_liked_by stores the number of likes per post by the User of photos or videos posted by the Influencer on Instagram. The requests GET methods scraping.get("edge_liked_by", None) and edge_liked_by.get("count") extract the value of the attributes "edge_liked_by" and "count", and save the value of "count", i.e. the number of likes per post in the variable edge_liked_by, as shown in Figure 11.

Stage 5: Creating, writing and saving the Profile and Instagram Data

In this stage, once the profile data id, owner, edge_media_to_caption, edge_media_to_comment and edge_liked_by of the Instagram Influencer Target Group (see Table 2) and data extraction of graphql, user, edge_owner_to_timeline_media, edges and node ends, the Instagram data is created, written and stored in a CSV file, called "Instagram_data_not_clean.csv".

The Python code Instagram Data Web Scraping (see Figure 12) starts with import json, import re and import pandas as pd.

To see the number of data, the number of columns, the data type of each column and the number of nulls of the CSV file, a number of PANDAS functions are necessary, as shown in Figure 12.

The function read_csv("Instagram_data_not_clean.csv") loads the data file in a variable df = pd.read_csv("Instagram_data_not_clean.csv").

The function DataFrame(df) transforms df into a Data Frame and loads it in the variable df = pd.DataFrame(df).

The function df.shape gets the number of rows (registers) and the number of columns (attributes) of the Data Frame.

The function df.info gets the types of data.

The function pd.isnull(df).sum( )) gets the total of null data per attribute.

The results of PANDAS functions: Shape, Info and isNull may be observed in Table 3a and 3b.

No missing data in the "Instagram_data_not_clean.csv" file, but the column Edge_media_to_caption has emojis, extra inverted commas, accents, special characters, uppercase and lowercase. Once all of this is eliminated, the identification is made manually, and the whole column is transformed into lowercase. An Excel file is created called "data_clean.xls".

Therefore, the Instagram profile is saved in a CSV file, not clean, and then cleaned in an Excel file. As shown after the Shape, Info and isNull PANDAS results in Figure 12.

The function open("Instagram_data_not_clean.csv", "w", newline = ") receives the following parameters: a file name, a letter "w" for a file writing and a new line parameter newline = "", to add an empty line, as shown in Figure 13.

```
  if keys == 'edge_media_to_comment':
      edge_media_to_comment  =  scraping.get('edge_media_to_comment',
None)
      edge_media_to_comment = edge_media_to_comment.get('count')
```

Source(s): Authors' elaboration

Figure 11.
Instagram scraping for Edge_media_to_comment. Extraction of the number of comments per post by the User of photos or videos posted by the influencer on instagram

```
if keys == 'edge_liked_by':
    edge_liked_by = scraping.get('edge_liked_by', None)
    edge_liked_by = edge_liked_by.get('count')
```

Source(s): Authors' elaboration

Figure 12.
Instagram Scraping for Edge_liked_by. Extraction of the number of likes per post by the user of photos or videos posted by the influencer on instagram

The WRITEROW [16, 17] function writes items in a sequence, separating them by a comma character. After creating the chain, the writerow( ) function writes "six columns" on the CSV file: "id", "owner", "edge_media_to_caption", "edge_media_to_comment", "edge_liked_by" and "isILandNSWused", for the Publication ID, the Instagram Influencer name, the description of the photo or video posted by the Influencer on Instagram, the number of User comments per post, the number of User likes per post and a numerical attribute isILandNSWused, which is "1" if the publication belonged to the IL and NSW contain in the BoW and "0" if not, for each Influencer of the Target Group (see Table 2), respectively, as shown in Figure 13.

Stage 6: Analyzing the GFL by the Influencer Target Group

In this stage, once the Instagram profile of the Influencer Target Group (see Table 2) is clean and loaded in an XLS file, as well as the BoW that contains the IL and NSW. The two of them, "data_clean.xls" and "BoW.xls", are used as parameters in a function read_excel("data_clean.xls") and read_excel("BoW.xls") that loads the Excel data files in a variable file_clean = pd.read_excel("data_clean.xls") and file_BoW = pd.read_excel("BoW.xls"). And then, it transforms into a Data Frame: DataFrame(file_clean) and DataFrame(file_BoW) that are loaded in the variables df_file_clean = pd.DataFrame(file_clean) and df_file_BoW = pd.DataFrame(file_BoW), respectively, as shown in Figure 13.

Thus, the XLS files contain the clean and lowercase text of the publications per post of the Influencer Target Group "data_clean.xls" (i.e. the Data Frame df_file_clean) and the IL and NSW, the ILandNSW language "BoW.xls" (i.e. the Data Frame df_file_BoW).

A numerical variable called isILandNSWused is defined, which initializes from zero.

The function FOR for i in df_file_clean.index swipes the Data Frame df_file_clean by its index to enter the column "edge_media_to_caption" for each row iteration of i. The value is stored in the variable df_caption_post.

The function IF if nan verifies the result of the function isCaptionPostNull(df_caption_post). If the result is "TRUE", the post contains a "NaN'value" and therefore is ignored since the function re.search( ) cannot process these values. If the result is "FALSE", the function check_ILandNSW(df_file_BoW,df_caption_post) is called, through which a value from one to zero is obtained if this is coincident or not with a BoW in the post. Therefore, the value of the function check_ILandNSW(df_file_BoW,df_caption_post) is assigned to the variable isILandNSWused; otherwise, the value of isILandNSWused remains as 0.

Then, with all the results, the row analyzed is saved through the function writer.writerow( ), as shown in Figure 13.

(a) Results for number of rows (publications) and number of columns (attributes)

Number of rows	Number of columns
120	5

(b) Results for data type and total null data

Attribute	Data type	Total null data
Id	Object	0
Owner	Object	0
Edge_media_to_caption	Object	0
Edge_media_to_comment	Int64	0
Edge_liked_by	Int64	0

Source(s): Authors' elaboration

Table 3. CSV file "Instagram_data_not_clean.csv" Shape, Info and isNull results

```
  import json
  import re
  import csv
  import pandas as pd

  df=pd.read_csv('instagram_data_not_clean.csv')
  df=pd.DataFrame(df)
  df.shape
  df.info
  pd.isnull(df).sum())
  data_not_clean = open('instagram_data_not_clean.csv', 'w',newline='')
  writer = csv.writer(data_not_clean)

writer.writerow(['id','owner','edge_media_to_caption','edge_media_to_commen
t','edge_liked_by','isILandNSWused'])

  file_clean = pd.read_excel('data_clean.xls')
  df_file_clean = pd.DataFrame(file_clean)
  file_BoW = pd.read_excel('BoW.xls')
  df_file_BoW = pd.DataFrame(file_BoW)

  isILandNSWused = 0
  for i in df_file_clean.index:
      df_caption_post = df_file_clean['edge_media_to_caption'][i]
        nan = isCaptionPostNull(df_caption_post)
        if nan:
           isILandNSWused = 0
           pass
        else:
            isILandNSWused = check_ILandNSW(df_file_BoW,df_caption_post)

  writer.writerow([df_file_clean['id'][i],df_file_clean['owner'][i],
df_file_clean['edge_media_to_caption'][i],df_file_clean['edge_media_to_comm
ent'][i],df_file_clean['edge_liked_by'][i], isILandNSWused])

  def check_ILandNSW(BoW, caption_post):
      isBoWinCaptionPost = 0
      for ILandNSW_word in df_file_BoW['ILandNSW_word']:
          if re.search(ILandNSW_word, caption_text):
              isBoWinCaptionPost = 1
          else: pass
      return isBoWinCaptionPost
  def isCaptionPostNull(text):
      return text != text
```

Figure 13.
Python code instagram data web scraping

Source(s): Authors' elaboration

The function def check_ILandNSW(BoW, caption_post) has two parameters BoW and caption_post. The first represents the words belonging to the BoW. The second post was extracted from the Influencer post.

A numerical variable called isBoWinCaptionPost is defined, which initializes from zero. This variable has the function of defining whether there are ILandNSW words from the Data Frame df_file_BoW in the text of the column "edge_media_to_caption" of the Data Frame df_file_clean.

Then, a FOR for ILandNSW_word in df_file_BoW["ILandNSW_words"] sweeps the column "ILandNSW_words" of df_file_BoW["ILandNSW_words"] and extracts each IL and NSW "ILandNSW_word" of them. The function re.search(ILandNSW_word, caption_text) verifies whether that ILandNSW_word is contained or not in caption_text. If ILandNSW_ word is contained, a value of one is assigned to the variable isBoWinCaptionPost; otherwise, the value remains zero. Finally, this function returns the value of the variable isBoWinCaptionPost (0 or 1), as seen in Figure 13.

The function def isCaptionPostNull(text)function verifies whether the text is or not "NaN". As the "NaN" values are not the same as any other value, not even to the same "NaN", one value returns a comparison with itself. If it is equal to itself, it returns a "TRUE", and if not, a "FALSE".

Stage 7: Visualizing the Dashboard generated on Power BI

When the previous step ends and the data analysis is complete, different visualizations are conducted using the tool Microsoft Power BI. These visualizations seek to respond to the different management indicators and observe how data behave. Some of the results of this step are shown below.

The number of publications by language type. To calculate this indicator, the option "pie chart" is used, in which publications that comply or do not with the ILandNSW language are differentiated by percentage. "Inclusive" language type means that the language belongs to the ILandNSW language, while "non-inclusive" means the contrary, as shown in Figure 14.

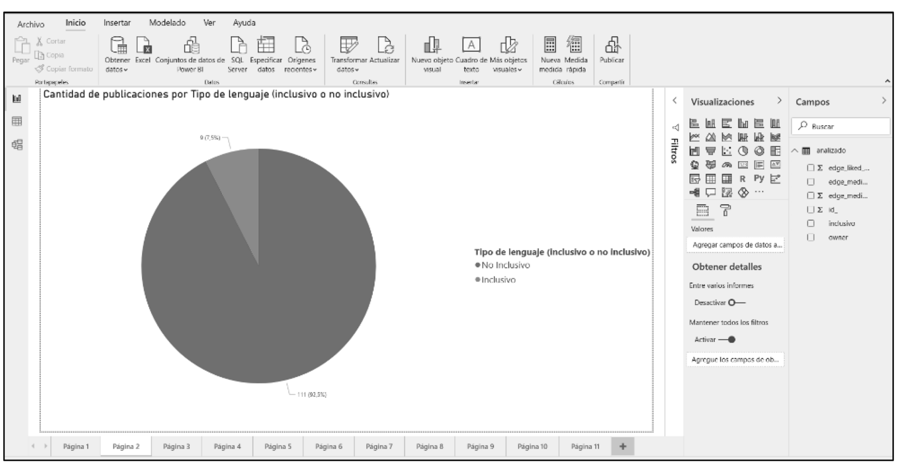
The number of publications by Influencers and language type. The option "grouped bar chart" is employed to calculate this indicator, which shows two columns per Influencer. These columns show the number of publications by language type. The red column represents the publications that do not comply with the ILandNSW language, and the blue is those that comply with it. See Figure 15.

The number of likes. A visualization called "Tarjeta" (card) shows the total number of likes in all publications employed, as seen in Figure 16.

The number of comments. A visualization called "Tarjeta" (card) shows the total number of comments in all publications employed, as seen in Figure 17.

The number of publications. A visualization called "Tarjeta" (card) shows the total number of publications employed, as seen in Figure 18.

Publications with more likes. To calculate this indicator, the option "Table" is employed, which consists of a list with a description written by Influencers on each post, the user who wrote the publication and the number of likes of the same. This list is arranged in decreasing order by the number of likes, as shown in Figure 19.



Source(s): Authors' elaboration

Figure 14. The number of publications by language type

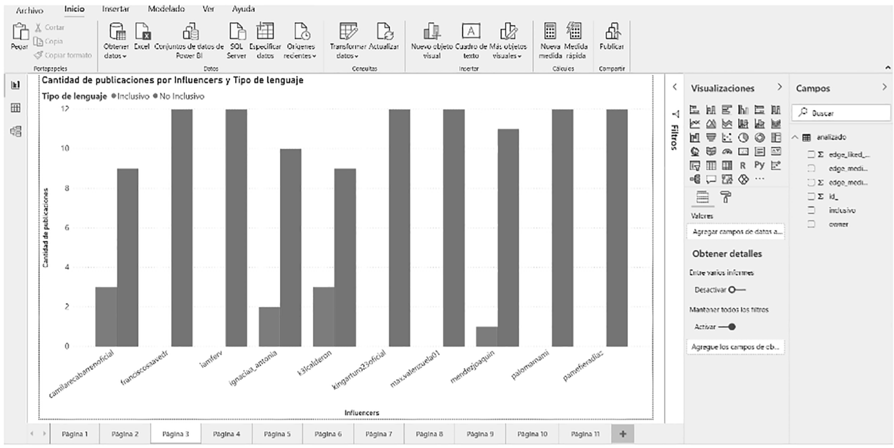


Figure 15. The number of publications by influencers and types of language

Source(s): Authors' elaboration

Source(s): Authors' elaboration

Figure 16. The number of likes

Source(s): Authors' elaboration

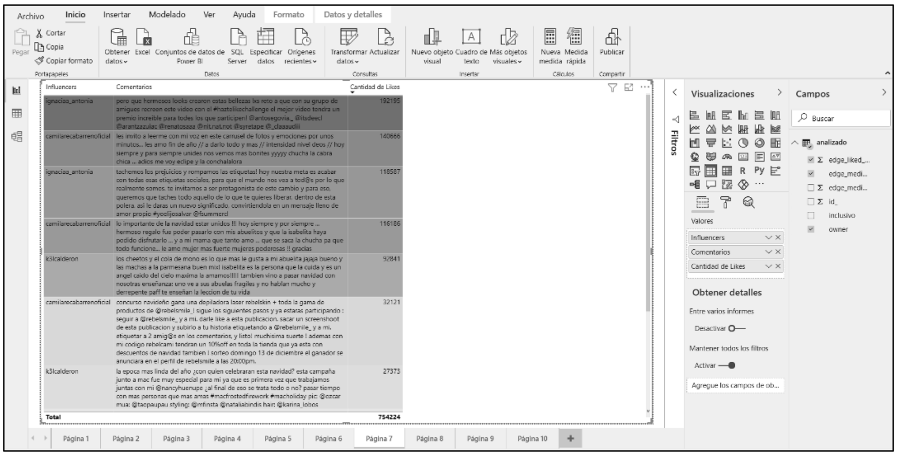
Figure 17. The number of comments

Source(s): Authors' elaboration

Figure 18. The number of publications

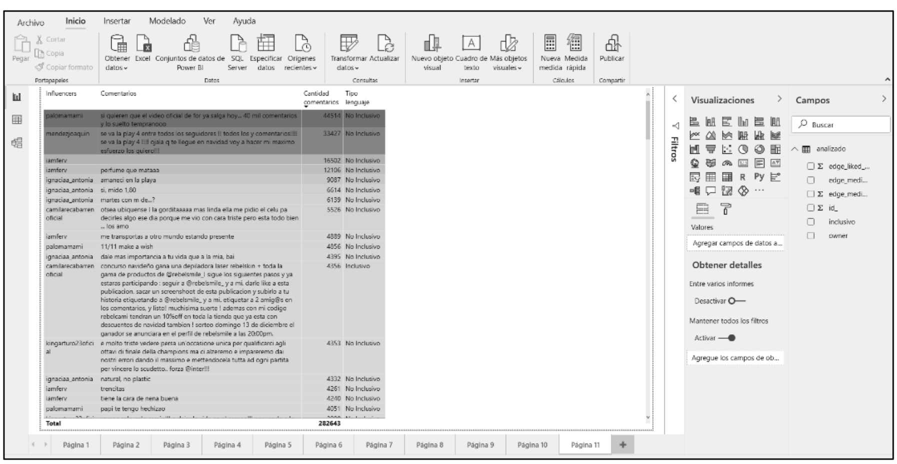
Publication with more comments. To calculate this indicator, the option "Table" is employed, which consists of a list with a description written by Influencers on each post, the user who wrote it and the number of likes of the publication. This list is arranged in decreasing order by the number of comments, as shown in Figure 20.

The number of likes and comments made by Influencers. To calculate this indicator, the option "grouped bar and line chart" is used to show the relationship between the number of likes and the number of comments by an Influencer. See Figure 21.



Source(s): Authors' elaboration

Figure 19. Publications with more likes



Source(s): Authors' elaboration

Figure 20. Publications with more comments

Finally, the dashboard is generated after creating the charts, which aims to provide a global overview of all management indicators analyzed in the study. Figure 22 shows that the dashboard created allows for visualizing the results in such a way that they are more interactive or intuitive and for visualizing the diverse relationships that may exist between data; for example, between the number of likes and comments.

The dashboard contains two panels that allow for implementing filters to constrain data. If a field of these filters is selected, the data supplied to the other charts are automatically constrained to comply with the selected filter. At a glance, the "pie chart" shows a clear difference between the number of publications that meet the ILandNSW language, with only 7.5% of total publications complying with the ILandNSW language under study and 92.5% not complying. Thus, it is concluded that this type of language is not usually employed by Influencers in their publications on the SN Instagram.

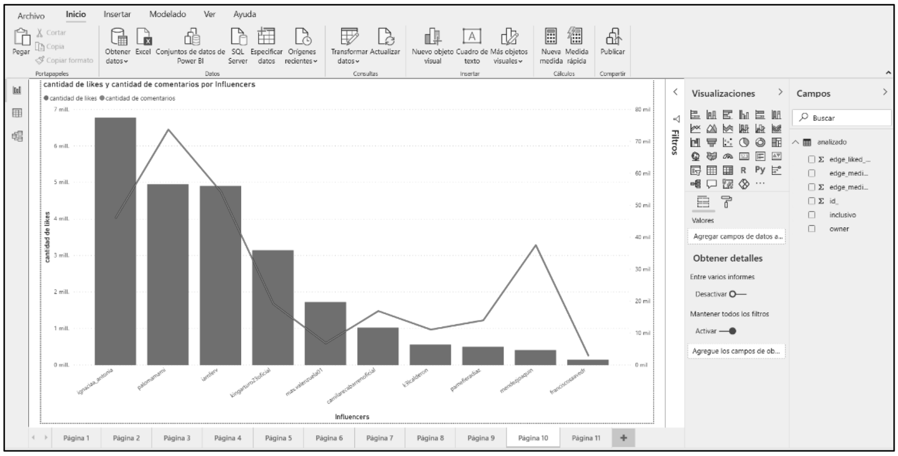


Figure 21.
The number of likes and comments made by Influencers

Source(s): Authors' elaboration

Figure 22.
Dashboard with management indicators analyzed in the study

Source(s): Authors' elaboration

Only four of the ten influencers occasionally use the ILandNSW language under study in their publications. Of these, the ones who use this ILandNSW language the most are Camila Recabarren (@camilarecabarrenoficial) and Raquel Calderón (@k3lcalderon), each of them with three posts, followed by Ignacia Antonia (@ignaciaa_antonia) with two and finally Joaquín Méndez with only one. In addition, of these four influencers, Camila Recabarren declares herself to be a feminist who supports the LGBT movement, but this is not reflected in her publications since more than 50% of her posts do not use IL and NSW.

The top places in the likes ranking are occupied by the posts of Fernanda Villalobos (@iamferv), Ignacia Antonia (@ignaciaa_antonia) and Paloma Castillo (@palomamami). Here, it may be observed that in the top ten rankings, there is no publication using the ILandNSW language under study. Additionally, a clear relationship between the number of likes and the types of language used can be observed: publications without the IL and NSW receive the most likes from followers. If the filter "type of language" is applied. In that case, the top publications for the type of language (belonging or not to the ILandNSW language under study) can be obtained, in which the difference between the number of likes among publications can be observed.

The number one post in the publication's ranking does not belong to the ILandNSW language studied and was written by Fernanda Villalobos (@iamferv), having 1,765,918 likes. In turn, the top publication that contains this language is made by Ignacia Antonia (@ignaciaa_antonia), which has 192,195 likes. Thus, it is clear that there is a significant difference in the number of likes between posts not including and including the ILandNSW language. Meanwhile, it is observed in Figure 23 that the publications with ILandNSW language made by Ignacia Antonia (@ignaciaa_antonia), who has the post belonging to the ILandNSW language with the most likes, have more likes than those without the ILandNSW language studied.

A relationship is also found between the number of comments and the Type of Language: publications with more comments are those not belonging to the ILandNSW language. This can be observed in a ranking similar to the number of likes. As in the previous ranking, if the number of publications belonging to the ILandNSW language under study is analyzed, there is one publication by Camila Recabarren (@camilarecabarrenoficial) with 4,356 comments, while if looking at the ranking of publications not belonging to the ILandNSW language, there is one post by Paloma Castillo (@palomamami) that has 44,514 comments. Therefore, a significant difference in the number of comments between the top post of the different types of language may be observed, as shown in Figure 24.

In sum, more publications must comply with the ILandNSW language, and these publications also have more reactions from Users. Therefore, it is inferred that the use of IL and NSW still needs to be more widespread in the community of the SN Instagram since its use is not constant but only occasional. In addition, the posts (publications) that use the ILandNSW language under study receive little reactions from Users.

Influencers	Comentarios	Cantidad Likes	Tipo lenguaje
ignaciaa_antonia	amaneci en la playa	999868	No Inclusivo
ignaciaa_antonia	volvamos alla?	834323	No Inclusivo
ignaciaa_antonia	martes con m de...?	762131	No Inclusivo
ignaciaa_antonia	si, mido 1,80	745915	No Inclusivo
ignaciaa_antonia	que tengan una linda noche buena	656704	No Inclusivo
ignaciaa_antonia	natural, no plastic	648565	No Inclusivo
ignaciaa_antonia	una sorprendente	620733	No Inclusivo
ignaciaa_antonia	dale mas importancia a tu vida que a la mia, bai	573883	No Inclusivo
ignaciaa_antonia	hoy me hice un picnicdisfrute tanto mi hamburguesa light de vacuno#hamburguesaslacrianza	434516	No Inclusivo
ignaciaa_antonia	pero que hermosos looks crearon estas bellezas lxs reto a que con su grupo de amigues recreen este video con el #haztelikechallenge el mejor video tendra un premio increible para todes los que participen! @antosegovia._ @itsdeecl @arantzazuiac @renatosaaa @nit.nat.not @syretape @_claaaudiii	192195	Inclusivo
ignaciaa_antonia	si quedas atrapada en una isla ¿que harias? #salvajes @primevideolat	189528	No Inclusivo
ignaciaa_antonia	tachemos los prejuicios y rompamos las etiquetas! hoy nuestra meta es acabar con todas esas etiquetas sociales, para que el mundo nos vea a tod@s por lo que realmente somos. te invitamos a ser protagonista de este cambio y para eso, queremos que taches todo aquello de lo que te quieres liberar, dentro de esta polera. asi le daras un nuevo significado, convirtiendola en un mensaje lleno de amor propio #yoelijosalvar @fsummercl	118587	Inclusivo
Total		**6776948**	

Source(s): Authors' elaboration

Figure 23. Likes ranking of Influencer @ignaciaa_antonia

Influencers	Comentarios	Cantidad comentarios	Tipo lenguaje
palomamami	si quieren que el video oficial de for ya salga hoy... 40 mil comentarios y lo suelto tempranooo	44514	No Inclusivo
mendezjoaquin	se va la play 4 entre todos los seguidores !! todos los y comentarios!!!! se va la play 4 !!!! ojala q te llegue en navidad voy a hacer mi maximo esfuerzo los quiero!!!	33427	No Inclusivo
iamferv		16502	No Inclusivo
iamferv	perfume que mataaa	12106	No Inclusivo
ignaciaa_antonia	amaneci en la playa	9087	No Inclusivo
ignaciaa_antonia	si, mido 1,80	6614	No Inclusivo
ignaciaa_antonia	martes con m de...?	6139	No Inclusivo
camilarecabarren oficial	otsea ubiquense ! la gorditaaaaa mas linda ella me pidio el celu pa decirles algo ese dia porque me vio con cara triste pero esta todo bien ... los amo	5526	No Inclusivo
iamferv	me transportas a otro mundo estando presente	4889	No Inclusivo
palomamami	11/11 make a wish	4856	No Inclusivo
ignaciaa_antonia	dale mas importancia a tu vida que a la mia, bai	4395	No Inclusivo
camilarecabarren oficial	concurso navideño gana una depiladora laser rebelskin + toda la gama de productos de @rebelsmile_! sigue los siguientes pasos y ya estaras participando : seguir a @rebelsmile_ y a mi. darle like a esta publicacion. sacar un screenshoot de esta publicacion y subirlo a tu historia etiquetando a @rebelsmile_ y a mi. etiquetar a 2 amig@s en	4356	Inclusivo
Total		**282643**	

Source(s): Authors' elaboration

Figure 24.
Comment ranking of Influencer @palomamami

5. Conclusions

Regarding the Instagram influencers, after the identification and selection stages, only ten influencers from the top Influencers in Chile were identified, which is the critical point in this study. In total, data from 120 publications were extracted: Instagram Influencer name, publication ID, publication description (what the Instagram Influencer wrote on the post), the number of comments and the number of likes per post (publications) were obtained. Then, a numerical attribute isILandNSWused was added, which was "1" if the publication belonged to the IL and NSW and "0" if not.

Concerning the BoW, this was created before the text analysis stage and included words belonging to the Influencer Target Group ILandNSW language. This BoW may grow if new words used in the ILandNSW language studied are discovered. As for language, the BoW is contrasted with the content written by the Influencers to analyze if its words are contained in it.

Regarding the research questions of this study:

What is the level of use of IL among influencers in Chile on Instagram?

With the GFL Clustering Methodology implemented and the use of tools for processing the obtained data (Stages 1, 2, 3, 4 and 5), only 9 out of 120 publications were found to contain the ILandNSW language of the Influencer Target Group. After visualizing the information (Stages 6 and 7), it may be observed that of 120 posts made by Influencers on the SN Instagram, only 7.5% incorporated the IL and NSW in the descriptions written by diverse Influencers.

What words allow for determining the minimum degree of use of GFL? What is the relationship between Influencers and the use of ILandNSW language in digital marketing?

According to the results of this study, this type of ILandNSW language needs to be integrated into the various actions posted commonly on SN Instagram.

It is also observed that the publications with the most likes are comments that do not contain IL and NSW. Therefore, publications with this type of language could attract Chile's Instagram influencers more.

In future work, the database (128 ILandNSW words) of the BoW of IL and NSW needs to be expanded to deepen the identification of the studied language since currently there are only guidelines for using this ILandNSW language rather than a list of words belonging to it. Creating an ILandNSW dictionary in other languages is also necessary for the future, as well as working with a larger pool of Influencers. Additionally, a web tool should be created to allow organizations to assess the use levels of ILandNSW language.

6. Managerial implications

The originality of this work lies in its attractive implications for nonprofit and for-profit organizations, government bodies and private enterprises in the measurement of the success of campaigns with an IM communicational strategy and to incorporate inclusive and non-sexist content for their consumers to contribute to society. Additionally, this study contributes guidelines for DC creators who aim to conduct strategic management with a market orientation, as well as for organizations who desire both to contribute to society through strategies for business communication and annual report and to define their online communication, product commercialization and branding strategies to generate a positive attitude toward the brand. Data could be retrieved from influencers as they are of free access regardless of the people involved.

7. Limitations and potential future research directions

Due to the limitations of the API of the SN Instagram, a limited number of text data were used, which allowed for retrieving the last 12 publications of each studied profile. In addition, this study only includes the Spanish language and is applied to a sample of influencers from Chile.

Another matter that could be addressed by further work is the implementation of an algorithm in Machine Learning to identify and classify ILandNSW language in such a way that complete sentences are retrieved, and their meaning is analyzed to know if what Influencers write genuinely belongs to the ILandNSW language under study.

Notes

1. Betel nut is the seed of the fruit of the areca palm. It is also known as areca nut. The common names, preparations and specific ingredients vary by cultural group and individuals who use them. https://adf.org.au/drug-facts/betel-nut/
2. Power BI: Microsoft Power Platform, https://powerbi.microsoft.com/
3. Social media scraping collects data from social media platforms such as TikTok, Instagram, Facebook, Twitter and the like. Usually, it is done automatically, using ready-made scraping software or custom-built scrapers. It is possible to scrape many data points like followers, likes and the number of views or shares, to name a few. https://proxyway.com/guides/what-is-social-media-scraping
4. Social media scraping provides a great way to collect valuable data for research or commercial purposes. Moreover, Instagram is the most lucrative platform today. However, it is also tricky to scrape due to technical and legal challenges. https://proxyway.com/guides/how-to-scrape-instagram
5. A JSON URL (an acronym of JavaScript Object Notation) is a file format that enables stock data, and this is through this URL, your Custom Counter will be able to display a number. https://help.smiirl.com/article/133-what-should-i-do-to-enable-my-custom-counter-to-display-a-number
6. Contains the description of what the Instagram Influencer wrote on the post (publication).

7. Contains the number of comments per post by the User of photos or videos posted by the Influencer on Instagram.
8. Contains the number of likes per post by the User of photos or videos posted by the Influencer on Instagram.
9. Return a writer object responsible for converting the user's data into delimited strings on the given file like object. *CSV fil*e can be any object with a write( ) method. If *CSV file* is a file object, it should be opened with newline = ". https://docs.python.org/3/library/csv.html
10. This function in the CSV module returns a writer object that converts data into a delimited string and stores it in a file object. The function needs a file object created with an open( ) function and with write permission as a parameter. Every row written in the file issues a newline character by default. The newline = " to prevent an additional line between rows. https://www.knowledgehut.com/tutorials/python-tutorial/python-csv
11. The CSV (Comma Separated Values) format is the most common import and export format for spreadsheets and databases. https://docs.python.org/3/library/csv.html
12. The Requests Session object allows to persist specific parameters across requests to the same site. To get the Session object in Python Requests, it is necessary to call the requests.session( ) method. The Session object can store such parameters as cookies and HTTP headers. Google: How do I use Session object in Phyton Requests?
13. A status code informs of the status of the request. For example, a 200 OK status means the request was successful, whereas a 404 NOT FOUND status means that the resource it was looking for was not found. Google: What is status code in Phyton?
14. Do requests not consider a 304 as "Ok"? A property called "Ok" in the Response object returns True if the status code is not a 4xx or a 5xx. Response.ok returns True if status_code is less than 400; otherwise, False. Python requests are generally used to fetch the content from a particular resource URL. Whenever it makes requests to a specified URL through Python, it returns a response object. Now, this response object would be used to access certain features such as content, headers, etc. This article revolves around how to check the response.ok, out of a response object. https://stackoverflow.com/questions/22494794/does-requests-codes-ok-include-a-304
15. The JSON format structure to browse "Instagram_data_not_clean" file is ["graphql"] ["user"] ["edge_owner_to_timeline_media"] ["edges"] ["node"]. See Figure 5.
16. This function writes items in a sequence (list, tuple or string) separating them by comma character. https://www.knowledgehut.com/tutorials/python-tutorial/python-csv
17. CSV in Python adds an extra carriage return on Windows. https://stackoverflow.com/questions/3191528/csv-in-python-adding-an-extra-carriage-return-on-windows

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Does the distribution of R&D incentive among production factors matter? A dynamic general equilibrium model for Türkiye

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Abstract

Purpose – This study aims to explain the effect of research and development (R&D) incentives on economic growth, focusing on the case of Türkiye. A one-sector endogenous growth model has been constructed. The model includes three actors: firm, consumer and government. The consumer derives utility from consumption, supplies human capital and engages in saving. The representative firm invests in R&D to maximize the current value of profit flows by choosing how much input it will use and how much R&D it will undertake. The public sector provides incentives for labor and capital used in R&D production. R&D has been defined as a function that endogenously increases total factor productivity (TFP).
Design/methodology/approach – In line with the stated purpose, this study presents a dynamic general equilibrium model. Then, this study calibrates the model parameters with Türkiye's data.
Findings – The results imply that incentives for R&D personnel instead of physical capital have a stronger impact on economic growth.
Practical implications – The findings of this study point to an important conclusion on how to distribute R&D incentives across the two main factors in R&D production, labor and capital. Incentives given to R&D personnel are more effective in Türkiye.
Originality/value – This study shows that the R&D incentives provided by the public sector can be important in emerging countries where many firms have just started their R&D activities. In this study, the authors worked on Türkiye as an emerging country. This study discusses policies on how the R&D incentives will be more effective on economic growth in Türkiye. This study considers that these policies may apply to all emerging countries, due to similar R&D activities in countries that cannot export technology and mostly import technology.

Keywords One-sector growth model, Research and development, Technological change, Government policy, Dynamic general equilibrium

Paper type Research paper

1. Introduction

A productive innovation ecosystem is needed to engage in R&D activities, improve innovation performance and make them sustainable. The innovation ecosystem gets stronger

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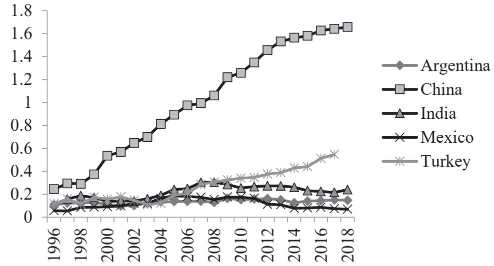
with skilled labor and technology investments. Therefore, it is not a coincidence that innovation performance is higher in developed countries. The effects of R&D expenditures in developing countries do not always yield positive results. The reason for this is that the already limited innovation capacity of developing economies cannot reach the necessary support in terms of relevant institutions and resources (Kleiner-Schäfer and Liefner, 2021; Wan *et al*., 2022). According to Aubert (2005), R&D and innovation initiatives in emerging economies get negatively affected by the low level of education and ineffective information infrastructures in those economies. Aubert (2005) claims that this prevents the formation of a powerful private sector, especially in emerging economies while weakening the innovation ecosystem.

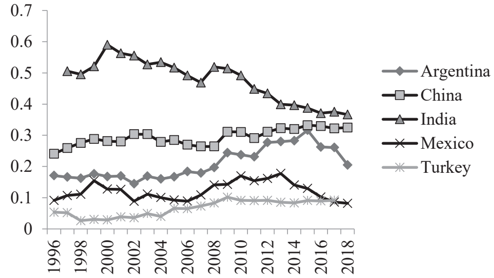
Most R&D activities in emerging economies are carried out by the private sector in recent years. The share of Gross Domestic Expenditure on R&D (GERD) in the gross domestic product (GDP) data for selected emerging economies are shown in Figures 1 and 2. These figures support the claim that the private sector leads to R&D expenditures in developing countries.

In emerging economies, where most of the R&D activities are conducted by a weak private sector, an important part of the technology need is met by foreign direct investments (FDI). The impact of imported technology on the innovative performance of emerging countries has been discussed widely in the literature. Most of the studies indicate that technology import made through the FDI channel positively affects innovation performance (Coe and Helpman, 1995; Kokko, 1996; Coe *et al*., 1997; Liu and Wang, 2003; Sinaniand Meyer, 2004; Salomon and Shaver, 2005; Zhang, 2017). Regarding the effect of technology import on technology production in developing economies, Wang and Kafouros (2009) emphasize that FDIs do not



Source(s): UNESCO (Science, technology, and innovation)

Figure 1.
GERD performed by the business enterprise as a percentage of GDP



Source(s):UNESCO (Science, technology, and innovation)

Figure 2.
GERD performed by the government as a percentage of GDP

reduce the need for R&D in these countries. Therefore, technology import acts as an input to produce new technologies in developing countries. In other words, the technology export of these countries is based on technology import.

In this study, a growth model for a closed economy, that is, a growth model without technology imports is constructed. The aim is to identify how the public sector should support R&D in an economy that grows with its R&D activities and is not dependent on FDI for growth. For this purpose, an R&D production function has been stated and a growth model in which this production function affects economic growth endogenously has been constructed. In the R&D production function, apart from the final production function, the efficiency of the R&D personnel and R&D capital in technology and innovation production has been determined. The determination of the effectiveness of R&D production factors is important to produce a policy for regulating the distribution of R&D incentives between R&D personnel and R&D capital.

2. Literature review

In the Romer model, which is regarded as the pioneer in the literature of R&D-based growth models, R&D is embedded in an industry that creates a patent and sells it to the intermediate goods sector. This patent, produced by the R&D sector, is used in the production of final goods with human and physical capital (Romer, 1990). In other words, there is a horizontal interaction between the sectors in the Romer model. Following Romer's model, Aghion and Howitt (1990) and Grossman and Helpman (1993) proposed R&D-based growth models. These three models have asserted that the increase in the labor force that will work in the R&D sector will positively affect growth in the long term. R&D has been addressed as a sector producing innovation and patents in the three models. There are similar and opposing perspectives in the literature. For instance, R&D has been modeled as a firm's expenditure to provide resources for innovation and productivity instead of a sector producing innovation and patent (Wakelin, 2001; Coad and Rao, 2010; Ngai and Samaniego, 2011; Coe and Helpman, 1995; Audretsch and Feldman, 1996).

The relationship between R&D expenditures and growth and the effects of R&D incentives at the firm and sector levels have been examined in the literature. We will first summarize the studies on the relationship between R&D expenditures and growth. We will then review the literature on the effects of R&D incentives on firms and the sector, specifically in the third section of the study. Many studies have revealed that R&D expenditures are effective on economic growth. Sample literature showing such studies is presented in Table 1.

Many studies conclude that R&D expenditures generate an increase in TFP and thus economic growth. Hence to ensure economic growth, the R&D activities of the firms are increased. Such activities increase the costs of the firms. To cover costs, public support policies have been developed where a part of the R&D expenditures of the firms are matched by the public. The number of studies modeling the effect of public support policies on economic growth with a theoretical approach is low. In these studies, R&D incentives are generally divided into two categories as direct and indirect incentives, and the effectiveness of these incentives on economic growth is investigated. In the study by Ghosh (2007), a dynamic general equilibrium model with a multi-sectoral endogenous growth model was built to measure the effect of alternative R&D policies, and the model was calibrated with the data ofCanada. The results obtained from the study showed that R&D incentives had a positive effect on the increase in productivity in the Canadian economy. Bye *et al.* (2009) calibrated a small open economy general equilibrium model calibrated with Norwegian data. It was found that R&D incentives for the formation of capital provided low R&D intensity, but they resulted in growth and an increase in welfare compared to direct R&D incentives. Segerstrom (1991) built a dynamic general equilibrium model with a different approach and

Author/ Authors	Sample	Method	Results
Mansfield (1972)	USA	Descriptive analysis	Positive effect on economic growth
Freire-Seren (2001)	21 OECD Countries	Panel Regression	Positive effect on economic growth
Zachariadis (2004)	13 OECD Countries	Panel System Estimation	Positive effect on TFP
Cameron *et al.* (2005)	14 Manufacture Industry from the UK	Equilibrium Correction Model (ECM) and Autodistributed Lag (ADL)	Positive effect on TFP
Křístková (2012)	Czechia	Computable General Equilibrium	Positive effect on economic growth
Inekwe (2015)	66 Countries with different income levels	Generalized Method of Moments (GMM)	It has no impact in low-income countries but is positive in middle-high-income countries

Source(s): Authors' compilation

Table 1. R&D expenditure-growth relationship: sample literature

divided the firms that carry out R&D activities as innovative firms and firms following these firms as forger firms. It was found in the model that incentives for innovation have a positive effect on growth.

Cheng and Tao (1999) have calibrated a small open economy general equilibrium model by Segerstrom (1991) with Slovenian data. In this study, where R&D has been modeled as an endogenous growth element, two different results emerged in the case of R&D function being linear and convex. In the model with a linear R&D function, the effects of R&D incentives were unclear while in the case of a convex function, the R&D incentives were found to promote production. Bor *et al.* (2010) have calibrated the dynamic general equilibrium model they constructed for Taiwan and found that public R&D incentives will provide resources for economic growth via technological development and human capital impacts. In this study, it has been investigated which of these incentives is more effective on economic growth in a situation where public R&D incentives are given to R&D personnel and R&D capital in a closed economy.

3. The model

The model has three agents. These are sector-representative firms, consumers and the government. The functional relationships between these three actors in the economic model can be listed as follows:

(1) The consumer maximizes their utility and obtains wages by supplying labor to the firm. A part of this wage is paid for the goods and services provided by the firm. Saving finances capital accumulation and capital income is obtained from the firms in this way. Additionally, income tax is paid to the government, which is the third agent of this model.

(2) The firm maximizes profit. The supply labor by the consumer is equal to the demand of labor by the firm. The firm pays the wage arising from this equilibrium to the consumer. The same situation is valid for capital supply (savings) and the capital demand of the firm. The firm pays the interest rate arising from capital market equilibrium to the consumer as a price for renting. In addition to these payments, a certain percentage of the profit obtained is paid to the public sector as corporate tax. The revenue of the firm is

the goods and services purchased by the consumer and the public sector. Another source of income for the firm is the incentives provided by the public sector.

(3) The government funds the incentives and public expenditures with the income tax obtained from the consumer and the corporate tax levied on the profit of the producer.

(4) All supplies and demands are equal for the producer and the consumer in the model. A balanced budget has been ensured with collected taxes, provided incentives and public expenditures.

Numerical solutions of the model have been performed in Dynare (Juillard *et al.*, 1996) run under Octave (Eaton *et al.*, 2012). This software combination offers a numerical solution to dynamic general equilibrium models by including the necessary equation systems after introducing the model's parameters, endogenous variables and exogenous variables to the system. The distinction between endogenous and exogenous variables is quite important in the analysis of the model, for the concepts of endogeneity and exogeneity can directly affect the outcome of the model simulation.

3.1 Firm

The firm aims to increase TFP by making R&D expenditures while maximizing the current value of all profits achieved during its existence. R&D is an endogenous process aiming to increase the productivity of the production in the firm and is defined as follows:

$$RD_t = Q_t^{\theta} N_t^{1-\theta} \tag{1}$$

RD_t is R&D production at time t; Q_t represents the physical capital stock used in R&D; N_t represents the number of labor used in R&D production, and θ is the capital share in R&D production. In the model, the final good production function is in the form of a Cobb–Douglas production function.

$$Y_t = A_t K_t^{\alpha} L_t^{1-\alpha} \tag{2}$$

Y_t represents the final good production amount of the firm, and K_t and L_t represent the physical capital and labor force used in the production of final goods, respectively. α is a parameter indicating the share of capital used in the production of final goods.

It is assumed that the R&D expenditures, RD_t, directly translate to TFP, represented via A_t, as follows:

$$A_t = RD_t = Q_t^{\theta} N_t^{1-\theta} \tag{3}$$

As in equation 1, Q_t represents the stock of physical capital, N_t represents the number of labor and θ represents the share of capital in R&D production. We have notationally replaced RD_t and A_t. Making this substitution in the production function:

$$Y_t = RD_t^{\psi} K_t^{\alpha} L_t^{1-\alpha} \tag{4}$$

where we introduce $\psi < 1$ as a parameter that indicates that the R&D has diminishing impact on the production of final output. Given these specificaitons, the firm's nominal profit function at time t, is as follows:

$$\pi_t = [Y_t - (w_{1,t}L_t + (1-\tau_{s,t})w_{2,t}N_t) - (r_{1,t}K_t + (1-\tau_{q,t})r_{2,t}Q_t)](1-\tau_{p,t}) \tag{5}$$

π_t represents profit at time t; $r_{1,t}$ represents the interest rate to be paid on the capital used in the production of final goods; $r_{2,t}$ represents the interest rate to be paid on the capital used in R&D production; $w_{1,t}$ represents the wage paid to the labor used in the production of final goods; and $w_{2,t}$ represents the wage paid to the labor used in R&D production. In the model, labor used in the R&D production function is denoted by N_t, and capital used in the R&D production function is denoted by Q_t. The public sector provides firms with R&D incentives as much as $\tau_{s,t}$ for qualified labor N_t and $\tau_{Q,t}$ for capital Q_t used in R&D production. $\tau_{P,t}$ represents the corporate tax collected on the profit of the firm.

3.2 Consumer

The intertemporal utility function of the consumer is based on a constant relative risk a version form as follows:

$$\sum_{t=0}^{\infty} \beta^t \frac{c_t^{(1-\varphi)} - 1}{1-\varphi} \tag{6}$$

where c_t represents the consumption demand, β is the utility discount parameter and φ represents intertemporal substitution. The consumer faces a budget constraint, defined as follows:

$$c_t + s_t \leq [w_{1,t}L_t + w_{2,t}N_t](1-\tau_m) + (1+r_t)s_{t-1} + \pi_t \tag{7}$$

The labor supplied by the consumer to the firm, LS_t, is exogenous. The labor supply of the consumer is met by the firm's demand and the available labor is employed in two different ways. The firm uses a part of this labor supply in the R&D production (N_t) and the other part in the final good production (L_t). Therefore, the firm makes two different wage payments to the consumer identified through w_{1t} and w_{2t}. The consumer pays an income tax, τ_m, to the public sector over these wages. The consumer buys services with some of its remaining wage (c_t) and saves the remaining part (s_t). s_{t-1} on the income side of equation7 shows the previous period savings of the consumer. The savings made by the consumer in period $t-1$ were covered as income in the consumer's budget in period *t-1*. Also on the income side of the consumer budget, π_t is the residual net profit received from the firm.

3.3 Government

The government finances expenditures, including the incentives it provides to firms, with the taxes it collects. Also, there is no public borrowing and the government budget is balanced. Tax revenues consist of production tax collected from firms and income taxes collected from consumers. The public provides R&D incentives ($T_{D,t}$) to firms with these tax revenues. The government provides incentives for R&D only. Therefore, the public R&D incentive expenditure equation is as follows:

$$T_{D,t} = \tau_{s,t}(w_{2,t}N_t) + \tau_{q,t}(r_{1,t}Q_t) \tag{8}$$

Income tax collected out of wage income is:

$$T_{m,t} = [w_{1,t}L_t + w_{2,t}N_t]\tau_m \tag{9}$$

Out of the profits made, tax collection is done as:

$$T_{p,t} = \tau_{p,t}\pi_t \tag{10}$$

3.4 Closure of the model

The model has a balanced government budget:

$$T_{D,t} + G_t = T_{m,t} + T_{p,t} \tag{11}$$

Regarding the asset market equilibrium, savings done by the consumer finance the physical capital used in the production of final goods and the capital used in R&D activities. That is;

$$S_t = K_t + Q_t \tag{12}$$

Labor market equilibrium is such that the labor demand by the firm for final output production and R&D activities are met by the consumer's supply of labor. Labor demand is equal to the sum of demand for final output production and R&D activities, i.e. $LD_t = L_t + N_t$. With no demographic dynamics and inelastic labour supply, this demand is equal to an exogenous labor supply, LS_t. Hence;

$$LD_t = LS_t \tag{13}$$

4. Calibration and scenario analysis

The model has been calibrated with the data collected from Türkiye. Model parameters have been calculated by giving hypothetical values to some parameters depending on the data of Türkiye. Data from 2015 were used due to the year being a relatively recent year devoid of economic tribulations. Hence year 2015 is a good candidate for a representative point on a steady state. The basic data of Türkiye for 2015 are shown in Table 2.

Given model calibration, three scenarios are investigated through the numerical solution of the model's steady state. The first scenario considers increasing the R&D capital incentives, $\tau_{q,t}$. The second scenario focuses on increases in R&D labor incentives, $\tau_{s,t}$. The third scenario considers simultaneous increases. For each case, the model is solved for different values of the parameter investigated. That is, under Scenario 1, the model's steady state is solved for different values of $\tau_{s,t}$. By examining numerical solutions for different variables of the model, the impact of these two policy alternatives is investigated. It should be emphasized that the numerical solutions refer to steady states. That is, transitional dynamics between steady states are not discussed.

Symbol	Database	Definition	Amount
C	**TURKSTAT (National Accounts)**	Household Consumption Data	1.412 (billion TL)
G	**TURKSTAT (National Accounts)**	Public Expenditure	325 (billion TL)
K	**International Monetary Fund (IMF)**	Capital Stock	3.707 (billion TL)
$\mathbf{r_1}$	**Central Bank of the Republic of Türkiye**	Interest rate (average, annual)	0.094 (rate)
Q	**TURKSTAT (R&D Accounts)**	R&D CapitalStock (Calculated by authors using R&D investment)	193 (billion TL)
L	**TURKSTAT (EmploymentDataset)**	Employment	26,621 (thousand, count)
$\mathbf{w_1}$	**TURKSTAT**	The average wage (annual)	36,159 TL
N	**TURKSTAT (R&D Accounts)**	R&D personnel (full time equivalent)	122,288 (count)
T_D	**TURKSTAT (R&D Accounts)**	R&D Incentives (total)	8,036 million TL
T_P	**General Directorate of Budget and Financial Control**	Corporation tax (total)	33,388 million TL

Source(s): Authors' compilation

Table 2.
Calibration data (Türkiye, 2015)

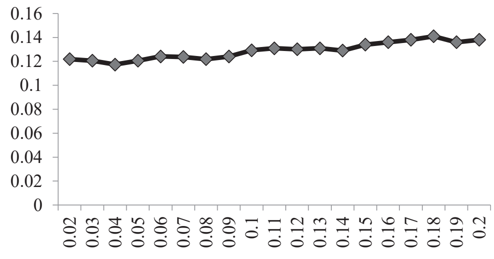
4.1 Scenario 1: Increasing R&D capital incentives while R&D personnel incentives are fixed

Increasing public incentives for the physical capital used in R&D (*Qt*) reduces the costs incurred by the company while reaching the technologies needed. This can create two different behaviors in the firm, as pointed out by Lach (2002). In his study, Lach (2002) calculated a ratio called the R&D incentives effect for the R&D expenditures that a company can make without R&D incentives and the R&D expenditures made by receiving R&D incentives. According to this ratio, it has been concluded that while R&D incentives increase R&D expenditures in small firms, it creates a negative but statistically insignificant effect on large firms. Hence, there are two possibilities. The R&D incentives will either increase the firm's R&D expenditures or create a crowding-out effect that reduces R&D expenditures (Lach, 2002). Accordingly, in case of an increase in R&D capital incentives, the first variable to be examined in the model is the interest rate that determines the rental price of the capital. The incentive initially impacts the cost of capital to the firm and thus would change the use of capital in R&D.

Figure 3 shows the steady-state values of r_2 for each unit increase of $\tau_{q,t}$, i.e. R&D capital incentives. According to Figure 1, as $\tau_{q,t}$ increases, an upward trend is observed in interest rates. This implies that as incentives increase, the cost of capital used in R&D increases. This is most likely due to higher capital usage. Figure 4 shows that there is indeed a slight increase in capital usage. The increase in incentives increases the demand for capital, causing a capital cost increase that may even offset the incentives.

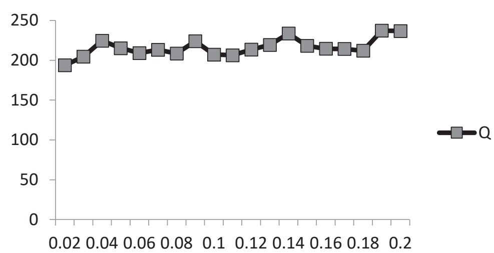
4.2 Scenario 2: increasing R&D personnel incentives while R&D capital incentives are fixed

In this scenario, R&D personnel incentives are increased while capital incentives are held constant. Such an action would change the relative prices of labor used in R&D and labor used in final output production. For,



Source(s): Authors' calculations

Figure 3. r_2 in case of an increase in R&D capital incentives ($\tau_{q,t}$)



Source(s): Authors' calculations

Figure 4. R&D capital stock in case of increase in R&D capital incentives

$$\frac{\mathrm{w}_{2,\mathrm{t}}}{\mathrm{w}_{1,\mathrm{t}}} = \frac{\psi(1-\theta)\mathrm{L}_t}{(1-\tau_{\mathrm{s,t}})(1-\alpha)\mathrm{N}_t} \tag{14}$$

This is consistent with the findings of Wallsten (2000). Firms that want to benefit from the support provided by the government increase the price of this production factor by increasing their demand for R&D personnel (Wallsten, 2000). Hence an increased use of labor is likely.

What is the effect of wage increases on capital prices? Factors of production are substitutes, at least to a certain degree. Thus, in addition to a reallocation of labor between alternative uses, capital and labor would be substituted in R&D as well. Figure 5 shows the steady-state values of the R&D capital interest rate in each unit increased by τ_{S}.

As can be seen in Figure 5, increasing R&D personnel incentives decreased capital prices. This is a cross effect and it might imply factor substitution. While the wage level increased in the factor market, capital prices have been decreasing.

Incentives for the R&D production factors have different effects on total output. Figure 6 shows the effects of incentives for R&D production factors on total output. Figure 6 shows that the increase in the R&D personnel incentives (τ_{s}) creates a higher total output level compared to the increase in R&D capital incentives (τ_{Q}). Therefore, it can be said that R&D incentives increase the productivity of production factors with labor-focused incentives having an edge.

The government offers R&D incentives and collects taxes to finance these incentives. One of these taxes is the income tax. Increasing expenditures such as R&D incentives should lead to an increase in income tax rates. Figure 5 shows the effect of increases in incentives, i.e. τ_{Q} and τ_{S}, on income tax (τ_{m}) rates.

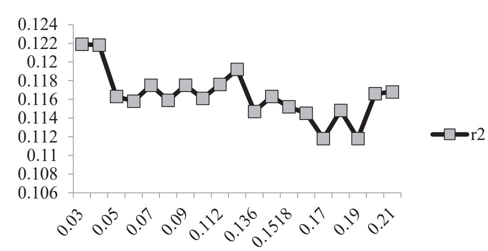


Figure 5. r^2 in case of an increase in R&D personnel incentives (τ_s)

Source(s): Authors' calculations

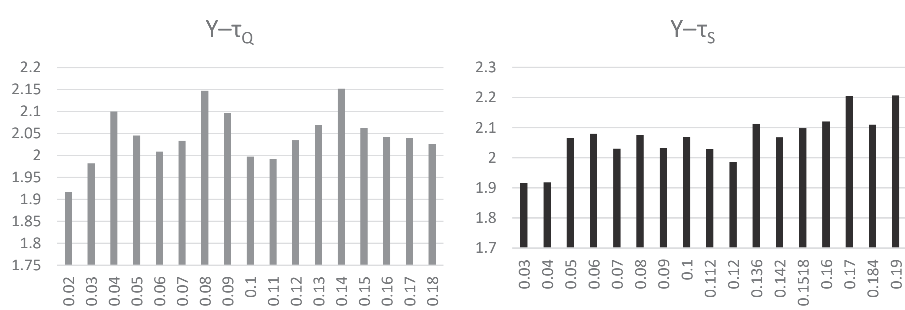


Figure 6. Comparison of the effects of Q and S increases on total output

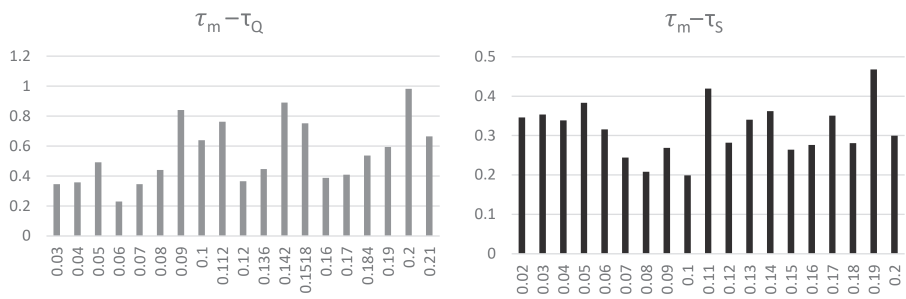
Source(s): Authors' calculations

According to Figure 7, the increase in capital incentive rates (τ_Q) necessitates a higher income tax than the increases in labor incentive rate (τ_S). This indirectly shows that R&D capital incentives are more costly than R&D personnel incentives. Of the increases in capital and labor incentives, the capital incentive is causing higher costs and also negatively affects social welfare. Because the high rate of income tax will cause a decrease in the goods and services that the consumer will buy. Therefore, of these two scenarios, it can be said that the optimum results in terms of both social welfare and TFP increase are achieved with labor-focused incentives.

4.3 Scenario 3: increasing both R&D capital and R&D personnel incentives

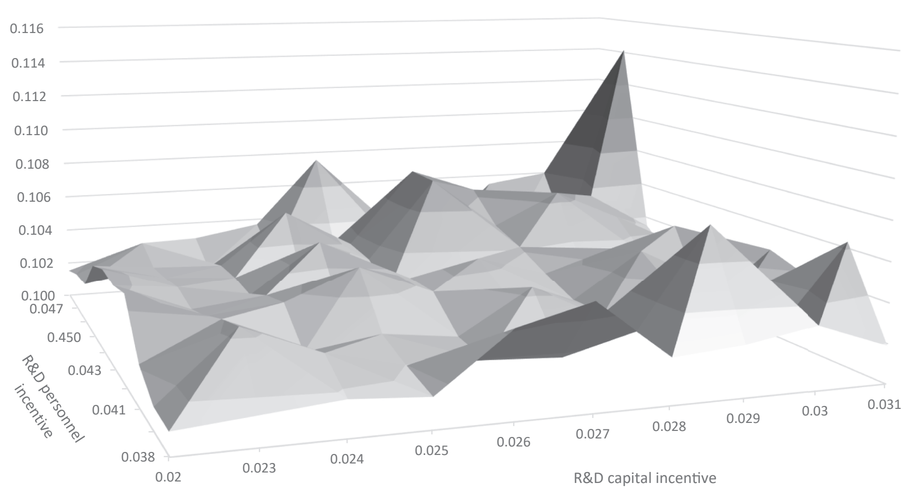
Determining the effects of simultaneously increasing incentive rates on capital accumulation and productivity increase are important for the incentive policies to be implemented.

Figure 8 shows in three dimensions the share of R&D capital Q in total output Y in case of increasing capital and labor R&D incentive ratios together. The figure shows the R&D



Source(s): Authors' calculations

Figure 7.
Effects of labor and capital incentive increase on the income tax rate



Source(s): Authors' calculations

Figure 8.
R&D capital per output with simultaneous changes in labor and capital incentives

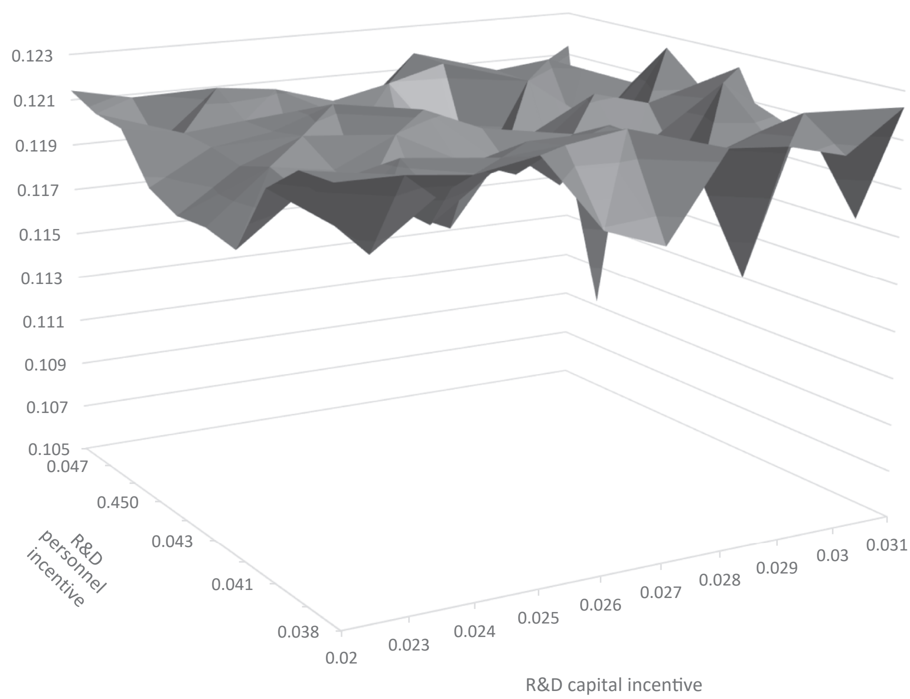
personnel incentive rates on the right vertical axis and the physical capital incentive rates involved in R&D production on the horizontal axis. In Figure 8, the increasing trend of R&D capital is parallel to both incentive rate increases. In other words, with the increase of both incentive rates together, the share of R&D capital in Y has increased.

Figure 9 shows the steady-state values of r_2 when τ_Q and τ_S incentive rates are increased simultaneously. In the figure, R&D personnel incentive rates are shown on the left horizontal plane, while the right side of the horizontal plane shows R&D physical capital incentives. r_2 fluctuations in Figures 1 and 3 are seen to be smoother in Figure 9 and do not contain any trends. Hence, the impact on capital price is in a sense well-balanced. The net effect of the policy on R&D capital is an increase in R&D capital, which is shown in Figure 8.

Increases in R&D capital impact R&D production. In Figure 10, the left vertical line shows the incentive rates for the R&D personnel, and the horizontal line shows the incentive rates for the R&D physical capital.

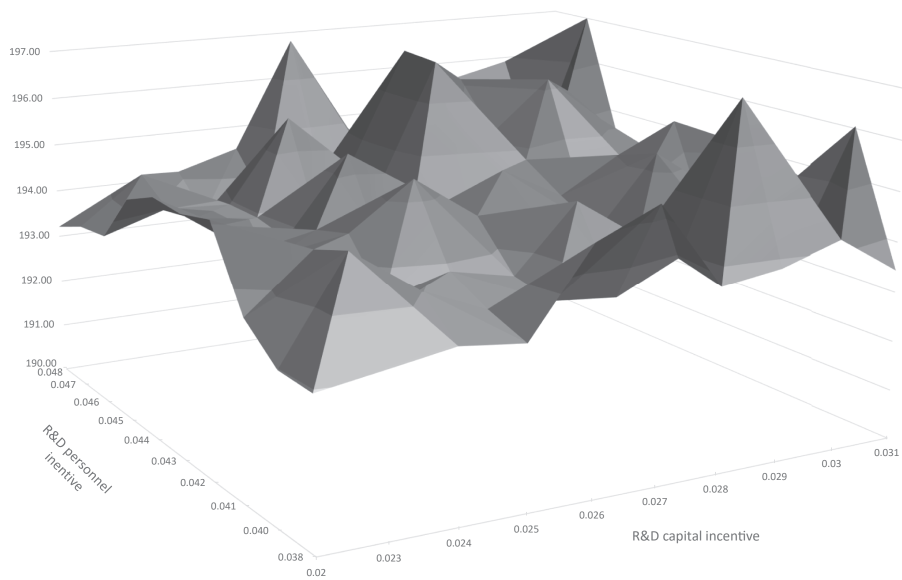
Figure 10 shows the R&D steady-state values when R&D capital and R&D labor incentives are increased together. Looking back at Figure 8, the increase in the numerical value of R&D is similar to the increase observed for R&D capital per output. The increase in the R&D capital would increase the numerical value of R&D, which had similar effects on the total output. These effects are shown in Figure 11, which shows the total output Y in three dimensions in the case of increased incentives for both R&D production factors.

In Figure 11, the vertical line involves the R&D personnel incentive rates and the horizontal line involves the R&D physical capital incentive rates. Increasing incentives for both R&D production factors generate an increase in total output Y.



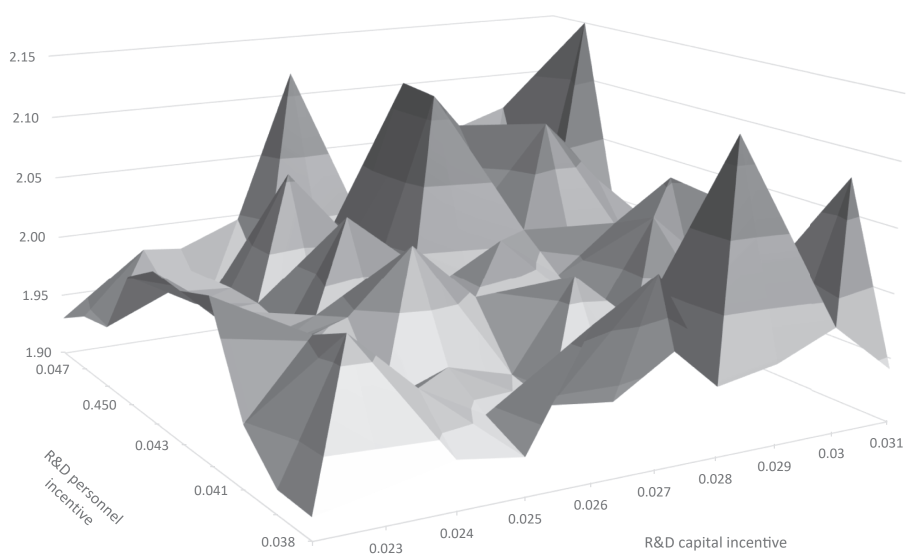
Source(s): Authors' calculations

Figure 9.
Impact of a simultaneous increase in labor and capital incentives on r_2



Source(s): Authors' calculations

Figure 10. Impact of a simultaneous increase in labor and capital incentives on R&D expenditures



Source(s): Authors' calculations

Figure 11. Impact of a simultaneous increase in labor and capital incentives on final output (Trillion TL)

Remember that Figure 6 shows the final output obtained as a result of the increases made by keeping either capital or labor incentive rates constant in the previous two scenarios. When τ_Q is constant, it can be seen that the total output in the case of τ_S increase is above the total output in Figure 11, where both incentive rates are increased. Also, if both incentive rates are increased in Scenario 3, the income tax rate imposed by the government on the consumer to ensure the government budget balance and to finance these incentives increases. This situation is shown in Figure 12.

In Figure 12, the left vertical line shows the R&D personnel incentive rates and the horizontal line shows the R&D capital incentive rates. Compared to Figure 7, the income tax rate τ_{M} in Figure 12 is below the income tax rate due to changes in capital incentives (the$\tau_{\mathrm{M}} - \tau_{Q}$ rate) and above the income tax rate due to changes in labour incentives (the $\tau_{\mathrm{M}} - \tau_{S}$ rate). As a result, increasing both incentive rates produces ineffective results compared to Scenario 2. Because in Scenario 2, higher total output and lower income tax rates are obtained.

5. Discussions

In the dynamic general equilibrium model we have set up, it is assumed that firms are engaged in R&D activities. Besides, R&D activities have been handled as a production function and a policy has been designed to increase the efficiency of production factors used in this production function. In the next step, the model has been calibrated with data from Türkiye. Our findings are given in Section 4.

The constructed model has been simulated for three different scenarios and the findings of each of these three scenarios showed that the increase in R&D capital and R&D personnel incentives had a positive effect on economic growth. In which scenario these positive contributions of R&D incentives are more effective is important for both social welfare and efficient use of resources. Therefore, the effects of these three scenarios on both TFP and social welfare should be carefully analyzed. Such an analysis could reveal how the incentives should be distributed between R&D capital and R&D personnel to ensure growth.

The three conducted scenarios have the following implications:

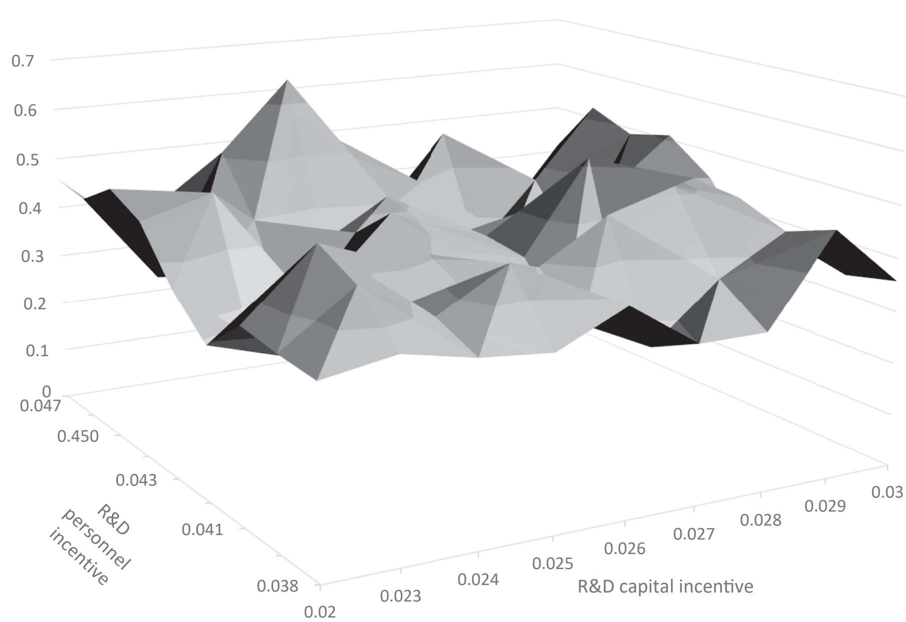


Figure 12. Impact of a simultaneous increase in labor and capital incentives on the income tax rate

Source(s): Authors' calculations

(1) *Scenario 1*: In this scenario, the incentive rate on capital used in R&D (τ_Q) was increased, keeping the incentive rate on labor used in R&D (τ_S) constant. This exercise increased the firm's demand for R&D capital and increased capital prices. As a result, the firm's capital accumulation is suppressed. On the other hand, due to the increasing capital prices, the cost of capital incentives has also increased. The public sector financed these incentives from the consumer by increasing the income tax rate as a requirement of the fiscal balance. This has resulted in a decrease in social welfare.

(2) *Scenario 2*: In this scenario, the incentive rate on labor used in R&D (τ_S) was increased by keeping the incentive rate on capital used in R&D (τ_Q) constant. This has caused a high substitution between factors of production and lowered interest rates. On the other hand, R&D capital formation was at a similar level to the increase in Scenario 1. But in Scenario 2, R&D capital formation is less costly. Besides, in Scenario 2 compared to Scenario 1, total output Y is higher and income tax rates are lower. This scenario is the one in which social welfare is optimal compared to other scenarios.

(3) *Scenario 3*: In the last scenario, the incentive rate on capital used in R&D (τ_Q) and the incentive rate on labor used in R&D (τ_S) are increased simultaneously. This scenario generates a lower increase in the total output level compared to Scenario 2. However, income tax and interest rates, which increased in Scenario 1, remained lower in Scenario 3. Still, Scenario 3 has not produced as optimal results as Scenario 2.

6. Conclusion

The main result from the analysis of the constructed model is that in Scenario 2, the increase in R&D personnel incentives increased productivity. As a result, it has been concluded that economic growth is more prominent in Scenario 2 than in Scenarios 1 and 3. This result is an expected result, especially for Türkiye as an emerging economy. As Aubert (2005) stated, the shortage of skilled labor in emerging economies hinders the development of R&D activities. Model results support Aubert (2005). The increase in skilled labor, in other words, the increase in human capital accumulation, could accelerate economic growth.

Skilled labor is also important for the development of basic research outputs, which is the most important type of R&D in innovation production. Therefore, Türkiye needs to produce appropriate policies to achieve growth and development goals. These policies should have the potential to affect all segments of society. For example, bringing education to international standards, allocating research infrastructure to universities that are the engines of basic research, and providing necessary support are the most important policies to be followed. In addition to these policies, after providing the necessary basic research infrastructure, it is very important to establish applied research grounds where basic research can be applied. Once these steps are followed successfully, thanks to the high-value-added products produced by Türkiye will get the chance to improve its market share in international markets. In this case, creating an improvement in Türkiye's economic indicators will provide an opportunity to close the gap between developed countries and Türkiye.

Unfortunately, the results could not be compared to other studies in the literature. As far as the authors can determine, the impacts of incentives on R&D and growth are mostly studied in an empirical context supported by econometric analysis. Such studies do not consider incentives provided via factors of production. Therefore, a comparable analysis could not be identified. It could be a fruitful endeavor to conduct modelling studies similar to this one for different countries. The results from countries at different development levels may provide unique policy implications.

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Innovation in business model as a response to the sharing economy

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Abstract

Purpose – The sharing economy (SE) is significantly affecting traditional companies, which have felt a need to adapt their business model. The aim of this study is to identify the different types of adaptation developed by companies within a SE context, and to examine how they relate to their characteristics.

Design/methodology/approach – A content analysis involving 149 real-world adaptation cases was carried out, after which a Kruskal–Wallis test and a multiple correspondence analysis were used to explore the relationships between the types of adaptation identified, the business characteristics and the strategic decisions taken for these adaptations.

Findings – Through the analyses proposed in the study, the main conclusions suggest that the way companies adapt to SE is related to business characteristics and the strategic decisions taken for these actions, demonstrating throughout the article what types of adaptations are made depending on variables such as sector of activity or business orientation.

Originality/value – This study is the first to examine the variables affecting the decisions among traditional companies in response to the SE. In addition, this work explores the SE from the business point of view, shedding light on the participation in SE by traditional companies.

Keywords Sharing economy, Business model innovation, Content analysis, Acquisition, Internal development, Partnership

Paper type Research paper

1. Introduction

In recent years, there has been a tremendous growth in the number of sharing economy (SE) platforms aimed at renting or selling second-hand goods that has profoundly modified consumer behavior and business activities (Agarwal and Steinmetz, 2019). This trend has given rise to the development of an alternative form of consumption that advocates a sustainable economic system through a more efficient exploitation of resources and products (Hamari *et al.*, 2016; Jiang *et al.*, 2016). As a result, the SE has had important socioeconomic and business implications, including the elimination of intermediary companies in operations, direct connection between consumers or the lengthening of the useful life of products.

The SE was first seen as a threat to the manufacturers of durable goods and traditional service providers because of its negative influence on industries like hospitality, transportation, fashion, finance and even distribution channels (Keko *et al.*, 2018).

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However, it has recently come to be seen as an opportunity for established business models to create and offer greater value for existing customers (Garud *et al.*, 2022), to acquire new customers, to reduce internal costs through resource and energy efficiency (Chien, 2022; Hsu, 2023), to achieve sustainable development goals (Sadiq *et al.*, 2023) and, for organizations, to expand their reputation by positioning themselves in the market as "sustainable" organizations (Ciulli and Kolk, 2019).

As such, traditional companies have started to adapt their business models to SE principles through alternatives such as business model innovation or vertical integration (Chen and Wang, 2019) taking into account that the efficient use of network externalities and external contributions in innovation efforts toward the SE can create competitive advantages (Belezas and Daniel, 2022). However, so far, few studies have examined this area (Zervas *et al.*, 2017), and our study attempts to deepen the SE literature by (1) analyzing if there are differences in the types of adaptation used according to the characteristics of the company itself and their strategic decisions taken for these adaptations (Zervas *et al.*, 2017), (2) identifying what characteristics and strategic decisions are more related to different types of adaptations toward SE (Ciulli and Kolk, 2019), (3) broadening the overall understanding of the SE phenomenon through qualitative analysis (Rojanakit *et al.*, 2022) of real business cases (Agarwal and Steinmetz, 2019) and (4) explaining how business model innovation can play an important role in providing alternatives through SE (Eckhardt *et al.*, 2019).

In an effort to address the research gaps mentioned above, we conducted a Kruskal–Wallis test and a multiple correspondence analysis (MCA) among 149 cases of firm adaptations toward SE, and in doing so, identifying important theoretical and practical implications.

From a theoretical point of view, the main implications are (1) the extension of the development and explanation of the different forms of adaptation to the SE and their illustration through examples, (2) the enrichment of the existing academic literature on the SE with an approximate distribution of the relationship between the different forms of adaptation carried out by firms to the SE and the characteristics of the firms, (3) the linking of the SE literature with existing literature on business model innovation and (4) the exploratory association of the strategic decisions that each type of adaptation implies for the firm. The ideas provided will open up new lines of research for future studies.

From a practical point of view, the main implications are (1) the relationship of concrete examples of adaptation with the adaptation options developed in the literature on SE, giving ideas for company managers, (2) at the same time provides ideas about the consequences that these adaptations will imply for companies, thus helping marketing and innovation professionals from traditional companies to take decisions on how to adapt or react to changes in the market related to SE and (3) explanation for emerging platforms on the distribution of business characteristics that may be most closely related to the different types of adaptation, yielding indications about future threats or opportunities.

2. Theoretical framework

Recently, there have been major changes affecting markets in terms of production, marketing, corporate governance and business models (Edelman *et al.*, 2017). Among the changes deserving to be highlighted are the technological advances that have enabled an extensive development of information technologies and important advances in online and mobile communications (Battisti and Brem, 2021), the awareness of climate change and the repercussions that consumer behavior may have on the environment (Hamari *et al.*, 2016). These changes are causing, among other things, a shift away from product ownership in favor of temporary product sharing, resulting into the development of "SE platforms" (Kumar *et al.*, 2018) that affect traditional companies in multiple ways, as described in section 2.1.

2.1 Impact of the sharing economy on traditional markets

The emergence and growth of SE, a scalable socioeconomic system that employs technology-enabled platforms to provide users with temporary access to tangible and intangible resources (Eckhardt *et al.*, 2019), have a significant effect on traditional durable goods manufacturers and service providers. Not only does it alter consumer (purchasing and usage) behavior, it also affects the mode of operation of manufacturers (Li *et al.*, 2020), their market share and the role played by consumers (Matzler *et al.*, 2015).

From the point of view of people's purchasing behavior, and according to the European Commision (2018), at a European level, only 33% of collaborative platform users claim that they will continue to use products/services through traditional business models in the same quantities as before accessing these platforms. By contrast, 32% of them affirm to have replaced to some degree the services they used through traditional channels with services offered through collaborative platforms. This shows that the effects of the SE on consumption patterns in established markets are a worrying reality for traditional companies.

From a business perspective, all sectors and industries are being affected to a greater or lesser extent by the SE (Keko *et al.*, 2018). SE poses a threat to established companies as it cannibalizes purchases and reduce prices (Richard and Cleveland, 2016) by promoting the replacement of individual property acquisition by shared ownership (Sanasi *et al.*, 2020) or even by short-term renting (Belk, 2014). This can be clearly seen in hospitality and transportation, which are the sectors that have been most affected (Gerwe and Silva, 2020). For example, Zervas *et al.* (2017) found that a 1% increase in Airbnb listings leads to a reduction of 0.05% in quarterly hotel revenues, which is in line with recent research by Hossain (2020). Additionally, Airbnb's entry makes the hotel industry more heterogeneous, forcing high-quality hotels to reposition themselves at the higher end of the market, while lower quality accommodations move to compete on price with Airbnb (Chang and Sokol, 2022). In the transportation sector, Kim *et al.* (2018) demonstrated that mobility markets such as cabs have significantly reduced their number of trips in relation to the growth of Uber. Mouratidis *et al.* (2021) argued that the average number of vehicles owned per household has significantly reduced when using the SE, and that for every vehicle used in shared mobility the number of vehicles in circulation has proportionally been reduced.

In addition, the SE has also led to significant changes in distribution channels because the sales force of the B2B2C sector has been replaced by these service providers (Kumar *et al.*, 2018). As such, the SE challenges traditional marketing channels and supply chains. The concepts of ownership and its transfer are deeply embedded in the roles of traditional channel members, while in the SE, consumers see access as an accepted way to obtain resources that were previously acquired through traditional channels (Ferrell *et al.*, 2017).

To cope with the negative consequences described above, companies have begun to adapt to the SE as it is described in section 2.2.

2.2 Business model innovation in the face of the SE

The shift toward the new modes of consumption that characterize the SE may offer new options for companies to innovate (Ciulli and Kolk, 2019), to continue serving their customers (Sanasi *et al.*, 2020), or to design new business models and value propositions to better adapt themselves to the new demand logics (Massi *et al.*, 2021). In this way, traditional companies can leverage their experience and the strength of their brands to adapt to SE (Richard and Cleveland, 2016) or give their product a new form of use (Klotz, 2018).

To take advantage of these opportunities, some companies have already begun to adapt their business models to the principles of SE (Chen and Wang, 2019), and earlier studies have identified different forms of adaptation (see Table 1).

Belk (2014)	Offering free content while providing other sources of income Acquire a collaborative platform Create a collaborative platform
Matzler *et al.* (2015)	Sell the use of the product Support customers in their desire to resell goods Exploit unused resources and capabilities Provide repair and maintenance services Expanding into new markets with collaborative consumption Develop new business models through the SE
Richard and Cleveland (2016)	Extending the brand to peer-to-peer rental services
Klotz (2018)	Add product rental services
Chen and Wang (2019)	Acquire a collaborative platform Create a collaborative platform
Kang *et al.* (2019)	Develop/use a collective mailing service
Ciulli and Kolk (2019)	Internal development Partnership Acquisition
Li *et al.* (2020)	Cooperating with collaborative platforms

Source(s): Table by the authors

Table 1. Types of business adaptation to the SE

Belk (2014) and Matzler *et al.* (2015) were the first to suggest some classifications of adaptation options, on the basis of which new forms of adaptation were later proposed such as extending the brand to peer-to-peer rental services (Richard and Cleveland, 2016), adding product rental to the service offering of companies (Klotz, 2018), developing or using collective shipping services through agreements (Kang *et al.*, 2019) or cooperating with SE platforms (Li *et al.*, 2020). Other authors, such as Chen and Wang (2019), explore already established options like acquisition or companies creating their own platforms. More recently, Ciulli and Kolk (2019) have proposed a new classification of adaptive actions that distinguish between internal development, partnership and acquisition.

At the same time, we observe a lack of research that has examined whether these alternative options of adaptation depend on a company's specific characteristics (Ciulli and Kolk, 2019), especially within a B2B context (Agarwal and Steinmetz, 2019), where academic studies have analyzed the main barriers for industrial companies to enter the SE (Govindan *et al.*, 2020), and the challenges they face to develop sharing-based business models (Melander and Arvidsson, 2021).

To shed light on this issue, the next section describes the methodology used to analyze, in a B2B context, whether the adaptation options observed in the market are related to the business characteristics of the companies involved.

3. Methodology

Given that business reality is, in some cases, ahead of academic studies in terms of the development and analysis of new business models (Bocken *et al.*, 2014), an exhaustive study of real cases of adaptation has been carried out following a procedure similar to the one developed by Ciulli and Kolk (2019) and Urbinati *et al.* (2017).

For the identification of the cases, we followed a process divided into five sequential steps, which took place between July 2021 and January 2022.

First, we identified the economic sectors with the greatest presence of SE, and which are the most important exchange platforms in each sector based on the information provided by consulting firms like PwC (2015, 2018) or organizations like the European Commision (2016, 2018). This resulted in the following list of sectors: accommodations, automotive, financial, machinery/industrial equipment, fashion, labor service, catering, and retail and logistics.

Second, we focused on identifying specific cases of companies that are active in the sectors we identified and that have innovated to adapt to the SE. Using Google Chrome browser, we consulted both general and news section results by adding the term "SE" to each of the sectors. Because it was a general keyword search, millions of results were obtained.

Third, to reduce the enormous number of results we obtained in the previous step, new, more refined and specific search keywords were used for each sector to obtain more precise results. Table 2 contains the keywords/headlines used to perform the searches.

Accommodation	Hotel SE
	Hotel sharing
	Hotel adapt to SE
Automotive	Cars SE
	Mobility SE
	Geely Holding Group SE
	Daimler SE
	Group Volkswagen SE
	Toyota Motor Corporation SE
	Nissan SE
	Volvo SE
	Hyundai Company SE
	Tesla Motors SE
	Groupe Peugeot Société Anonyme (PSA) SE
	Renault SE
	Kia Motors SE
Financial	Bank SE
	Finance SE
Industrial machinery/equipment	Machinery SE
	Construction SE
	Equipment SE
	B2B SE
	Sharing machinery
Fashion	Fashion SE
	Collaborative fashion
	Fashion companies subscription
	Fashion clothing rental
	Rental services in fashion
	H&M SE
	Nike SE
	Levi's SE
Labor services	Corporations SE
	Manufacturer SE
	Corporations crowd work
	Shared economy in labor services
	Shared economy in labor insurance
Restoration	Catering SE
	Delivery sharing service
Retail and logistics	Logistics SE
	Shared transportation
	Retail SE
	Supermarket SE
	Department store SE
	Retailers SE
	Wholesalers SE

Source(s): Table by the authors

Table 2.
Sectors and search keywords

In the fourth stage of the process, more specific information was collected for each of the identified cases to generate a more complete description. To this end, the website of the exchange platform and/or company related to the specific example was visited and press releases on the innovation of the business model developed by the actors involved were consulted. In turn, this search made it possible to identify alternative keywords, resulting in the identification of new cases. In addition, for each registered company, an exhaustive search was carried out for information on business characteristics such as turnover, age, sector of activity and commercial orientation. The entire process of identification, information collection and analysis described above resulted in a total sample of 149 adaptation cases [1].

Finally, the information obtained for each case was recorded and coded using content analysis, and different variables were defined to characterize each individual case. As a result, a database of 10 variables describing the identified business cases was formed.

3.1 Content variables and coding

The variables used to characterize the adaptation cases are described in Table 3. Some of them characterize the companies themselves and others have to do with the decisions made to adapt to the SE.

As far as the commercial orientation of companies is concerned, we distinguished three options: a consumer orientation (B2C), a business orientation (B2B) or a mixed (B2B and B2C) orientation. The size of the companies was defined according to the 2019 turnover in millions of euros (MM€). Because most companies are large, we opted in favor of classifying them in terms of their size relative to each other.

The variables "the type of adaptation" and "the part of the business model adapted" were codified following Ciulli and Kolk (2019). Specifically, three categories were used to describe the "types of adaptation." "Internal development" encompasses companies that have used

Sector	Size	Business orientation	Age
1 = Industry 2 = Transportation and storage 3 = Construction 4 = Trade 5 = Hospitality and tourism services 6 = Other services	1= <2 2 = 2–10 3 = 10–50 4= >50	1 = B2C 2 = B2B 3 = B2B and B2C	1= <10 2 = 10–50 3 = 50–100 4= >100
Type of adaptation 1 = Internal development 2 = Acquisition 3 = Partnership	Adapted business model part 1 = Value proposition 2 = Customer interface 3 = Business infrastructure 4 = Entire new business model		Brand decision 1 = New brand 2 = Extension
Consumption change 1 = App 2 = Rent 3 = No	Duration (years) 1 = 0–1 2 = 1–5 3= > 5		Country 1 = China 2 = EEUU 3 = Spain 4 = Japan 5 = United Kingdom 6 = Europe 7 = Asia 8 = America 9 = World

Source(s): Table by the authors

Table 3. Variables structure and coding

their own resources to adjust their business to SE. Within the category of "partnership" are identified those companies that have modified their business models through collaboration agreements with other institutions. By contrast the category "acquistion" includes the total or partial purchase of other companies or platforms as a way to adapt.

The variable "adapted business model part" has four categories. The "value proposition" one encompasses those cases whose change action involved the addition of a new product/service offered to existing customers. An example of this would be a new home delivery service offered by a supermarket. The "customer interface" option represents those adaptation actions that involved offering a new or existing product/service to a new segment of consumers. An example would be the development by an insurance company of a special insurance for users of shared mobility, which is a segment hitherto unexploited by the company. The "business infrastructure" category refers to adaptation options that involve changes in the way the company's resources (e.g. labor, equipment, machinery or tools) are managed. This is the case with the joint creation among several companies of an innovation ecosystem to cooperate in the use of resources or hiring of labor. Finally, the creation of a complete "new business model" frames cases of adaptation that involve the creation of an entirely new business model for the company. An example of this would be the offering of shared mobility services by car companies.

Additionally, we also looked at whether the modification or creation of new business models involves a "brand decision." This variable classifies cases of adaptation into two categories depending on whether the change implies the creation of a new brand related to the created/adapted business model ("new brand" category), or it only involves the integration of these business model changes within the firm's existing brand portfolio ("brand extension" category).

Whether these adaptation options involve some type of "consumption change" when purchasing goods or services was also analyzed and different categories were identified. The "app" category implies the use mobile applications to interact with the company. The "rent" option involves not acquiring ownership of the product but entering into temporary rental contracts with the companies. The "no" category means that the modes of consumption did not change at all.

3.2 Sample description

Table 4 shows the characteristics of the companies involved. The most prominent sector is industry (56%), followed by other services (22%) and commerce (11%), while they are mostly very large companies, 49% of them with a turnover over € 50 M, and 26% between € 10 M and € 50 M. In addition, most of the companies operate in both B2B and B2C contexts (77%) and have significant experience in the market, with 67% of them having been in business for more than 50 years.

The type of adaptation most frequently developed is partnership (63%) and the least common form is acquisition (16%). Regarding the adapted business model, the most frequent options are the adaptation of the customer interface (33%) and the creation of a new business model (31%).

In terms of brand decision, in most cases (71%) companies kept using their current brand (brand extension), while a minority of 29% preferred to create a new brand.

Most of the adaptation cases did not directly involve changes in the form of consumption (51%), while some others (39%) opted to use an application to offer products.

Finally, the geographical profile of the adaptation actions developed is centered on three categories: worldwide (28%), Europe in general (25%) and the USA (23%). The duration of these adaptations varies between 1 and 5 years (59%).

Table 4. Business and actions characteristics of SE adaptation

Sector	%	Size	%	Age	%	Business orientation	%
Industry	56	<2	11	<10	*2*	B2C	20
Other services	22	2–10	14	10–50	31	B2B	3
Trade	11	10–50	26	50–100	47	B2C and B2B	77
Hospitality and tourism services	9	>50	49	>100	20		
Transport and storage	2						
Adapted business model part	%	Type of adaptation	%	Country	%	Duration	%
Entire new business model	31	Acquisition	16	World	28	<1	18
Business infrastructure	7	Partnership	63	Europe	25	1–5	60
Customer interface	33	Internal development	21	EEUU	23	>5	22
Value proposition	29			Spain	6		
				China	4		
Brand decision	%	Consumption change	%	United Kingdom	4		
Extension	71	App	39	America	4		
New brand	29	Rent	10	Asia	3		
		No	51	Japan	3		

Source(s): Table by the authors

4. Analysis and results

4.1 The Kruskal–Wallis test

First, for data analysis, the Kruskal–Wallis test was performed using SPSS software. The Kruskal–Wallis test is a non-parametric (one-factor) test that analyzes the variances of categorical variables and compares differences between three or more groups (Tufféry, 2011).

This test has been used by recent studies (see Chang *et al.*, 2019; Rita *et al.*, 2021) with similar aims to the present study, that is, to explore the relationships between qualitative variables. In the context of our study, this test will help to understand how firm characteristics (e.g. sector, size, business orientation and age), and the strategic decisions taken for these adaptations (part of the adapted business model, brand decision, consumption change, country and duration) are related to the different types of adaptation carried out by firms to the SE. More specifically, the test will allow us, through the use of the Kruskal–Wallis chi-square, to test the null hypothesis that:

H0. There are no significant differences in the dependent variable (i.e. that there are no differences in the use of the different type of adaptation) between the groups of independent variables (firm characteristics and strategic decisions).

As shown in Table 5, the Kruskal–Wallis chi-square p-value is <0.1 in several cases, and in others even <0.01 so that we can reject the null hypothesis at this level of significance. More specifically, Table 5 shows how, with respect to the characteristics of the companies, there are significant differences in the types of adaptation used according to the business sector. This indicates that not all companies engage in the same adaptation activities toward the SE, but that, depending on the sector in which they operate, they are oriented toward one type of action or another. This is also the case for business orientation, although with a lower significance ($p < 0.1$), which shows that there are significant differences in the implementation of the types of adaptation according to the business orientation of the company. However, there are no significant differences in the use of adaptation options according to the size or age of the enterprise, indicating that it cannot be claimed that companies, large or small, old or new, adapt in different ways.

Independent variables	KW chi-square	DF (degree of freedom)	p-value (Chi-Square)
Sector	10.11	2	0.006***
Size	1.20	2	0.549
Business orientation	5.88	2	0.053*
Age	3.02	2	0.220
Adapted business model part	13.55	2	0.001***
Brand decision	39.06	2	0.000***
Consumption change	48.65	2	0.000***
Country	5.1	2	0.078*
Duration	2.14	2	0.342

Note(s): * is 10% of significance. ** is 5% of significance. *** is 1% of significance
Source(s): Table by the authors

Table 5.
Kruskal–Wallis test

In terms of the strategic decisions taken for these adaptations, it can be observed that there are significant differences in the use of adaptation actions depending on the part of the business model being adapted, the branding decision and the change in consumption. This shows that, depending on the strategic decisions taken in terms of change in the business model, brand or way of interacting with the consumer, they are oriented toward one type of adaptation action or another. Although with less significance ($p < 0.1$), significant differences are also detected at country level, while no differences are found in terms of the duration of the actions.

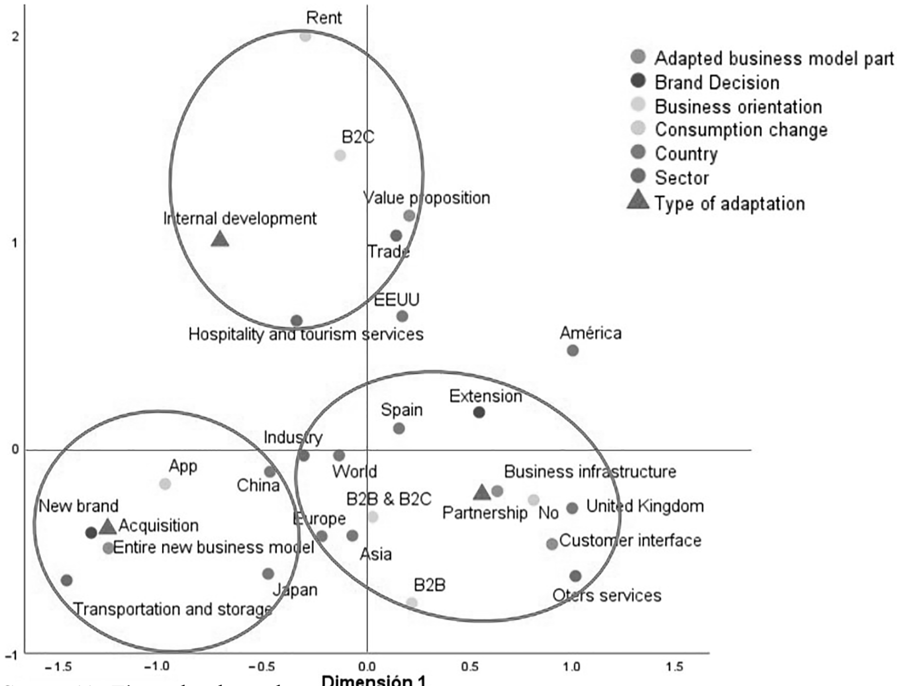
Therefore, according to the results of the Kruskal–Wallis test, most of the variables are related to significant differences in the form of adaptation, although it is not specified how these variables are related to each other. Therefore, in the next section, we show the results of the MCA to explore more concretely the distinction between these three types of adaptation.

4.2 Multiple correspondence analysis

An MCA was used to explore the relationships of the set of variables that we identified in the previous section that presented significant differences in the use of the different types of adaptation. The reason why we opted for this analysis is because it is a powerful technique to recognize patterns and associations in a dataset with multiple categorical variables (Arimond and Elfessi, 2016; Das *et al.*, 2018). It also allows the elaboration of graphical representations that help interpret data conveniently by simplifying the structure of associations between categories (Das *et al.*, 2018). Therefore, its main objective is to obtain a graphical representation of the original data matrix framed in as few dimensions as possible by considering the effect of each variable on all others and showing the co-occurrence of categories in a lower dimensional space (Parchomenko *et al.*, 2019). Ultimately, MCA is presented as the most suitable method for dealing with a wide diversity of qualitative metrics, extracting the optimal quantification describing the relationships between the categories of each variable, as well as the relationship between these variables (Arimond and Elfessi, 2016).

For the reasons mentioned above, MCA provides a better fit with the objectives and data collected in this study, which involves 7 variables coded into 29 categories for a total of 149 cases.

Using the SPSS program, the MCA creates different dimensions and estimates their eigenvalue under the assumption that those with a higher eigenvalue magnitude get a higher explained variance (Das *et al.*, 2018). For the choice of dimensions, the analysis was carried out for a maximum of four dimensions. However, only two of them were retained because they explained most of the variance (78.6%). This result is considered of good quality as they accounted for more than 50% of the total inertia (Chang *et al.*, 2019) (Figure 1). The variables



Source(s): Figure by the authors

Figure 1.
Multiple correspondence analysis results

identified and transferred to the graph show a good degree of dispersion, which indicates the quality of the variables and data obtained (Parchomenko *et al.*, 2019), making it possible to obtain a correct interpretation of the distances between the different variables.

In line with the characteristics of the MCA, Figure 1 can be interpreted based on the closeness of the points on the graph, with categories that are close together being more similar than categories that are far apart (Arimond and Elfessi, 2016). Based on this criterion, the categories were grouped into three distinct groups, taking the type of adaptation action as the center.

The first group, located in the lower left corner, is centered on “acquisition” as a form of adaptation. This group is made up of a total of seven categories belonging to six different variables. Thus, “acquisition” as a form of adaptation is highly related to (1) the “creation of a business model” and (2) the “creation of a new brand” for such action. In addition, companies that adapt through acquisition also develop and implement (3) their own “applications” for interaction with consumers, which means changing the way they interact with their customers. The sector most highly linked to this form of adaptation is (4) “transportation and storage,” and it is related with Asian countries, such as (5) China and Japan. This means that the acquisition implies important changes at the business level, involving the incorporation of a completely new business model for the company, the creation of new brands and the use of mobile applications to manage customers relationships. The structure of the group is shown in Table 6.

A clear example of this group is United Parcel Service (UPS), a company providing package delivery. This company, after a number of partial acquisitions on the Roadie platform, in the last quarter of 2021, finally acquired full ownership of the platform. Roadie is

	Firm characteristics	Strategic decisions
Acquisition	**Sector** Transportation and storage **Country** China Japan	**Brand decision** New brand **Consumption change** App **Adapted business model part** Entire new business model
Internal development	**Sector** Hospitality and tourism services Trade **Business orientation** B2C	**Consumption change** Rent **Adapted business model part** Value proposition
Partnership	**Sector** Industry Other services **Business orientation** B2B and B2C B2B **Country** Spain World Asia United Kingdom Europe	**Adapted business model part** Business infrastructure Customer interface **Consumption change** No **Brand decision** Extension

Source(s): Table by the authors

Table 6.
Group structure

a crowdsourced delivery platform that offers shared distribution services and connect users who made trips by car and users who need to send or receive something. With this acquisition, UPS wanted to develop an alternative market that has experienced remarkable growth in recent years. As a result, the company was able to reach a different target audience compared to its traditional customer base by incorporating the Roadie platform and using mobile applications to interact with their new customers. The service is available in the USA, closing 2021 with more than 200,000 registered drivers and coverage in more than 20,000 zip codes across the country, reaching 90% of US households.

The second group, located in the upper central part of Figure 1, represents the category of "internal development." This group is characterized with six categories that belongs to a total of five different variables. It presents a greater dispersion of values compared to group 1, although they have an acceptable proximity among themselves in general and with the category of internal development in particular. This form of adaptation is related to (1) the expansion of a market strategy aimed mainly at the final consumer "(B2C)," and the participation in (2) "trade" and "hotel and tourism services." In addition, "internal development" as an adaptation option is also broadly related to the adjustment in (3) the "value proposition" of the business model, and the development and implementation of "rental" options to market the company's products through monthly subscriptions or by other means, allowing consumers to change the way they consume the company's products. To summarize, this adaptation option is mainly related to companies in the service sector that are oriented to the final consumer and that use rental as a new way of interacting with their customers by modifying their value proposition.

The German multinational retail chain MediaMarkt is an example of a company that belongs to this group. In 2020, it decided to realign its strategy by offering rental services (rent) for some of its products. Its current objective is to ensure that the service section gains weight over product sales. In 2019 only 7% of the company's revenues in Spain came from services (2 M€), such as rental or leasing, electricity sales and alarms. The rationale of this strategy is that customers are currently valuing the enjoyment of the product more than the ownership itself.

Finally, the third group, located in the lower right part of Figure 1, has to do with the category of "partnership." This group is the most complete and complex because it includes a total of 14 categories belonging to the 7 variables used in the analysis. Therefore, it presents categories with a remarkable level of grouping and other variables with a greater dispersion of points within the graph. However, they have an acceptable internal proximity in general and with the category of partnership in particular.

On one hand, the categories most strongly related to "partnership" are (1) the adjustment in the "company's infrastructure" as part of the adapted business model and (2) the "no" incorporation of substantial changes in the way customers consumes the company's products. This means that the changes implied by this option take place at an internal level and neither affects the way they relate to customers nor their brand decision because (3) the companies expand their own existing brands. In addition, companies that adjust through partnerships also develop and implement adjustments to (4) the "customer interface" as part of the adapted business model and (5) are geographically located in widely dispersed and varied areas, such as European countries like the UK, Spain and "rest of Europe countries," the "rest of Asian countries" and "the world" as a whole.

The use of partnership as a form of adaptation, on the other hand, can be explained by a business characteristic as the sector, (6) related to different sectors, ranging from "industry" sector to "other services." Market strategies that characterize this group include (7) companies that develop market strategies exclusively focused on other companies "(B2B)," and others that develop a mixed strategy focused on both companies and consumers "(B2B and B2C)." This shows that, at a first glance, there is no clear pattern of business characteristics in relation to this option.

To illustrate the types of companies included in this group, we can mention services companies, like the disinfection services company Cloralex, which entered into an alliance in 2020 with the Airbnb platform to promote new cleaning standards in the face of the new situation caused by COVID-19. With this alliance, Cloralex aimed to expand its market by reaching a different consumer segment, while obtaining an important opportunity to increase its number of customers through access to all users of the platform. Another company included in this group is the great industrial conglomerate Geely Holding Group. In addition to the many other actions designed to adapt to the SE in recent years, in 2021 this company formed an innovation ecosystem with the Renault Group through a collaboration agreement. This ecosystem allowed both groups to share resources, technology and even infrastructure to deepen innovation focused on the development of hybrid vehicles in the Chinese and South Korean markets.

5. Discussion and implications

The main findings of the analyses discussed in this study suggest that the way firms adapt to SE is related to business characteristics and the strategic decisions taken for these adaptations. This finding is in line with earlier studies (Klotz, 2018; Li *et al.*, 2020), which stated that not all firms will obtain similar results by adapting in the same way. Instead, there are circumstances, conditions and markets in which it may be more convenient to act in a certain way or not to do so. Therefore, this study sheds light on the gap in the analysis of the different uses of forms of adaptation toward SE and its opportunities (Mai and Ketron, 2022), while extending the previous study by Ciulli and Kolk (2019) by looking at the variables that affect established firms' decisions to enter SE through different approaches.

More specifically, the results of this study show through the Kruskal–Wallis test that there are differences in the use of adaptation options depending on both the characteristics of the companies and strategic decisions taken for these adaptations. Subsequently, the MCA analysis was conducted to precisely identify how each form of adaptation is related. Table 6 shows the characteristics and strategic decisions that can be associated with adaptations toward SE.

These results suggest that acquisition, as a way of adapting to SE, implies important changes at the business level. These changes include the creation of new business models, the development of new brands and changes in the way a company relates to customers in the transportation and storage sectors industry. Such adaptations are complex and costly decisions that require a long-term vision. These results are consistent with the literature that view acquisition as a form of growth that involves an extensive economic effort on the part of the traditional company (Jordão *et al.*, 2014), and that can offer a solution to complex problems such as adjusting to technological changes or strengthening the competitive position (Child *et al.*, 2001). Therefore, as this adaptation form involves costly operations and proposes solutions to complex and ambitious issues, it makes sense that they involve major business changes over time.

By contrast, internal development as a way to adapt is more common among companies in the commerce/tourism sector. They choose to change their business model internally without the need for drastic changes, except in terms of value propositions. As such, the aim of this form of adaptation is to generate synergies in the company's traditional activity, taking advantage of its knowledge of the market and exploring these new business opportunities provided by the SE. These results are in line with the characteristics of internal development. Compared to acquisition, it involves a slower growth process, a lower monetary cost versus a greater need for time invested, and greater risks, due to the need to maintain the entire process internally from start to finish (Francis and Smith, 1995). However, this form of adaptation also involves taking advantage of the company's market experience, by giving it a greater ability to recognize opportunities, understanding which resources are available and needed, and developing synergies from these resources. It can be used as a springboard to approach these new opportunities (Karim and Mitchell, 2004). As these are companies with more limited economic resources and a high level of experience in the market, internal development is the most appropriate way to adapt, allowing them to use all their knowledge and capabilities, and assuming an acceptable cost for the realization of these actions (Lee and Lieberman, 2010).

Finally, partnership is the most commonly used form of adaptation and companies that opted in favor of this option present a more complex profile. There is no clear pattern as far as the relationship between business characteristics and this option is concerned because we identified companies in a wide variety of sectors, including industry and services. However, this is consistent with the view of partnership as an essential strategy for business development at all levels, regardless of business characteristics (Kanter, 1994). This may explain why in recent years the analysis of innovation in business models has been focused mainly on the study of partnership (Coombes, 2022) as the basis for achieving disruptive innovations and adapting the company to changes in the market structure (Carlborg *et al.*, 2021).

Moreover, these complex partnerships are in line with the increase of complex and specialized innovation models observed recently in business partnership and innovation literature (Xie and Wang, 2020). It shows that it is becoming increasingly complicated for a single company to engage in innovation independently, and it is more and more necessary to work together with other actors to create and capture value through innovation (Adner, 2006), for instance with universities, researches institutions, other companies, technological centers, suppliers or end users (Cantù *et al.*, 2021). This applies to smaller companies that do not have enough resources to develop this innovation process by themselves (Zhang *et al.*, 2021) and to larger companies that want to remain competitive in highly dynamic environments (Joseph *et al.*, 2021). This has given rise to what we understand as innovation ecosystems, i.e. networks of hierarchically heterogeneous and independent organizations that collaborate for the co-creation of a value proposition (Thomas and Ritala, 2022; Konietzko *et al.*, 2020; Moreau *et al.*, 2018).

In general, this study has allowed us to analyze real cases of adaptations toward the SE by traditional companies, identify and classify them according to their characteristics and the different types of adaptation used. In this way, by analyzing and coding qualitative data on a total of 149 cases of adaptation, it has been possible to obtain a fairly broad perspective of how these cases work. Furthermore, this article has given us the possibility to relate the types of adaptation to changes in business models, linking and extending existing literature on the SE, business models innovation, and even finding relationships with the literature on innovation ecosystems.

In addition, this study also raises a number of managerial implications for traditional companies and emerging platforms alike. First, by identifying 149 real-life cases of adaptation, we demonstrate that there are different approaches that traditional firms can take to compete in an SE context. To this end, the characteristics of each of the adaptation options used are detailed and explained, providing company managers with concrete examples of companies that have adapted, which could raise their awareness of the potential role that their adoption could play in their company. In addition, the identification of relationships between adaptation options and certain variables on business characteristics provides a table. This table allows managers of traditional businesses to determine which options are most developed based on their specific characteristics and how they relate strategic decisions. This provides information to managers of traditional companies that are thinking of adapting to SE and therefore eliminates part of the uncertainty of this decision.

With regard to SE platforms or start-ups, the activities of traditional companies can represent both an opportunity and a threat. On the one hand, they may present opportunities for partnerships or even acquisitions that allow these emerging platforms to thrive in the market. On the other hand, they may also risk affecting their market share. As a result, this study provides an explanation for emerging platforms on the distribution of business characteristics that may be most strongly related to each type of adaptation. It offers clues about future threats or opportunities.

6. Limitations and future lines of research

This study also has some limitations. Although it takes a first step toward the study of the variables that affect the decisions of established companies to adapt to the SE, it has an exploratory nature because it is based on qualitative data identified in secondary sources. Future studies could extend this line of research by using quantitative data that would allow a more in-depth examination of the relationships between company characteristics and adaptation modes. Second, collecting information from secondary sources using keywords for the Internet search of adaptation cases may have led to the omission of certain keywords. The inclusion of these keywords might have yielded different results and could have resulted into the underuse of other important search terms and the under-identification of other business cases. As such, future research may involve expanding the number of search terms being used to identify as many cases as possible.

In addition, while this study indicates that the partnership option has been by far the most used form of adaptation by companies to adjust their business models to the SE context, it does not provide an explanation for why that is the case, which is something future research can examine in greater depth. Moreover, most companies included in this study are large, making it difficult to draw conclusions about smaller companies. As such, future research can also include smaller companies, and see what the similarities and differences are when looking at the size of a company.

Note

1. The complete list of companies, sectors and types of adaptation can be requested from the authors.

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Innovations and development of artificial intelligence in Europe: some empirical evidences

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Abstract

Purpose – The objective of this paper is to analyze the relationship between innovation and the development of artificial intelligence (AI) and digital technologies in Europe. The use of digital technologies among European companies is studied through a composite index, while the relationship between innovation and AI is studied through a log-linear regression model. The results of the model have made possible to develop interesting indications for economic and industrial policy.

Design/methodology/approach – The use of digital technologies among European companies is studied through a composite index of AI and information technology (ICT) (using the Fair and Sustainable Welfare methodology) with the aim of measuring territorial gaps and to know which European countries are more or less inclined to its use, while the relationship between innovation and AI is studied through a log-linear regression model.

Findings – In the paper, two different methodologies were used to analyze the relationship between innovation and the development of digital technologies in Europe. The synthetic indicator made possible to develop a taxonomy between the different countries, the log-linear model made possible to identify and explain the determinants of innovation.

Originality/value – The description of the biunivocal relationship between innovation and AI is a topical and relevant issue that is treated in the paper in an original way using a synthetic indicator and a log-linear model.

Keywords Innovation, Artificial intelligence, Policies

Paper type Research paper

1. Introduction

A country's innovation is an important factor influencing the artificial intelligence (AI) endowment of firms. Indeed, companies operating in countries with a high level of innovation tend to be more advanced in their adoption and use of AI. There are several reasons why this is the case. First, more innovative countries tend to have a more advanced technological culture and infrastructure, which means that firms have access to more resources and technological knowledge. This allows them to invest more in AI research and development and use it more effectively. More innovative countries tend to have a more favorable

JEL Classification — O25, O31, O32

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environment for entrepreneurship and for the development of innovative start-ups, which are often at the forefront of AI adoption and use (Makridakis, 2017). This, in turn, can stimulate a virtuous cycle of innovation and AI development, in which more advanced firms attract highly skilled talent and investment, prompting other firms to follow suit. Ultimately, the level of innovation in a country can have a significant impact on the AI endowment of firms. However, there are also other factors, such as the availability of quality data and access to skilled talent, that can affect the ability of firms to use AI effectively. The level of AI in companies can influence innovation in a country (Agrawal *et al.*, 2019). Companies that invest in AI research and development and use AI effectively can become market leaders in their sector and stimulate innovation in other sectors. Furthermore, the adoption of AI by businesses can lead to greater efficiency and productivity, reducing costs and improving the quality of products offered (Perifanis and Kitsios, 2023).This in turn can stimulate economic growth and innovation in other sectors. Therefore, innovation and AI development are interdependent factors, where innovation can lead to AI development and vice versa. The presence of a favorable technology ecosystem and business environment can foster the development of both, helping to create a virtuous circle of innovation and economic growth. To better understand the relationship between innovation and AI development, it is important to consider some key factors that influence both. This means that businesses must have access to adequate funding, infrastructure and support services, as well as a culture of innovation and collaboration (Ziakis *et al.*, 2022). Finally, the availability of high-quality data is a key factor for AI development. Companies need data to train their machine learning algorithms and improve their data processing capabilities. Therefore, countries that invest in creating an open and accessible data environment can stimulate the development of AI (Gao and Janssen, 2020).

To achieve the goal of making the link between AI and innovation more virtuous, the 'Digital Europe' program was launched. It is certainly a central element of the Commission's overall response to the challenge of digital transformation and is included in the proposal on the Multiannual Financial Framework (MFF) for the period 2021–2027. Its objective is to provide a spending instrument adapted to the operational requirements of capacity building in the areas identified by the European Council and to exploit synergies between them. The program aims, *inter alia*, to develop and strengthen core competences in AI, such as data resources and archives of AI algorithms, and to make them accessible to all businesses and public administrations; to ensure that the essential capabilities needed to secure the EU digital economy, society and democracy are available and accessible to the EU public sector and businesses; and to improve the competitiveness of the EU cybersecurity industry; expand the optimal use of digital capabilities, in particular high-performance computing, AI and cybersecurity, in all sectors of the economy, areas of public interest and society, including the implementation of interoperable solutions in areas of public interest, and facilitate access to technology and know-how for all businesses.

To better understand the phenomenon, this study aims to analyze the use of digital technology among European firms through a composite index of AI and information technology (ICT) (using the Fair and Sustainable Welfare Methodology) to measure territorial gaps and to know which European countries are more or less inclined to its use, and to study the relationship between innovation and AI through a log-linear regression model.

To this end, this contribution is developed with the following structure:

(1) Survey of literature (paragraph 2),

(2) Description of the methodology for constructing the composite indicator and log-linear regression; in particular, the robustness of the methods and results will be discussed (paragraph 3),

(3) Description of the results obtained with the two methods (section 4),

(4) Discussion of the results (paragraph 5),

(5) Conclusions (paragraph 6).

2. Background

The relationship between innovation and the development of AI is one of the most relevant research topics in recent years, because the tumultuous development of AI is rapidly changing the concept of innovation and also the taxonomy of key factors that characterize the process of innovation growth. The virtuous relationship between innovative technologies and competitive advantage was extensively described many years ago by Porter (1985). Artificial intelligence and its applications are among the most innovative emerging technologies today. According to a recent study conducted by the World Economic Forum, a strong correlation emerged between companies' AI endowment and their ability to innovate. Companies that use AI improve their efficiency, reduce costs and improve the quality of their products. This can spur innovation in other sectors and contribute to overall economic growth. Moreover, as a recent McKinsey Global Institute report points out, the economic potential of AI is enormous and can help generate significant productivity and value-added gains in various sectors. However, the report also stresses the importance of effective regulation to ensure responsible use of AI and mitigate the risks associated with its adoption. In addition, to fully exploit the benefits of AI, it is important to create a corporate culture conducive to innovation and experimentation. The academic literature on this topic is quite extensive, and only the main papers that refer to these issues are reported in this paper. Among the most interesting survey papers are Mariani *et al.* (2023), Mariani *et al.* (2022), which propose a systematic overview of innovation research strands revolving around AI. The results provide an up-to-date overview of the existing literature, embedded in an interpretive model that allows us to distinguish all the main modes and consequences of the introduction of AI in the context of innovation. The first and fundamental aspect to be investigated is that of the relationship between the introduction from AI, innovation and organizational change. In Haefner *et al.* (2021) there is an interesting analysis of how Artificial Intelligence (AI) reshapes companies and how innovation management is organized. Consistent with rapid technological development and the replacement of human organization, AI may actually force management to rethink the entire innovation process of a company. Verganti *et al.* (2020) propose a framework for understanding AI design and innovation. Specifically, the authors note that as creative problem solving is significantly conducted by algorithms, human design increasingly becomes a sensemaking activity, i.e. understanding the problems that should or could be addressed. This shift in focus requires new theories and brings design closer to leadership, which is inherently a sensemaking activity. Allam (2016) analyzes how AI transforms businesses and organizes innovation activities. AI could force companies to restructure the entire innovation process in response to rapid technological progress and human resource reorganization. Society in general sees AI as a representation of unlimited possibilities. Lee *et al.* (2019) provide a brief overview of AI, current issues faced in AI development, and explain how it transforms business models. The case study of two companies that have innovated their business models using AI shows its potential impact. The paper illustrates how executives can create an innovative AI-based culture by reformulating the process of AI-based business model innovation. Companies that successfully leverage AI can create disruptive innovation through their new business models and processes, enabling them to potentially transform the global competitive landscape. Wang *et al.* (2022) show that the increasing evolution of business and the latest Artificial

Intelligence (AI) means that different business practices are enhanced by the ability to create new means of collaboration. The experimental result suggests that digital transformation is generally considered essential and enhances business innovation strategies.

It is also important to examine the relationship between the introduction of AI, innovation and the emergence of new businesses. May *et al.* (2020) analyze the role of AI for digital innovation and how it affects the process of business creation, we conduct an in-depth case study of a heavily funded imaging AI company. The case study reveals four tensions caused by AI that a digital enterprise must address and four ways to counter them: (1) managing excessive expectations of AI, (2) designing work routines for AI, (3) dealing with users' opposing perceptions of AI, and (4) integrating domain expertise with AI.

The introduction of AI then also impacts the area of corporate social responsibility. Buhmann and Christian (2021) apply a deliberative approach to propose a framework for responsible innovation in AI. This framework foregrounds discursive principles that help offset these challenges of opacity. To support better public governance, we consider the roles and mutual dependencies of organizations developing and applying AI, as well as civil society actors and investigative media in exploring pathways for responsible AI innovation. Cockburn *et al.* (2018) aim to hypothesize that deep learning represents a general method of invention and outline some preliminary implications of this hypothesis for management, institutions, and policy. Also important is the aspect of new job profiles required by the market. Kakatkar *et al.* (2020) show that AI is a very fast emerging technology that is being applied in many areas. A wide range of innovative solutions are being developed and some have already reached the market. However, the specific business models for AI are less clear and still developing. Companies face multiple challenges, from regulation to human resources and data collection. Managing AI-based innovations will be particularly difficult for small businesses, where problems are often more pronounced than in larger industries. Explicit challenges for managing AI-based innovations include the necessary focus on managing expectations and ensuring historical metadata expertise, which is essential for many AI-based solutions. Policies to support AI-based innovation should therefore focus on the human aspects. This includes increasing the availability of AI experts, but it also concerns the development of new job profiles, such as AI training experts. AI innovators also need clear regulation of AI and investment in research on key challenges, such as explainable AI.

A final point to explore in the literature is the relationship between strategic forecasting and research. Mühlroth and Grottke (2020) apply strategic foresight in technology and innovation management to detect discontinuous changes early, assess their expected consequences, and develop a future course of action to achieve superior business performance; they derive theoretical and practical implications for enterprise technology and innovation management and suggest future research opportunities to further advance this field. Soni *et al.* (2020) analyze the overall impact of AI-from research and innovation to deployment-and address the most influential academic achievements and innovations in the field of AI; their impact on business activities and thus on the global marketplace. The paper also helps investigate the factors responsible for AI advancement and provide a better understanding of how AI can transform business operations and thus the global economy. Brem *et al.* (2021) describe Artificial Intelligence (AI) as an emerging technological field with immense potential for transformation. Here, they discuss the different ways in which AI is transforming innovation, introducing a conceptual framework in which AI plays the following two roles: creator and facilitator of innovation.

The literature survey has shown that there is evidence demonstrating a strong correlation between firms' AI endowment and their ability to innovate, and that AI represents a great opportunity for firms to innovate and remain competitive, but it is important to adopt a strategy of responsible use of AI and investment in research and development to fully exploit its innovative potential. The analyses that follow will attempt to empirically verify these considerations by econometrically identifying the links between innovation and the use of AI.

3. Materials and methods

3.1 Synthetic index

The approach used involves the construction of macro areas (pillars) by aggregating elementary indicators (Table 1). Both pillars and elementary indicators have been considered non-replaceable. To construct synthetic index, we adopted the following indicators all with positive polarity:

The matrix relating to data on European enterprises was divided into four progressive steps:

(1) Selection of a set of basic indicators based on an ad hoc evaluation model hinging upon the existence of quality requirements.

(2) Further selection aimed at balancing the set of indicators within the theoretical framework of the structure. Outcome indicators are impact indicators as the ultimate result of an action as a result of a stakeholder activity or process.

(3) Calculation of synthetic indices (pillars), by making use of the methodology proved more appropriate to obtain usable analytical information.

(4) Processing of a final synthetic index as a rapid empirical reference concerning the degree of digital technology of European enterprises.

Missing values were attributed via the *hot-deck* imputation and, where not possible, with Europe's average value.

The choice of the synthesis method is based on the assumption of a formative measurement model, in which it is believed that the elementary indicators are not replaceable, which is to say, cannot compensate each other.

Table 1. Macro areas and Indicators

Macro areas	Indicators
Artificial Intelligence	Percentage of enterprises analyzing big data internally using machine learning (VAR1)
	Percentage of enterprises analyzing big data internally using natural language processing, natural language generation or speech recognition (VAR2)
	Percentage of enterprises using service robots (VAR3)
	Percentage of enterprises with a chat service where a chatbot or a virtual agent replies to customers (VAR4)
	Percentage of enterprises that use one AI system (of E_CHTB, E_BDAML, E_BDANL, E_RBTS) (VAR5)
	Percentage of enterprises that use two AI systems (of E_CHTB, E_BDAML, E_BDANL, E_RBTS) (VAR6)
	Percentage of enterprises that use three AI systems (of E_CHTB, E_BDAML, E_BDANL, E_RBTS) (VAR7)
ICT	Percentage of enterprises with e-commerce sales of at least 1% turnover (VAR8)
	Percentage of enterprises' total turnover from e-commerce sales (VAR9)
	Percentage of enterprises provided training to their personnel to develop their ICT skills (VAR10)
	Percentage of enterprises that recruited/tried to recruit personnel for jobs requiring ICT specialist skills (VAR11)
	Percentage of enterprises that employ ICT specialists (VAR12)

Source(s): Eurostat, 2021 - our selection

The exploratory analysis of input data was performed by calculating the mean, average standard deviation and frequency, as well as correlation matrix and principal component analysis. Since this is a non-compensatory approach, the simple aggregation of elementary indicators was carried out using the correct arithmetic average with a penalty proportional to the "horizontal" variability.

Normalization of primary indicators took place by conversion into relative indexes compared to the variation range (*min-max*).

Attribution of weights to each elementary indicator has followed a subjective approach, opting for the same weight for each of them. Since, in some cases, the elementary indicators showed different polarity, it was necessary to reverse the sign of negative polarities by linear transformation.

For the synthetic indicator calculation, we used the Adjusted Mazziotta-Pareto Index (AMPI), which is used for the min-max standardization of elementary indicators and aggregate with the mathematical average penalized by the "horizontal" variability of the indicators themselves. In practice, the compensatory effect of the arithmetic mean (average effect) is corrected by adding a factor to the average (penalty coefficient) which depends on the variability of the normalized values of each unit (called horizontal variability) or by the variability of the indicators compared to the values of reference used for the normalization.

The synthetic index of the i-th unit, which usually varies between 70 and 130, is obtained by applying, with negative penalty, the correct version of the penalty method for variation coefficient (AMPI +/−), where:

$$\mathrm{AMPIi}- = \mathrm{Mri} - \mathrm{Sricvi} \tag{1}$$

where *Mri* e *Sri* are, respectively, the arithmetic mean and the standard deviation of the normalized values of the indicators of the i unit, and cvi = *Sri* / *Mri* is the coefficient of variation of the normalized values of the indicators of the i unit.

The correction factor is a direct function of the variation coefficient of the normalized values of the indicators for each unit and, having the same arithmetic mean, it is possible to penalize units that have an increased imbalance between the indicators, pushing down the index value (the lower the index value, the lower the level of digital technology).

This method satisfies all requirements for the statistical synthesis:

(1) Spatial and temporal comparison

(2) Irreplaceability of elementary indicators

(3) Simplicity and transparency of computation

(4) Immediate use and interpretation of the obtained results

(5) Strength of the obtained results

An influence analysis was also performed to assess the robustness of the method and to verify if and with which intensity the composite index rankings change following elimination from the starting set of a primary indicator. This process has also permitted us to analyze the most significant indicators.

The analysis was conducted using the *COMIC* (Composite Indices Creator) software, developed by ISTAT. The software allows calculating synthetic indices and building rankings, as well as easily comparing different synthesis methods to select the most suitable among them, and write an effective report based upon results.

3.2 Method: log-linear analysis

Log-linear regression belongs to the class of generalized linear models (GLM).

General Linear Models (GLM) are a flexible and powerful tool for modeling complex relationships between data and have a wide range of applications in fields such as psychology, economics, medicine and ecology. GLM extends the traditional linear regression model by allowing for non-normal error distributions and non-constant variances. They can handle a variety of response types, including continuous, binary, count and categorical data, and can incorporate multiple sources of variation, such as random effects and repeated measures. The most common log-linear regression is the Poisson regression. It is also possible to use two other distributions: the Gamma and the exponential. The response function defines how the response (dependent) variable is related to the model's independent variables. It is a mathematical function that describes the relationship between the mean of the response variable and the model's independent variables. The GLM model uses the response function to estimate the model parameters and to predict the values of the response variable based on the values of the independent variables. The choice of the appropriate response function depends on the properties of the response variable and the specifications of the research problem. Unlike linear regression, there is no exact analytical solution. It is therefore necessary to use an iterative algorithm.

We assume that the response variable is written as the logarithm of a function of the explanatory variables. In general, we can write the equation of the model in the following form:

$$\mathrm{Log(Y)} = a_1B_1 + a_2b_2 + .. + a_nB_n + \varepsilon$$

In exponential form can be written:

$$Y = e_1^{a1B} + e^{a2B2} + .. + e^{anBn} + \varepsilon'$$

These models allow us to estimate the net contributions of each variable and the probabilities of participation associated with different profiles constructed from different associations of variables. The effect of individual variables on the final ordering of the response function is investigated to derive indications of the relevance and significance of the variables and identify those with a greater explanatory power on the volunteer's life satisfaction.

As far as the goodness of fit is concerned, if χ^2, which is the equivalent of the Fisher's F-test of the linear model, is less than 0.001 for the LR (likelihood ratio), then the model is highly significant, and the variables contain a large amount of information.

4. Results

4.1 Result synthetic index

Tables 2–4 reveal a good variability. Tables 5–7 show significant correlations between AI e ICT macro areas ($r = 0.683$) and, in particularly, there are significant direct correlations between percentage of enterprises analyzing big data internally using machine learning (VAR1) and percentage of enterprises that use one AI system (of E_CHTB, E_BDAML, E_BDANL, E_RBTS) (VAR5) ($r = 0.907$), between percentage of enterprises analyzing big data internally using machine learning (VAR1) and Percentage of enterprises that use two AI

Table 2.
Mean, σ and frequency macro areas

	AI	ICT
Mean	100.969	101.903
σ	9.172	11.49
Frequency	29	29

Source(s): Eurostat, 2021 - Our elaborations systems (of E_CHTB, E_BDAML, E_BDANL, E_RBTS) (VAR6) (r = 0.708), between Percentage of enterprises with a chat service where a chatbot or a virtual agent replies to customers (VAR4) and Percentage of enterprises that use one AI system (of E_CHTB, E_BDAML, E_BDANL, E_RBTS) (VAR5) (r = 0.714) and Percentage of enterprises that use one AI system (of E_CHTB, E_BDAML, E_BDANL, E_RBTS) (VAR5) and Percentage of enterprises that use two AI systems (of E_CHTB, E_BDAML, E_BDANL, E_RBTS) (VAR6) (r = 0.779), between Percentage of enterprises with e-commerce sales of at least 1% turnover (VAR8) and Percentage of enterprises' total turnover from e-commerce sales (VAR9) (r = 0.651), between Percentage of enterprises provided training to their personnel to develop their ICT skills (VAR10) and Percentage of enterprises that recruited/tried to recruit personnel for jobs requiring ICT specialist skills (VAR11)) (r = 0.616).

The influence analysis describes the indicators that most influence the composition of rosters of European countries. In analyzing Tables 8–10, we can see that the most significant macro area is ICT (mean = 2.862, σ = 3.280) and the most important indicators concerns

	VAR1	VAR2	VAR3	VAR4	VAR5	VAR6	VAR7
Mean	3.31	1.207	2.034	2.207	5.931	0.897	0.103
σ	3.892	0.94	1.052	1.424	3.909	0.724	0.31
Frequency	29	29	29	29	29	29	29

Source(s): Eurostat, 2021 - Our elaborations

Table 3. Mean, σ and frequency AI macro area

	VAR8	VAR9	VAR10	VAR11	VAR12
Mean	20.103	17.966	21.31	8.966	20.897
σ	7.734	8.437	7.802	3.438	5.115
Frequency	29	29	29	29	29

Source(s): Eurostat, 2021 - Our elaborations

Table 4. Mean, σ and frequency ICT macro area

Macro areas	AI	ICT
AI	1.000	
ICT	0.683	1000

Source(s): Eurostat, 2021 - Our elaborations

Table 5. Correlation matrix of the macro areas

Indicators	VAR1	VAR2	VAR3	VAR4	VAR5	VAR6	VAR7
VAR1	1.000						
VAR2	0.216	1.000					
VAR3	0.215	0.173	1.000				
VAR4	0.497	0.180	0.495	1.000			
VAR5	0.907	0.305	0.504	0.714	1.000		
VAR6	0.708	0.452	0.614	0.610	0.779	1.000	
VAR7	0.475	0.169	0.098	0.273	0.418	0.208	1.000

Source(s): Eurostat, 2021 - Our elaborations

Table 6. Correlation matrix of the AI's indicators

percentage of enterprises with e-commerce sales of at least 1% turnover (VAR8) (mean = 1.793, σ = 1.864), percentage of enterprises with a chat service where a chat-bot or a virtual agent replies to customers (VAR4) (mean = 1.621, σ = 1.622) and percentage of enterprises that employ ICT specialists (VAR12) (mean = 1.517, σ = 1.567).

Table 7.
Correlation matrix of the ICT's indicators

Indicators	VAR8	VAR9	VAR10	VAR11	VAR12
VAR8	1.000				
VAR9	0.651	1.000			
VAR10	0.552	0.531	1.000		
VAR11	0.415	0.353	0.616	1.000	
VAR12	0.313	0.503	0.570	0.611	1.000

Source(s): Eurostat, 2021 - Our elaborations

Table 8.
Influence Analysis: mean and s of the shifts of the rankings by basic indicator removed of macro areas

Macro areas	Mean	σ
IA	2.621	2.833
ICT	2.862	3.280
Mean	2.741	3.057
σ	0.121	0.223

Source(s): Eurostat, 2021 - Our elaborations

Table 9.
Influence Analysis: mean and s of the shifts of the rankings by basic indicator removed of AI's indicators

Indicators	Mean	σ
VAR1	0.621	0.762
VAR2	1.276	1.236
VAR3	1.034	1.066
VAR4	1.621	1.622
VAR5	0.414	0.683
VAR6	0.345	0.603
VAR7	0.690	1.289
Mean	0.857	1.037
σ	0.436	0.346

Source(s): Eurostat, 2021 - Our elaborations

Table 10.
Influence analysis: mean and s of the shifts of the rankings by basic indicator removed of ICT's indicators

Indicators	Mean	σ
VAR8	1.793	1.864
VAR9	1.448	1.567
VAR10	1.379	1.518
VAR11	1.379	1.324
VAR12	1.517	1.567
Mean	1.503	1.567
σ	0.154	0.173

Source(s): Eurostat, 2021 - Our elaborations

The values of the composite index of Artificial Intelligence (AI), information technologies (ICT) and digital technology are described in Table 11, Table 12 and Figure 1,

In particular, as regards digital technology, the “best” performances are grouped in north-eastern Europe, in particular in Denmark, Finland, Belgium, Sweden and Lithuania, but the most digital European nation is Ireland (total index 135.6, AI index 124.2, ICT index 123.9) followed by Malta (index 126.0) and Denmark (index 125.7). Italy ranks 24th (out of 29) in the ranking of digital technology (index 111.18), in particular 10th in the ranking of AI (index 103.3) and 26th (index 85.9) for the use of ICT, a clear sign that AI is widespread in the few companies that use ICT.

The synthetic index can be useful to get an idea of the use of digital technologies at a territorial level, but above all it can constitute a support for the decisions of European policy makers who must encourage companies to develop them, as part of one of the 6 priorities of the European Commission 2019–2024, namely «A Europe ready for the digital age».

In this *scenario*, a type of “compensatory” or “add-on” regional development policy ends up accentuating the differences between regions, which are due to the different regional response to policies stimuli. Instead of fostering convergence, traditional policies create underdevelopment traps.

Peripheral regions are the ones most exposed to loss of competitiveness since the rules governing the economic system promote the aggregation of factors and “classic” regional

Nations	Value	Rank
Ireland	124,24	1
Malta	120,90	2
Finland	114,36	3
Lithuania	113,50	4
Denmark	110,86	5
Belgium	106,11	6
Portugal	104,24	7
Sweden	103,85	8
Slovakia	103,52	9
Italy	103,35	10
Spain	102,87	11
Germany	101,87	12
Czechia	101,55	13
Norway	100,00	14
Austria	99,78	15
Luxembourg	99,56	16
Croatia	99,50	17
France	99,50	18
Netherlands	98,04	19
Estonia	97,65	20
Romania	95,16	21
Bulgaria	93,51	22
Poland	93,09	23
Slovenia	93,09	24
Bosnia and Herzegovina	92,03	25
Cyprus	91,77	26
Latvia	89,69	27
Hungary	89,68	28
Greece	84,86	29
EUROPE	100,00	

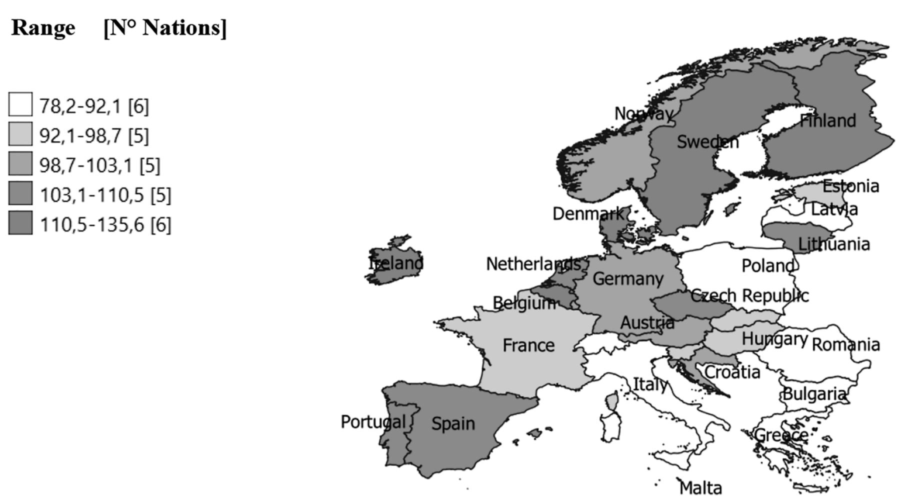
Source(s): Eurostat, 2021 - Our elaborations

Table 11.
Synthetic European index ranking of AI

Nations	Value	Rank
Belgium	126,28	1
Denmark	125,53	2
Ireland	123,96	3
Finland	115,77	4
Malta	114,45	5
Sweden	112,36	6
Czechia	108,05	7
Netherlands	107,08	8
Spain	104,10	9
Norway	103,62	10
Croatia	103,21	11
Hungary	102,44	12
Germany	102,31	13
Portugal	101,71	14
Austria	101,23	15
Cyprus	100,96	16
Luxembourg	99,65	17
Slovenia	99,04	18
France	97,17	19
Lithuania	97,16	20
Poland	96,19	21
Estonia	94,40	22
Slovakia	94,36	23
Bosnia and Herzegovina	91,44	24
Latvia	91,30	25
Italy	85,97	26
Greece	85,75	27
Romania	85,31	28
Bulgaria	84,38	29
EUROPE	100,00	

Source(s): Eurostat, 2021 - Our elaborations

Table 12.
Synthetic European index ranking of ICT



Source(s): Figure by authors

Figure 1.
Territorial distribution of the European synthetic index of digital technology

policy is unable to counter this trend, despite generous financial compensation. An effective regional policy should work on two levels: modify the response function of regional economy and also provide an investment able to generate diffuse positive externalities. Moreover, interventions should be minimal and aimed at creating stronger connections between economic agents and, in particular, combining production activities with services, to foster the servitization that probably influences "soft" factors inside the regional economy.

4.2 Results of loglinear regression

For the estimation of the Model, the synthetic innovation indicator European Innovation Scoreboard (EIS) (source Eurostat, 2021) will be used as the dependent variable (response) which provides a comparative analysis of innovation performance in EU countries, other European countries and regional neighboring countries. It helps countries assess the relative strengths and weaknesses of their national innovation systems and identify challenges to be addressed, while the variables described in Table 1 will be used as independent variables.

Table 13 gives several indicators of the quality of the model (or goodness of fit). These results are equivalent to the R^2 and to the analysis of variance table in linear regression and ANOVA. The most important value to look at is the probability of Chi-square test on the log ratio. This is equivalent to the Fisher's F test: we try to evaluate if the variables bring significant information by comparing the model as it is defined with a simpler model with only one constant. In this case, as the probability is lower than 0.0001, we can conclude that significant information is brought by the variables.

Table 14 highlights the circumstance that one can reject the assumption that the dependent variable (response) is a constant.

Statistic	Independent	Full
Observations	27	27
Sum of weights	27,000	27,000
DF	26	14
−2 Log(Likelihood)	265,633	225,108
R^2(McFadden)	0.000	0.153
R^2(Cox and Snell)	0.000	0.777
R^2(Nagelkerke)	0.000	0.777
AIC	269,633	253,108
SBC	272,225	271,250
Deviance	3,041	0.688
Pearson Chi-square	2,507	0.648
Iterations	0	14

Source(s): Eurostat, 2021 - Our elaborations

Table 13. Regression of variable EIS

sStatistic	DF	Chi-square	Pr > Chi^2
−2 Log(Likelihood)	12	40,525	<0.0001
Score	12	66,945	<0.0001
Wald	12	99,263	<0.0001

Source(s): Eurostat, 2021 - Our elaborations

Table 14. Test of the null hypothesis H0: Y=Constant (Variable EIS)

Table 15 shows the estimated value of the coefficients for the fitted model. To assess whether a variable provides significant information, a statistical test is displayed. In our case, we note that the 8 out of 12 variables and the intercept have a significance level above 95%.

The fact that 8 variables and the intercept are highly significant highlights a certain robustness of the results and allows us to make the following considerations. Let us then analyze the eight significant variables starting from the sign of the coefficient.

Var1 Percentage of enterprises analyzing big data internally using machine learning has a high level of significance and a positive coefficient. This means that this variable contributes significantly to explaining the values of the development indicator and that high values of this variable correspond to high values in the development indicator.

Var2 Percentage of enterprises analyzing big data internally using natural language processing, natural language generation or speech recognition also has a high level of significance, the sign of the coefficient is positive and therefore shows the same type of contribution to the explanation of the synthetic development indicator as the previous variable. In this case, it can be said that it reinforces the previous result because it gives an indication of the fact that not only the use of AI contributes to the growth of the development indicator, but also the greater technological advancement of companies using AI.

Also significant is the Var3 Percentage of enterprises using service robots which in this case links the development indicator to a higher density of companies using robots.

Var5 Percentage of enterprises that use one AI system although significant, does not contribute to the increase in the values of the development indicator, a sign that the use of AI systems, being positive for individual companies, has no advantages in aggregate terms for generating development.

Var 8 Percentage of enterprises with e-commerce sales of at least 1% turnover is significant but has a negative coefficient and does not contribute to increasing the values of the development indicator. This can be explained by the fact that the threshold of at least 1% turnover from e-commerce is too restrictive and in this class of companies we find many companies with a very low rate and very low innovation capacity.

Var 9 Percentage of enterprises' total turnover from e-commerce sales is, on the other hand, significant and has a positive coefficient, a sign that it contributes positively to development. In this case, these are highly innovative companies that contribute to a positive environment for development.

Source	Value	Standard error	Wald Chi-square	Pr > Chi^2	Wald lower bound (95%)	Wald upper bound (95%)
Intercept	4.146	0.179	536.656	<0.0001	3.795	4.497 ****
VAR1	0.156	0.055	7.915	0.005	0.047	0.265 ****
VAR2	0.180	0.066	7.545	0.006	0.052	0.309 ****
VAR3	0.231	0.090	6.598	0.010	0.055	0.407 ****
VAR4	0.032	0.056	0.314	0.575	−0.079	0.142
VAR5	−0.164	0.056	8.522	0.004	−0.273	−0.054 ****
VAR6	−0.096	0.155	0.384	0.536	−0.400	0.208
VAR7	−0.071	0.156	0.208	0.649	−0.377	0.235
VAR8	−0.028	0.008	11.716	0.001	−0.044	−0.012 ****
VAR9	0.015	0.006	5.452	0.020	0.002	0.027 ***
VAR10	0.027	0.009	9.434	0.002	0.010	0.044 ****
VAR11	0.030	0.016	3.656	0.05	−0.001	0.061 ***
VAR12	−0.015	0.013	1.412	0.235	−0.039	0.010

Note(s): ****>99%, ***>95%, **>90% * >80%
Source(s): Eurostat, 2021 - Our elaborations

Table 15.
Model parameters for the components (Variable EIS)

Var 10 Percentage of enterprises provided training to their personnel to develop their ICT skills is, on the other hand, significant and has a positive coefficient, a sign that it contributes positively to development. In this case, these are highly innovative companies that contribute to a positive environment for development.

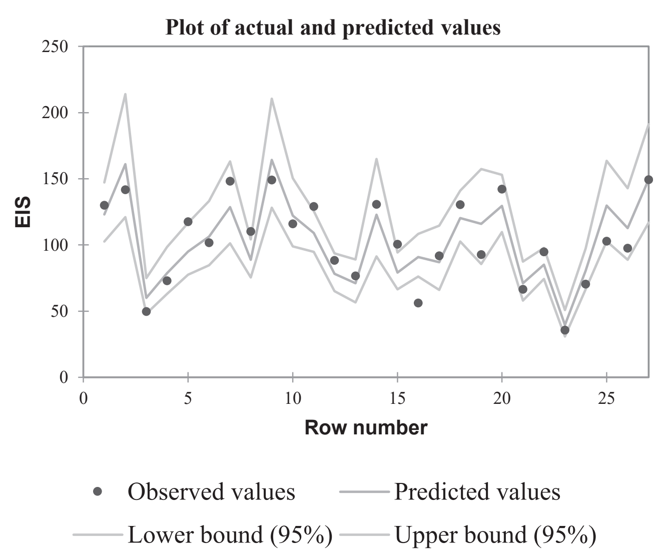
Same for Var11 Percentage of enterprises that recruited/tried to recruit personnel for jobs requiring ICT specialist skills where the higher density of companies that are attentive to the recruitment of ICT specialists is a factor that helps to raise the overall degree of innovation in the system.

The final form of the model equation is:

Equation of the model for the components (Variable EIS) is the next:

$$\begin{aligned}\mathrm{Pred(EIS)} = \exp(&4,14622375444966 + 0,156046146184724 * \mathrm{VAR1}\\ &+ 0,180208302806588 * \mathrm{VAR2} + 0,230830981290547 * \mathrm{VAR3}\\ &+ 3,16502935587467\mathrm{E} - 02 * \mathrm{VAR4} - 0,163615810079877 * \mathrm{VAR5}\\ &- 9,60363061293875\mathrm{E} - 02 * \mathrm{VAR6} - 7,10923298992073\mathrm{E} - 02 * \mathrm{VAR7}\\ &- 2,78755781037564\mathrm{E} - 02 * \mathrm{VAR8} + 1,48118398932973\mathrm{E} - 02 * \mathrm{VAR9}\\ &+ 2,67788822721428\mathrm{E} - 02 * \mathrm{VAR10} + 3,01547375831776\mathrm{E} - 02 * \mathrm{VAR11}\\ &- 0,014861020511171 * \mathrm{VAR12})\end{aligned}$$

Figure 2 highlights the distribution of the actual and predicted values of the EIS, which as can be seen, and expect for one outlier, always remain within the tolerance limits, sign that the results are robust.



Source(s): Figure by authors

Figure 2. Actual vs predicted values

5. Discussion and policies

Analyzing the results of the synthetic indicator and the resulting country taxonomy, it can be seen that Peripheral regions are the ones most exposed to loss of competitiveness since the rules governing the economic system promote the aggregation of factors and "classic" regional policy is unable to counter this trend, despite generous financial compensation. An effective regional policy should work on two levels: modify the response function of regional economy and also provide an investment able to generate diffuse positive externalities. Policies should be minimized and focused on building networks between economic agents. Linking productive activities with services and fostering servitisation that influences 'soft' factors within the regional economy become priority interventions. In this *scenario*, a type of "compensatory" or "add-on" regional development policy ends up accentuating the differences between regions, which are due to the different regional response to policies stimuli. Instead of fostering convergence, traditional policies create underdevelopment traps. The analysis of the results of the regression model shows how development is the overall capacity of a territorial economic system, both on a regional and national basis, which is enhanced by investments that aim to make the business system innovative. It is a matter of creating innovative ecosystems in which businesses, the higher education system and institutions cooperate together to increase the overall level of innovation of the economic system. It is the strictly targeted investments that create the virtuous circuits that can grow not only individual companies, but the entire business system and the entire economic system. It is the demand for innovation that drives the supply of innovation, but for the system to grow it is necessary that this demand can be satisfied within the same territorial context. And to do this, all policies must be coordinated and aimed at creating innovation ecosystems. In this sense key policies to foster AI innovation and development in businesses is to invest in research and development and support financially the universities and companies conducting AI research to help them to develop new AI technologies and applications that can be used by businesses. In addition, governments can incentivize innovation through tax breaks and subsidies to companies that invest in research and development. In addition to research and development, it is crucial that companies invest in training their employees so that they are able to use new AI technologies. In addition, companies can create partnerships with universities and research centers to access talent and resources specialized in AI. Another important policy to foster the virtuous circle between innovation and AI development is to promote data sharing. Companies that share data can benefit from new discoveries and applications of AI, as the availability of more data enables the development of more accurate and useful machine learning models. It is important that governments and businesses work together to appropriately regulate the use of AI to minimize the associated risks and ensure that innovations are used ethically and responsibly. In this sense, it is important to develop common standards for data security and privacy protection, and rules for the use of AI in sensitive areas such as healthcare and public safety. The virtuous circle between innovation and AI development in businesses requires policies and strategies that foster research and development, employee training, data sharing and appropriate regulation. Only in this way can businesses maximize the benefits of AI and minimize the associated risks, for a future in which technological innovation serves economic and social progress. These policies should help create an ecosystem conducive to innovation and AI deployment in businesses, fostering the virtuous circle between innovation and AI development. However, it is important that these policies are not undifferentiated, but are adapted to the specific regional as well as national context and to the needs of firms with a territorial dimension. The innovation differentials between the different European countries which we measured with the synthetic indicator can therefore be explained by the different capacities to create innovation ecosystems, the level of investment in research and development, the quality of the higher education system to meet the innovative training demands of companies, and the ability of institutions to create incentives that can stimulate not simply companies, but primarily innovative companies.

6. Conclusions

In the paper, two different methodologies were used to analyze the relationship between innovation and the development of digital technologies in Europe. The synthetic indicator made it possible to develop a taxonomy between the different countries, the log-linear model made it possible to identify and explain the determinants of innovation. It is the demand for innovation that drives the supply of innovation, but for the system to grow it is necessary that this demand can be satisfied within the same territorial context. And to do this, all policies must be coordinated and aimed at creating innovation ecosystems. In this sense key policies to foster AI innovation and development in businesses is to invest in research and development and support financially the universities and companies conducting AI research to help them to develop new AI technologies and applications that can be used by businesses. In addition, governments can incentivize innovation through tax breaks and subsidies to companies that invest in research and development. The innovation differentials between the different European countries which we measured with the synthetic indicator can therefore be explained by the different capacities to create innovation ecosystems, the level of investment in research and development, the quality of the higher education system to meet the innovative training demands of companies, and the ability of institutions to create incentives that can stimulate not simply companies, but primarily innovative companies.

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Further reading

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