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Econometric versus machine learning methods for time-series forecasting: a case study for the platform economy

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ABSTRACT

Platform economy is an innovative concept that supports the use of digital platforms for business models. In order to take maximum benefit of such platforms, not only the surrounding context is important, but also the ability to precisely determine their destination and to adapt accordingly. With this in mind, we proceeded to the theoretical and applicative analysis of the same, undertaking to underline, based on a comparative analysis of specific econometric versus machine learning methods, how to better forecast short time-series, so as to predict the evolution of the number of participants to such particular platforms. Overall, we identified an important limitation of the Long Short-Term Memory networks, one of the most advanced and effective machine learning techniques for univariate time series forecasting, namely the complexity of computations and the uncertainty regarding the accuracy of results, as compared to the econometric approach, herein mainly represented by SARIMA models. Despite the intensive utilization of machine learning techniques, the current research evidenced the outperformance of the implemented econometric models in some cases. Further research might consider conformal machine learning techniques, to obtain uncertainty quantification too, including a larger number of Long Short-Term Memory networks specific architectures.

Keywords: *Platform Economy; Time Series Forecasting; Machine Learning; Long Short-Term Memory (LSTM); SARIMA Models; Teleconference Platforms; Hybrid Forecasting*

JEL classification: *C53, C45, C32, L86, O33*

1. INTRODUCTION

Platform economy is an innovative concept that supports the use of digital platforms for business models. In this case, business analysts support the digital innovation in a competitive market. The platforms make the interconnection between various stakeholders like entrepreneurs, consumers and businesspersons that can share resources and various products (Chen, 2019). The platform economy is any digital platform that connects various networks of people using the internet. The role of online platforms is to match various groups like customers, producers, advertisers, users etc. and to support their interactions and, maybe, transactions (Codagnone, 2022). Crossed network externalities ensure the creation of value and profit.

The platform economy also influences the labor market due to improvement in connectivity and technological progress. Job opportunities can be found using apps and online outsourcing platforms.

Few examples of platforms in marketplace are related to service provision (Bolt, Airbnb, Uber), goods (e.g. Amazon, AliExpress, Overstock, Thrive Market, Target, Uncommon Goods), payments (e.g. Stripe, Square, Gumroad, PayPal, Amazon Pay), software development (e.g., Huawei, Apple, Samsung, Oppo, Soni, Microsoft, Dell, Lenovo Salesforce) etc.

There are many advantages of platform economy: no trade barriers, fast data circulation, higher participation of users and creation of open economic systems (Chen, 2019). There are three major challenges related to platform economy:

1. Revisions of regulations and laws for platform-based firms are necessary because of issues related to safety, fair competition, rights protection, taxes etc. However, some experts consider that the actual legal framework should be used also for platform economy and others support the idea that the clients are those who rate the platform and ensure self-regulation (Chen, 2019). The connection between people and personal data might be considered an ethical problem in the use of economy platform. The data on behavior should be subject to privacy (Codagnone, 2022);
2. The power structure between platform workers and their platforms deals with different typologies of workers: primary dependent workers that completely count for platform's earnings; partially dependent workers for whom platforms provide just a part-time job; supplemental workers that benefit of additional earnings from platforms (Chen, 2019). The challenges are related to less workers' protection, jobs' marketization, higher competition supported by no

barriers that determine high pressure in terms of working conditions and payment. Fragmentation of the work is a disadvantage for online labor platform and for platform economy in general. Another issue is related to competition and the potential results inducing monopolistic tendencies in a platform economy (Codagnone, 2022);
3. Workforce ecosystem management beyond the company refers to enterprises that make use of open talent economy. However, many firms do not accept to engage in a new workforce ecosystem of open talent while practices and various policies are not regulated (Chen, 2019).

The period of COVID-19 pandemic contributed to intensification of digital transformation and augmented the volume of online services and the number of users. In this context, there are specific advantages and limitations of platform economy brought by the pandemic.

The recent global epidemic has enhanced the lock-ins. There are significant differences between sectors in terms of revenue share and traffic during the pandemic. For example, these parameters have improved for marketplaces at national level, search engines and social media, but have worsen for travel and tourism sectors. New platforms appeared during the medical crisis for education and health sectors. GAFAM incumbents strengthened their position on online markets and remained active in M&A. The companies with traditional business encountered a critical situation during the medical crisis because their capacity to support innovation and adaptation has been affected. This unfavorable situation represented an advantage for platform companies that increased their market share. Bluetooth Low Energy technology for COVID-19 contact tracing has been developed by Google and Apple, but despite their benefit, they raise many concerns on aspects related to privacy (Codagnone, 2022).

In the EU, there is the Observatory on the Online Platform Economy that should support the Commission to monitor and regulate online platforms. This entity also manages problems related to transparency in online transactions, ranking made for search engine results, rights for online intermediates. The Observatory tackles three dimensions: economic significance, power over users and consequences of power. A sample of 56 platforms was analyzed by the Observatory on the Online Platform Economy and some conclusions were drawn in terms of economic significance: few platforms concentrate a large share of revenues; the platforms in the sample attracted a large amount of funding; for collaborative economy and social media platforms, the parent companies attracted more funds than the parent firms of the other platforms. The share of companies that made direct online sales was 21% in 2021, compared to 16%, in 2019. 10% of the companies made sales through marketplaces in 2021, compared to 6%, in 2019. During the pandemic, in 2021, 74% of the people using Internet ordered various products and services using online platforms, compared to 70% in 2019. The dimension related to power over users discusses aspects related to vulnerability of businesses to modifications made in the policies related to platforms, popularity among customers and competitive strategies of online platforms. The consequences of power are seen by both users and companies. The number of working platforms has rapidly grown and it is expected to have almost 45 million people working on platform by 2050 (EU Observatory, 2023).

However, in order to take maximum benefit of such platforms, not only the surrounding context is important, but also the ability to precisely determine the purpose of their use, their destination and to adapt accordingly. Virtual conferences, for instance, involve the use of dedicated platforms and a related specific approach, being more than just basic online meetings, in terms of formality and goal, as conferences' scope is to disseminate information on longer periods of time (Whyman, 2023).

With this in mind, we proceeded to the theoretical and applicative analysis of the same, undertaking to underline, based on a comparative analysis of specific econometric versus machine learning methods, how to better forecast related short time-series, so as to be able to predict the evolution of the number of participants to such particular platforms.

Therefore, this introduction continues with the theoretical background, rendering, conceptually, aspects concerning collaborative/multi-participant decision-making and platforms designed for teleconference, being followed by a case-study revealing the results obtained in the matter in a specific case, namely the one of the Romanian Academy (RA). The last section of the paper provides the conclusions drawn, accompanied by related discussions and future directions of research.

2. THEORETICAL BACKGROUND

A basic model designed for activities concerning decisions consists in more stages: intelligence, proposal of models and alternatives, selection of the optimal decision, assessment of the impact of the decision implementation, that might suggest resuming the process (Filip, 2022). In the field of collaborative decision-making, the process model developed by Simon could be extended for multi-participant area. The stages of this model could include the following elements:

- Preparation involves establishing the main features of the analyzed issue (aim, field, actual context, criteria, potential restrictions) and the empowering decision unit;
- Collective understanding includes agreement on a common perspective on the issue and on the implementation of the process;
- Solution proposal is based on the identification and advancement of the other suitable models to manage the issue;
- Negotiation and debate are needed to stimulate proposals and gain support among parties;
- Decision making is based on general agreement or favorable vote of the majority;
- Control consists in the elaboration of the report with the description of decision-making (Filip, 2022).

The most common collaboration forms are close collaboration (exchange of ideas to make decisions), asymmetric collaboration between people making decisions and their assistants /consultants and soft collaboration with anonymous members of the team (Suduc et al., 2009).

In uncertain times like Covid-19 pandemic, postponing decisions is a usual practice, but sometimes the decisions should be made fast. The involvement of more people in the team might help in generating more ideas and making a relevant decision. This involvement of more people supposes acknowledgement of decisions, selection of few people who will make the decision, involvement of experts who will applicate the decision, creation of forum for discussions. Making the decision to set up a nerve center is also essential for platform economy. Critical small choices could be made by anticipating more scenarios, selecting the most important options from a long list and asking other people to make small choices (Vallarasi, 2022).

Teleconferencing is the manner of interconnecting a varied number of individuals being located into different geographic areas, allowing various collaborative tasks, based on the real time propagation of information using certain software and devices**.**

All sorts of platforms are nowadays available for supporting teleconferencing, each of them having particular features (Suduc et al., 2009) that make it appropriate for different contexts.

2.1 **Evaluation of existing teleconferencing platforms**

Taking into account the relevant technical characteristics, such as information transparency, precision or response time; the quality of application, including factors like effective transparency scalability and flexibility; and the quality of provision, which involves aspects like price, provider independence, reputation, ease of adaptation, or integration with other applications, among others, along with considerations such as the number of participants supported per session, time limits (particularly for free platforms), user-friendly interfaces, and compatibility with various end devices, the selection process can be made more efficient.

Given the fact that, depending on circumstances, some platforms might fit better in relation to others, we are going to describe, thereafter, the five most frequently used ones (Software Testing Help, 2023; Walsh, 2023; Zoho, 2023; Zoom, 2023; Cisco, 2023; Microsoft, 2023; Google, 2023; Google Workspace, 2023).

Zoho Meeting – platform popular especially among medium and large organizations (more than 280,000 entities using it), available both in free format, allowing for up to 100 participants, with a time limit of 60 minutes, as well as in paid for access format (amounting up to €20/month), allowing for a large number of participants, no more than 250, in the case of Meetings, and no more than 3000, in the case of Webinars, in continuous daily sessions, usable on desktop applications (Mac, Windows, and Linux) and mobile applications for Android and iOS, browser-based, with Firefox and Google Chrome extensions, with virtual background, permit for audio/VoIP, webcam and file sharing, consent for reminder notes, turning to video, adding events to calendar, analytics and reports, settings related to email, authentication in two steps and recording, for all versions (Software Testing Help, 2023; Zoho, 2023)

Zoom – high definition video and voice platform, highly popular among different sized groups of people, at organizational level including, being frequently considered also by educational institutions, with a user-friendly free variant, allowing for up to 100 participants, but imposing a time restriction of just 40 minutes/session, and a paid for one: Pro, Business, Business Plus and Enterprise, ranging from 100 to 1000 participants/meeting, authorizing 30-hour sessions, the price of the same starting from €139.90 /year, featured by easy access, from any type of device, based on desktop applications or mobile applications for iOS and Android, a high level of integration with other application (2000+), with powerful security issues, based on Secure Socket Layer encryption, permitting the writing and share of whiteboards, team chat or mail and calendar benefits, making records and transcribing features, irrespective of the version considered, the cloud storage and Essential Apps, among others, being available, instead, in exchange for payment (Software Testing Help, 2023; Walsh, 2023; Zoom, 2023).

Webex Meeting – platform destined for both few or more persons, even big companies, with Free, Starter, Business and Enterprise versions, the first one allowing for up to 100 participants and setting a time limit of 40 minutes, while the latter ranging from a maximum limit of 150 to 1000 participants and sessions of maximum 24 hours, the prices to be incurred starting from €13.50/month, with high level of application integration (100+), advanced security based meetings, shared content, video with specific layouts, instruments that allow optimization of voice and elimination of noise, traditional messaging, interface sharing, tools designed to make records, cloud storage and file transfer and organization, for all existing versions (Software Testing Help, 2023; Cisco, 2023).

Microsoft Teams – very popular platform designed for seamless efficiency and collaboration, used by physical and legal entities of various dimensions, even educational elements, available both for free, allowing the connection of no more than 100 participants per session, limited to one hour, and in return for a payment of \$4/month to \$12.50/month, for Teams Essential, 365 Personal, Family and Business, with a one-to-one and group meeting duration of up to 30 hours, for a volume of participants amounting to 300, integrated with Office applications, providing meetings with video and calling options, including meeting joining without accounts, and giving access to specific backgrounds, planned meetings, noise elimination, screen sharing, visualization of default Outlook calendar, activities distribution and file incorporation, and offering phone or online support, without limitation, for all versions considered (Software Testing Help, 2023; Walsh, 2023; Microsoft, 2023).

Google Meet – high-definition video conference platform, mainly recommended for small businesses, with a free format of up to 100 participants and maximum 60 minutes/session, and a paid for one, for Business Starter, Standard, Plus and Enterprise, in exchange for more than 6 dollars each month during one year, unifying between 100 to 500 participants, being a desktop and Android based application, integrated with a full series of Google products, like Google Calendar or Gmail, with high security benefits, the data being encrypted, providing support, including permit for whiteboard or screen sharing, allowing for getting live captions and offering features such as on-meeting hand raise and question and answer type poll, the recording and 30 GB to unlimited storage capacity being allowed, in exchange, just for the paid versions (Software Testing Help, 2023; Walsh, 2023; Google, 2023; Google Workspace, 2023).

The above rendered teleconferencing platforms, selected based on their renown and frequency of use, given the limited space of the paper, represent just a small part of the extensive list with such platforms, herein being included, without limitation: GoTo Meeting, TrueConf Online, Skype, Whereby, BlueJeans, Slack, Jitsi Meet, Blackboard Collaborate, BigBlueButton, Dialpad Meetings (Software Testing Help, 2023), all of them sharing some common elements related to time and cost-saving, as well as to increase in efficiency for both individuals and organizations of any kind.

2.2 **Managing a teleconference**

An effective meeting involves a particular attention, the meeting agenda having to include the description of objectives, topics to be covered, related participants, in terms of number and identity, persons to take the floor and approached specific topics, meeting time and length (Indeed, 2023) and so on. But achieving a high level of efficiency implies much more than that, the consideration of the main managerial functions: making plans, organize elements, leading, evaluating and checking (Richard, 2021) and their thorough implementation while dealing with meetings, becoming a must.

As for teleconferences, there are some particular aspects that should be considered in addition, the former being significantly different from face-to-face meeting in terms of technical issues, hardware and software items needed, related knowledge as for the utilization of applications, devices, functions etc.

Given the above-mentioned functions, we are going to reveal thereafter the most important steps to be taken into account when coming about teleconference management (IEE Computing Soceity, 2023; IEEE Computing Society, 2023; Casamo, 2023; Indeed, 2023; Stack, 2023; Condeco, 2016; FreeConferenceCall, 2022; Free Management Books, 2023; InTheBlack, 2020; and Martin, 2023).

Teleconference planning (3-6 months or more, in advance (IEEE Computing Society, 2023)) requires:

- Scheduling teleconferences in the most convenient moment of the day (most conferences occur between 10 a.m. and 2 p.m., on Tuesdays and Wednesdays), taking also into account the fact that participants to the meeting might be located in different time zones and they should be all gathered at the same time, also determining the probable length of it (most conferences last for about 45-60 minutes) (Casamo, 2023; Stack, 2023; Condeco, 2016; FreeConferenceCall, 2022; Free Managemetn Books, 2023; InTheBlack, 2023);
- Identifying the most appropriate locations in terms of signal, ambience, light and so on and recommend participants, in due time, to do the same (Indeed, 2023; FreeConferenceCall, 2022);
- Preparing the topics to be discussed, under a basic form and an extended version, so as to be able to keep the discussion going and

on track, avoiding idle times, the drawing up of some additional materials, just in case, being highly recommendable (Casamo, 2023; Free Managemetn Books, 2023; InTheBlack, 2023);

- Preliminary structuring of discussions, well determining the order and the intervention time of speakers (Casamo, 2023);
- Setting the budget relating to the host platform, data storage, professional staff support and other related costs, as the case may be (IEEE Computing Society, 2023);
- Predefining volunteer roles and training volunteers, such as chairs, moderators or technical experts, among others (IEEE Computing Society, 2023);
- Defining virtual meeting rooms as networking lounges, designating someone to monitor the same and to answer specific questions, if any (IEEE Computing Society, 2023);
- Selecting the most appropriate platforms, fit for the meeting related needs, given the number of participants, the facilities provided, the available financial funds etc. (IEEE Computing Society, 2023; Condeco, 2016);
- Choosing the proper teleconferencing equipment, consisting in computers, tablets, phones or similar devices (IEEE Computing Society, 2023; Martin, 2023);
- Getting acquainted with the technical aspects relating to the selected platform and equipment, in terms of needed functions, checking in advance the ability of adequately using the same (Casamo, 2023; Martin, 2023);
- Providing meeting related instructions, such as date, time and length, topics to be discussed, documents, notes, preliminary work or reading required, platform to be used and so on (Casamo, 2023; Indeed, 2022; Stack, 2023; FreeConferenceCall, 2022; Free management Books, 2023);
- Testing in advance the functionality of the platform and the internet connection, by conducting a few trials and asking the participants to do the same, to ensure you can hear one another, so as to avoid miscellaneous technological errors that might impede the proper conferencing process (Casamo, 2023; Indeed, 2022; Stack, 2023; Martin, 2023);
- Generating and sending the access codes one week, two days before and the very day of the meeting, to the right recipients (Indeed, 2022; Stack, 2023; FreeConferenceCall, 2022; Free management Books, 2023).

Teleconference organizing involves:

- Keeping the process simple, the presentation brief and the schedule short, as long as this does not affect the quality of the meeting (Indeed, 2022; Stack, 2023);
- Structuring the discussion during the process, as people have to be moderated in order to express their point of view about the discussed topics or in case of Q&A sessions, a well-established process in the matter being extremely important (Casamo, 2023);
- Sharing the whiteboard and all necessary materials, during the meeting;
- Setting breaks, mainly if the conference lasts for longer time intervals (for instance about or more than two hours) (IEEE Computing Society, 2023; FreeConferenceCall, 2022);
- Creating meeting minutes and recording the session, as long as this second facility is available, for their subsequent distribution to the target audience (IEEE Computing Society, 2023; Indeed, 2022; Free management Books, 2023).

Teleconference leading implies:

- Guiding the process, not allowing for unauthorized participants, for the ones being late, manifesting inappropriate behavior, yelling or speaking all at once and so on, being ready to mute or even to disconnect the same, depending on circumstances (Indeed, 2022);
- Welcoming and introducing the persons joining the meeting or at least presenting the speakers in brief (InTheBlack, 2020);
- Muting hosts and participants, whenever it is necessary, while not taking the floor, in order not to disturb discussions (Stack, 2023);
- Avoiding idle times, by taking the floor for expressing the own point of view about the topics discussed (one reason for having two hosts available) or by inviting the ones having been silent until then to express their opinion (IEEE Computing Society, 2023; InTheBlack, 2020);
- Ending the discussion in a positive note, making participants feel that their contribution was appreciated (InTheBlack, 2020).

Teleconference evaluating and controlling includes:

- Downloading and saving all materials recorded/posted/disseminated, to archive them for further use, if any (IEEE Computing Society, 2023);
- Getting feedback from participants so as to get their point of view about the teleconference strengths and weaknesses (IEEE Computing Society, 2023, Indeed, 2022);

- Learning lessons, in order to understand the steps to take for teleconferences to come in order to improve the entire process, both in terms of content and in terms of technical aspects(IEEE Computing Society, 2023; Indeed, 2022; Martin, 2023).

A proper teleconference management sets the grounds not just for an efficient fulfilment of the pre-established goals for a particular case, with unexpected events or less errors, even for acquiring a good notoriety of these services and for improving their trust in relation thereto.

3. MATERIALS AND METHODS

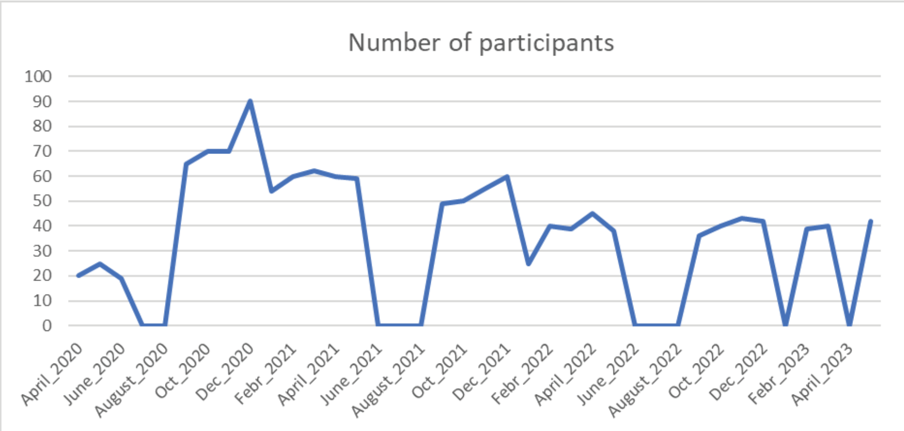
Time series forecasting is a vital task in data analysis and predictive modelling, involving the prediction of future values based on the past values of the same variable or the past values of other variables too. In the former case we have at our disposal a univariate time series, i.e., a single sequential dataset. This characteristic makes the forecasting of the future values more difficult because we have only the previous values of the same indicator and, based on its past behavior, we have to predict the future. In this context, machine learning methods proved to be essential for capturing intricate patterns and relationships within time series data, enabling accurate predictions and informed decision-making.

Considering the monthly volume of the participants in online meetings organized by the prestigious Romanian Academy in the period 2020:01-2023:05, a SARMA model is proposed to make forecasts for the next three months. Figure 1 suggests the evolution of the number of participants before and after the use of teleconferencing platform in the period April 2020-May 2023. Summer months are usually characterized by no participants, while ascending trends are observed in the first five months of each year and in the last four months of the year.

In the period April-August 2020, the platform was not used. In the period September-December 2020, the platform was intensively used with a maximum number of participants of 90 people. Since January 2021, the hybrid meetings have started, and the number of participants decreased. In the summer periods (June-August), no participants were registered in 2021 and 2022.

The evolution of the volume of participants to online meeting in the RA before and after the implementation of the teleconferencing platform

Figure 1



Source: Authors based on own data

SARIMA models extend the time series ARIMA models by considering repetition in the evolution of an indicator with a certain lag denoted by s. The seasonal element of the time series might be composed by: 1. an autoregressive seasonal part of order P, where P is the number of autoregressive seasonal components; 2. a moving average seasonal part of order Q, where Q is the number of moving average seasonal components; 3. components identified after a number of seasonal differencing D, where D is the number of differencing to achieve a stationary time series. The autocorrelation and partial autocorrelation functions (ACF and PACF) should be analyzed to identify a SARIMA process. If time series presents seasonal factors, then the values of PACF and ACF are significantly different from zero for moments showing seasonal and non-seasonal components. The stationary SARMA (p,q) x $(P,Q)_s$ with D=0 is written in its general form as:

$$\phi(L)\varphi(L^s)(y_t-\mu)=\theta(L)\Theta(L^s)\varepsilon_t. \qquad [1]$$

The seasonal components ensure the correlations decomposition by seasons and are represented by SAR(P) and SMA(Q):

$$\varphi(L^s)=1-\varphi_1 L^s-\varphi_2 L^{2s}-\cdots-\varphi_P L^{P_s} \qquad [2]$$

$$\Theta(L^s)=1-\Theta_1 L^s-\Theta_2 L^{2s}-\cdots-\Theta_Q L^{Q_s} \qquad [3]$$

The non-seasonal components are represented by AR(p) and MA(q):

$$\phi(L) = 1 - \phi_1 L - \phi_2 L^2 - \cdots - \phi_p L^p \qquad [4]$$

$$\phi(L) = 1 - \theta_1 L - \theta_2 L^2 - \cdots - \theta_q L^q \qquad [5]$$

The short-run impact is controlled by non-seasonal components. In practice, p and q are selected to have checked the following inequalities: $p < 0.5s$ and $q < 0.5s$.

We may have different periodicity for autoregressive and moving average seasonal components. In this case, (p,q) x $(P,Q)_{s,s'}$ is written as:

$$\phi(L)\varphi(L^s)(y_t - \mu) = \theta(L)\Theta(L^{s'})\varepsilon_t \qquad [6]$$

s- autoregressive component seasonality; s'-moving average component seasonality.

Before estimations, unit root tests or stationarity tests should be applied. In this case, Augmented-Dickey Fuller test (ADF), Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test, Phillips-Perron test (PP) are employed. The ADF test is based on three regression models (with tendency and constant, with constant and no trend and no constant) that include lagged variable to avoid errors' autocorrelation, knowing the process y_t:

$$\Delta y_t = \alpha y_{t-1} + \beta + \gamma t + \sum_{j=1}^{p} \delta_j \Delta y_{t-j} + \varepsilon_t \qquad [7]$$

$$\Delta y_t = \alpha y_{t-1} + \beta + \sum_{j=1}^{p} \delta_j \Delta y_{t-j} + \varepsilon_t \qquad [8]$$

$$\Delta y_t = \alpha y_{t-1} + \sum_{j=1}^{p} \delta_j \Delta y_{t-j} + \varepsilon_t \qquad [9]$$

$\alpha, \beta, \gamma, \delta_j$ – parameters, t-index for time and ε_t- white noise (null average, constant variance, uncorrelated with y_{t-j} for any j=1,2,..,p)

The null assumption considers non-stationary process, H_0: $\alpha = 0$. The null hypothesis of PP also states the existence of unit root, while in the case of KPSS, the null hypothesis assumes stationarity. The sequential testing procedure proposed by Dickey and Pantula is used to check for unit root starting with the time series double differenced, model with trend and intercept.

One of the most advanced and effective machine learning techniques for univariate time series forecasting is Long Short-Term Memory (LSTM) networks, introduced by (Hochreiter, & Schmidhuber , 1997). LSTMs are a specialized type of recurrent neural network (RNN) designed to handle the challenges posed by sequential data, such as long-range dependencies and vanishing gradient issues. These networks excel at capturing complex temporal patterns, making them particularly well-suited for modelling and predicting time-evolving phenomena (Zhang, 2003; Lippton et al., 2015; Lim and Zohren, 2021). Unlike traditional RNNs, LSTMs are designed to alleviate the vanishing gradient problem (Hochreiter, 1998; Rehmer and Kroll, 2020) and capture long-range dependencies within sequential data.

LSTMs achieve this by introducing memory cells that can store information over extended periods. An LSTM network consists of repeating units called cells, each of them having three main components: an input gate, a forget gate, and an output gate. These gates regulate the flow of information, allowing the network to selectively remember or forget past observations and decide what to pass on to the next time step. The structure of a LSTM cell is shown in Figure 2. Here, the symbols ⊗ and ⊕ are element-wise operations, c_t is the cell state vector, h_t is the hidden state vector (the output vector of the LSTM unit) and X_t is the input vector of the LSTM unit.

The input gate takes input from the current time step and decides which information to add to the memory cell. It involves a sigmoid activation function that transforms the input and decides how much of it should be added.

The forget gate determines what information to discard from the memory cell. It considers the previous memory cell output value and the current input, and it involves a sigmoid activation function to determine how much information to forget. The memory cell is updated based on the input gate and forget gate decisions. The input gate's output is element-wise multiplied (Hadamard product) with a candidate new value (tanh activation) and added to the previous memory cell value, as determined by the forget gate.

The output gate decides what to output from the memory cell. It considers the current input and the updated memory cell value. The output gate output is then passed through a sigmoid activation and elementwise multiplied with the tanh of the memory cell value to produce the final output.

All the LSTM cells are connected in a chain, allowing them to process sequential data one step at a time while maintaining a memory of past information. This type of architecture enables LSTMs to effectively capture and utilize long-range dependencies in time series data.

The equations describing the behavior of an LSTM cell are (Hochreiter and Schmidhuber,1997):

$$f_t = \sigma_g(W_f X_t + U_f h_{t-1} + b_f) \quad [10]$$

$$i_t = \sigma_g(W_i X_t + U_i h_{t-1} + b_i) \quad [11]$$

$$o_t = \sigma_g(W_o X_t + U_o h_{t-1} + b_o) \quad [12]$$

$$\tilde{c}_t = \sigma_c(W_c X_t + U_c h_{t-1} + b_c) \quad [13]$$

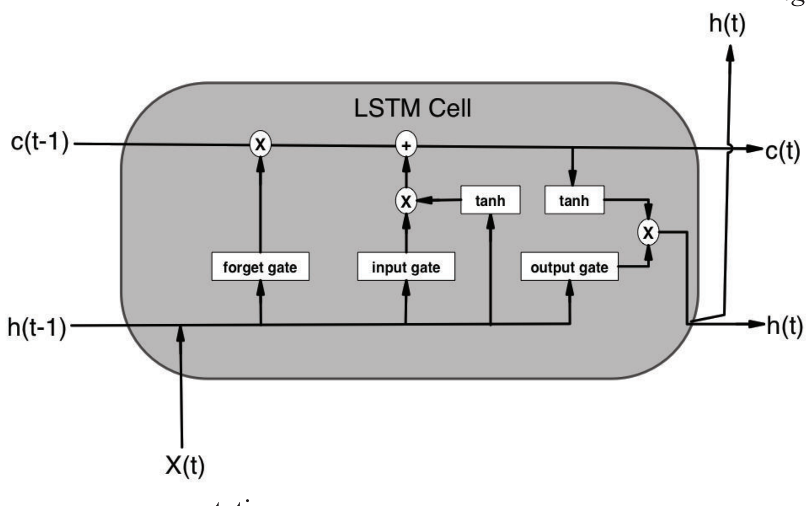
$$c_t = f_t \otimes c_{t-1} + i_t \otimes \tilde{c}_t \quad [14]$$

$$h_t = o_t \otimes \sigma_h\, c_t \quad [15]$$

where W_f, W_i, W_o, W_c are the weight matrices of the input for the forget, input, output and the memory cell connections, U_f, U_i, U_o, U_c are the corresponding matrices for the recurrent connections, $\otimes$ is used for the Hadamard product, $X_t \in \mathbb{R}^p$ is the input vector, $f_t \in (0,1)^h$, $i_t \in (0,1)^h$, $o_t \in (0,1)^h$ are the activation vectors for the forget, input and output gates, $h_t \in (-1,1)^h$ is the hidden state vector, $\tilde{c}_t \in (-1,1)^h$ is the cell input activation, $c_t \in \mathbb{R}^h$ is the cell state vector, b_* are the biases vectors for each gate. The superscript *p* stands for the dimension of the input space and for the number of hidden and the superscript *h*, for the number of hidden units. The activation functions for the forget, input and output gates, σ_g, is the sigmoid function, while σ_c and σ_h are both the hyperbolic tangent function.

The structure of an LSTM cell

Figure 2



Source: own representation

The key features of LSTM networks for time series forecasting can be summarized as follows (Chen et al., 2022):

- Long-Term Dependencies: LSTMs are capable of capturing relationships between distant time steps, enabling them to learn and exploit complex patterns that may span across the entire data sequence;
- Solving the Vanishing Gradient Problem: LSTMs use gating mechanisms to control the gradient flow during training, addressing the vanishing gradient issue commonly encountered in traditional RNNs. This enables more stable and effective training;
- Flexible Input Handling: LSTMs can handle varying lengths of input sequences, making them adaptable to time series data with irregular and/or missing data points;
- Multiple Memory Cells: LSTMs consist of multiple memory cells that allow the network to remember different aspects of the input sequence independently;
- Nonlinear Transformations: LSTMs apply nonlinear transformations to input data at each time step, allowing them to model intricate temporal patterns and fluctuations;

The effectiveness of LSTM networks in capturing intricate time series patterns has led to their widespread use and success in various real-world forecasting scenarios.

In the context of time series forecasting, LSTM networks can be trained to predict future values based on historical observations. They take a sequence of past data points as input and produce corresponding forecasts as output. By learning from past patterns, LSTMs can capture seasonality, trends, and other complex temporal relationships, enabling accurate predictions for various applications such as finance (Murat et al., 2020; Rundo et al., 2019), stock market forecasting (Jaydip and Mehtab, 2022; Sreelekshmy et al., 2017), weather prediction (Zahra and Suykens, 2020; Miao et aal., 2020; Yong et al., 2019), speech recognition (Oruh et al., 2022), handwriting recognition (Carbone et al., 2020), and more. For a review of LSTMs and their application see for example Yong et al. (2019) and the references therein.

To implement LSTM networks for time series forecasting, we proceeded as follows:

- pre-processed the data, structuring it into suitable input-output pairs for supervised learning;
- defined the LSTM architecture;
- trained the model using historical data, performing a grid search for the best hyperparameter values;

- used the trained model to make predictions on unseen future data points and assessed the prediction accuracy.

LSTMs has different architectures each with hyperparameters that can greatly influence the performance of the predictions. In our experiments we considered three LSTM models for one step ahead predictions and two models for three steps ahead predictions.

Stateless and stateful are two variations of recurrent neural networks (LSTM included) that have two different ways of handling sequential information and managing the hidden states across time steps. Stateless LSTM networks do not retain any information about previous time steps i.e., each input sequence is treated independently, and the network resets its hidden state after processing each sequence. Since stateless LSTMs do not consider temporal dependencies between sequences, they may struggle with capturing long-range patterns and dependencies in data. On the other hand, stateful LSTM networks maintain memory of previous time steps and carry forward their hidden states. This enables them to capture long-term dependencies and relationships between sequential data points. By preserving the context across time steps, stateful LSTMs are more effective in modelling complex patterns that span multiple sequences. While for univariate time series forecasting stateful networks seemed to be a better choice, in our case the data set is small, and time sequences that the network may learn are short, thus making stateless networks also appropriate. We employed both types of networks in our experiments, but due to the limited computational resources, we tried all combinations of hyperparameters for stateless networks and only a limited set for stateful versions, these models having higher demands for memory and computing power.

A parameter that we've also took into consideration when searching for the best network setup was related to shuffling or not the input sequences when training the network. Shuffling the data involves randomly rearranging the order of the input sequences before feeding them into the LSTM network during training. This practice is common in many machine learning tasks to prevent the model from learning spurious correlations that may arise from the sequential order of the data. However, when it comes to univariate time series forecasting, shuffling may not always be the best choice because shuffling can disrupt the inherent order of the sequences and hinder the model's ability to learn meaningful patterns. Time series data often follows trends, seasonality, and other sequential patterns that should be preserved to make accurate forecasts. Shuffling the data could result in the LSTM losing the ability to capture these crucial temporal relationships, leading to suboptimal performance. Conversely, there are situations where shuffling the data can be beneficial. For instance, if the time series data lacks strong temporal dependencies and each data point is relatively independent of its neighbors, shuffling could help the model generalize better and reduce overfitting. Additionally, shuffling might be advantageous when using stateful LSTMs, as it can mitigate the risk of the model memorizing the sequential order of the training data and improve its ability to generalize to unseen sequences. We experimented with both shuffling and non-shuffling approaches.

Another hyperparameter considered in our approach was the dropout rate. Dropout is a regularization technique commonly used in deep learning, including Long Short-Term Memory (LSTM) networks. Dropout is employed in LSTMs to mitigate overfitting, which occurs when a model becomes too specialized to the training data and performs poorly on new, unseen data. In the context of LSTM networks, dropout involves randomly setting a fraction of the output values of LSTM units to zero during both training and inference. This has the effect of temporarily "dropping out" certain connections within the network, forcing the model to become more robust and preventing it from relying too heavily on specific features or patterns in the training data. By introducing dropout, LSTMs become less likely to overfit and are better able to generalize to new sequences. The dropout rate should be carefully chosen through experimentation, as too high a dropout rate can lead to underfitting and reduced model capacity.

The other hyperparameters that we used to search for the network configuration with the best accuracy prediction was the number of neurons in the LSTM layer(s) and the number of training epochs.

In the pre-processing step we built a dataset suitable for a supervised learning method, as pairs of the form *(X, Y)* where *X* is the input vector and *Y* is the output value. In our specific case X is a vector consisting of a number of past values and Y is the next value in the timeseries that we want to predict.
If we denote by $X = (X_0, X_1, X_2, \ldots, X_T)$ our timeseries, the training and test sets are of the form:

$$\left(X_{t-nlags-1}, X_{t-nlags-2}, \ldots X_{t-1}, X_t\right), (X_{t+1}) \quad [16]$$

$$(X_{t-nlags-2}, X_{t-nlags-3}, \ldots X_t, X_{t+1}), (X_{t+2}) \quad [17]$$

$$(X_{t-nlags-3}, X_{t-nlags-4}, \ldots X_{t+1}, X_{t+2}), (X_{t+3}) \quad [18]$$

where *nlags* is the number of lags (past values) used to build sequences of data points to predict the value at $t+1, t+2$, $t+3, etc.$ (one point ahead forecasting) and of the form:

$$(X_{t-nlags-1}, X_{t-nlags-2}, \ldots X_{t-1}, X_t) , (X_{t+1}, X_{t+2}, X_{t+3}) \quad [19]$$

$$(X_{t-nlags-2}, X_{t-nlags-3}, \ldots X_t, X_{t+1}) , (X_{t+2}, X_{t+3}, X_{t+4}) \quad [20]$$

$$(X_{t-nlags-3}, X_{t-nlags-4}, \ldots X_{t+1}, X_{t+2}) , (X_{t+3}, X_{t+4}, X_{t+5}) \quad [21]$$

for three points ahead forecasting (i.e., to predict the values at ($t+1$, $t+2$, $t+3$), ($t+2$, $t+3$, $t+4$), ($t+2$, $t+4$ $t+5$) etc.).

4. RESULTS AND DISCUSSION

First, any potential detection of the unit root in data for the volume of participants to online meeting in the RA is verified. The ADF, PP and KPSS tests are applied using the sequential testing procedure previously mentioned, the results being seen in Table 1.

The results of tests to check for stationarity for the volume of participants to online meeting in the RA (2020:04-2023:05)

Table 1

Time series in:	**Type of model for ADF test:**	**ADF stat.**	**Type of model for PP test:**	**PP stat.**	**Type of model for KPSS test:**	**KPSS stat. (critical value at 1% level: 0.739)**
the second difference	No Constant and no Linear Trend	-6.838304 (<0.01)	No Constant and no Linear Trend	-30.37906 (<0.01)	Constant	0.079664
the first difference	No Constant and no Linear Trend	-6.85819 (<0.01)	No Constant and no Linear Trend	-7.788636 (<0.01)	Constant	0.096643
Level	Constant and Linear Trend	-5.145959 (0.0014)	Constant	-3.423024 (0.0164)	Constant	0.155896

Source: own calculations in EViews 9

Note: p-values in brackets for ADF and PP tests

The results suggest that the time series for the volume of participants to online conferences is stationary at 5% significance level. According to ADF and KPSS tests, the stationarity is verified at 1% significance level, while PP test suggests stationary data series at 5% significance level.

More SARMA models were run on this time series and only a valid model was identified that is presented in Table 2: SARMA (1,0) $(1,0)_{12}$ model. The parameters are significant at 5% level. DW statistic is approximately equal to 2, supporting errors non-serial correlation that might be observed also from the correlogram of residuals represented in the Appendix 1.

The results of estimation for SARMA (1,0) $(1,0)_{12}$ model

Table 2

Variable	Coef.	Std. dev.	t calc.	p-value
Constant	33.50398	12.81867	2.613687	0.0132
AR(1)	0.529696	0.128859	4.110656	0.0002
SAR(12)	0.678021	0.166548	4.071026	0.0003
Sigma squared	259.5667	58.12348	4.465781	0.0001
R-squared: 0.589801	Adjusted R-squared: 0.553607	F-statistic (p-value in brackets): 16.29551 (0.000001)	Durbin-Watson statistic: 1.949173	Jarque-Bera stat. (p-value in brackets): 1.266491 (0.530866)

Source: own calculations in EViews 9

According to Jarque-Bera test, we do not have proof to reject the normal distribution of errors at 1% significance level. Dynamic and static forecasts are provided in Appendix 1. The static forecasts perform better than the dynamic ones according to forecast accuracy measures. Accuracy measures like mean absolute error (MAE), root mean squared error (RMSE), mean absolute percentage error (MAPE) and Theil inequality coefficient present lower values for static predictions compared to dynamic ones. Own forecasts are provided for the horizon June 2023-August 2023. The short-run dynamic forecasts for the volume of participants to online conferences in the RA using SARMA (1,0) $(1,0)_{12}$ model (horizon: June 2023-August 2023) looks as follows: 34 (June 2023), 25 (July 2023) and 24 (August 2023), while the static ones indicate 14 (June 2023) and 0 (July and August 2023).

In our experiments with LSTM networks, we used the last 14 data points from the original timeseries to build the test set, to assess the quality of predictions, and the rest of data points for the training purposes.

We used 3 types of LSTM networks for one step ahead predictions, namely:

- A very simple structure with one LSTM layer and one output layer;
- A stacked approach where we use two consecutive LSTM layers and one output layer;
- A Bi-LSTM network: it consists of two LSTMs, which makes the input to flow in both directions, forward and backwards. This

approach was reported to substantially improve the forecasting accuracy [36].

For three steps ahead prediction we used two types of networks:

- A Stacked model with two LSTM layers outputting a vector that can be interpreted as a multistep forecasting;
- An Encoder-Decoder architecture, a special type of network design introduced by (Sutskever, 2014) for Seq2Seq problems with good performances for multi-step predictions (Chandra et al., 2021). Encoder-Decoder LSTM networks manage variable-length input and output sequences through a two-step process. Initially, they encode individual input sequences one by one, utilizing a latent vector representation. Subsequently, these sequences are decoded from the said representation.

Table 3 gives all the hyperparameters and their values that we considered when experimenting with LSTMs for our time series forecasting. We employed a grid search by varying all these parameters to find the best model in terms of minimum MSE.

The parameters of the networks and their values

Table 3

Parameter	Values	
Number of neurons in the LSTM layer(s)	50,100,150	
Number of lags	One step ahead prediction	Three steps ahead prediction
	1,2,3,4,5,6,7,8,9	4,5,6,7,8,9
Droupout rate	0, 0.2, 0.4	
Number of training epochs	100, 500, 1000	
Shuffling	True/False	

Source: own representation

We run the experiments using Python ver. 3.9 with Pandas 2.0.3, Keras 2.13.1, TensorFlow 2.13.0, Scikit-learn 1.3.0 and NumPy 1.24.3 libraries under the Windows 11 operating system. For all tests we used the Mean Squared Error as the loss function and the ADAM optimizer.

The activation function used for the LSTM units was the Rectified Linear Unit function (ReLU) (Nair and Hinton, 2010) which is more computational efficient than tanh or sigmoid functions and also helps mitigate the vanishing gradient problem, which can occur with sigmoid and tanh activation functions.

Due to the stochastic nature of the training process of the LSTMs, as well as in order to provide some uncertainty estimations, for each type of networks and for each value of hyperparameters, we repeated the experiments 30 times and reported the mean value of the RMSE together with its standard error.

In table 4 we present the results for the best model according to the RMSE on the test set, for each of networks used, in the case of one step ahead prediction.

Network configurations for the minimum value of the RMSE for one step ahead predictions

Table 4

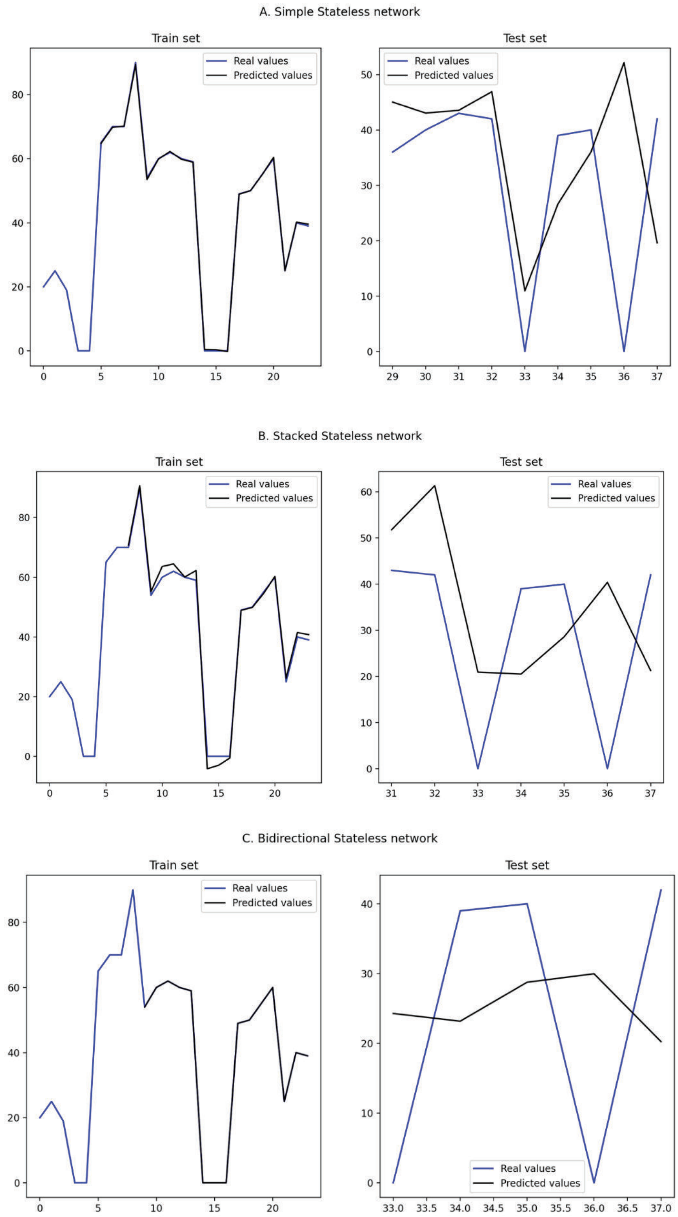
Network type	Simple	Stacked	BiLSTM
Min. RMSE	20.25	20.23	19.06
Std. Err. of RMSE	3.95	1.05	0.38
Number of Lags	5	7	9
Dropout rate	0	0.2	0.4
Number of neurons	150	150	150
Number of training epochs	1000	500	1000
Shuffle input data	False	True	True

Source: own representation

The minimum RMSE was obtained by BiLSTM, which is in line with previous research (Siami-Namini et al., 2019), but the differences between the three networks are not very consistent. As expected, increasing the number of neurons and the number of training epochs results in a better prediction and shuffling the input data gave better results in two cases. Increasing the number of lags used to predict the next value also decreases the RMSE, which means that longer sequences used for training purposes give better predictions.
In Figure 3 we show, in the case of the three LSTM network architectures (Simple, Stacked and BiLSTM), the real and predicted values for the training and testing sets.

The real values versus the predicted values for the three types of networks

Figure 3



Source: own representation

Table 5 shows the results obtained for three steps ahead predictions. Encoder-Decoder type of network outperforms the Stacked model, which is in line with other results (Du et al., 2019). However, this improved prediction comes with the cost of a longer training time. Again, a higher number of neurons leads to a better performance and a longer series of past values used to predict the future gives better results.

Figures 4 and 5 show sequences of real values versus predicted values for the Encoder-Decoder network described in Table 5, for the training set and the testing set.

Network configurations for the minimum value of the RMSE for three steps ahead predictions

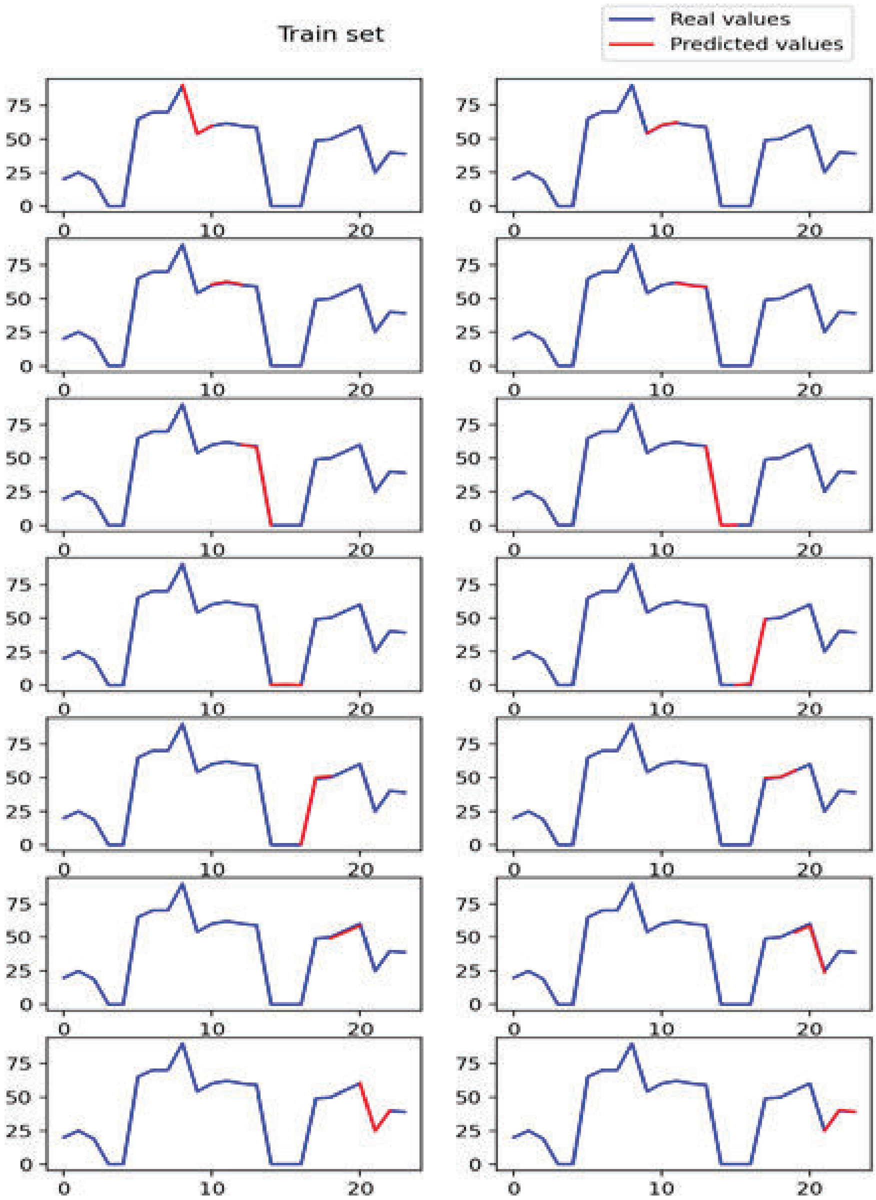
Table 5

Network type	**Simple**	**Stacked**
Min. RMSE	21.09	17.93
Std. Err. of RMSE	2.07	0.98
Number of Lags	9	8
Dropout rate	0	0.2
Number of neurons	150	100
Number of training epochs	100	500
Shuffle input data	True	False

Source: own representation

Train set: real values versus predicted values – three steps ahead prediction for the Encoder-Decoder model

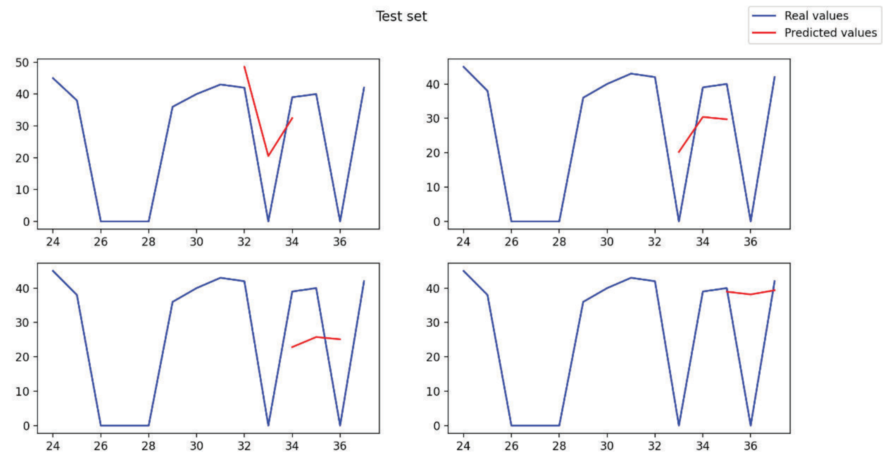
Figure 4



Source: own representation

Test set: real values versus predicted values – three steps ahead prediction for the Encoder-Decoder model

Figure 5



Source: own representation

In table 6 we compare the stateless and stateful approaches for the network configurations given in tables 3 and 5. The stateful configuration used a batch size of one, which is equivalent to online training. It can be easily observed that, in our case, stateful drastically degrades the prediction performance (Table 6).

A comparison between the stateless and stateful LSTMs

Table 6

Network type	Simple	Stacked	BiLSTM	Stacked	Encoder-Decoder
Min. RMSE – stateless	20.25	20.23	19.06	21.09	17.93
Min. RMSE – stateful	31.12	29.24	27.21	25.34	23.89
Number of Lags	5	7	9	9	8
Dropout rate	0	0.2	0.4	0	0.2
Number of neurons	150	150	150	150	100
Number of training epochs	1000	500	1000	100	500
Shuffle input data	False	True	True	True	False

Source: own representation

The minimum RMSE for stateless is registered for encoder-decoder, while the lowest value for stateful is observed in the same case. SARIMA approach has the advantage of much lower computational complexity than ML methods and the possibility of uncertainty quantification. In the case of LSTM, we have lower RMSE in one case, but the higher computational complexity is the main limitation of the method.

5. CONCLUSIONS

Quantifying platform work remains problematic, especially when seeking to generalize about the entire population. Surveys, administrative data, and big data all face limitations in this regard. The most reliable data sources recognize these shortcomings and utilize techniques such as triangulation, population-based weighting, and others to mitigate them (Pesole, 2021). In the overall EU and for each Member States, policymakers should explore mandating platforms to share administrative data in exchange for preferential tax treatment (as in Belgium) or as a condition for operating within their jurisdictions (as with AirBnB in Amsterdam) (Baselgia and Martinez, 2023). This approach can help ensure regulatory compliance and facilitate better socio-economic analysis.

According to Eurostat, in 2022, approximately 3.0% of individuals aged 15-64 participated in digital platform work for at least one hour in the preceding year, based on a pilot survey conducted in 16 EU countries and one EFTA country. The highest prevalence of platform work was observed among those with tertiary education (4.3%), while the lowest rates were found among individuals with lower secondary education (1.8%). Men were more likely to engage in platform work than women (3.2% vs. 2.8%). Eurostat initiated data collection on the emerging phenomenon of digital platform employment in 2022 through a pilot survey within the European Union Labour Force Survey (EU-LFS) (Eurostat, 2024).

Lafuente et al. (2024) assessed the performance of the global digital platform economy using a nonparametric network model (data envelopment analysis) applied to a sample of 116 states in 2019. The designed model accounts for geographic diversity and the complex interactions among governance entities, digital platforms, companies using platforms, and final users. Key findings reveal significant heterogeneity in countries' platform economy configurations, suggesting that a tailored policy approach could yield more effective results (Lafuente et al.,2024). To achieve qualitative improvements in the system, policies focused on accelerating the digital platform economy should be informed by an analysis of its key factors.

The comparative analysis of specific econometric versus machine learning methods, meant for identifying the most appropriate instruments useful for forecasting short time-series, particularly applied to the analysis the evolution of the number of participants to dedicated virtual platforms, in the case of the RA generated interesting results.

Concerning the econometric methods, the unit root ADF and KPSS tests applied revealed that all series are stationary, while the subsequent SARMA models used resulted in only one statistically validated variant. The static and dynamic forecasts indicated a superior performance of the former in relation to the latter in terms of accuracy, while the MAE, RMSE, MAPE and Theil inequality coefficient presented lower values for static predictions as against the dynamic ones. The forecasts provided for the horizon June 2023-August 2023 revealed an expected volume of participants to the online meetings of the RA of 34, in June 2023, 25, in July 2023, and 24, in August 2023, in the dynamic case, respectively of 14, in June 2023, and 0, in July and August 2023, in the static one.

As for the alternative approach, we resorted to LSTM networks, using the last 14 data points from the original timeseries to build the test set, to assess the quality of predictions and the remainder of them for the training purposes. Out of thev3 types of such networks, considered for one step ahead predictions, according to the RMSE on the test, the minimum value was obtained by BiLSTM, however the differences between the three networks not being significant. The increase of the number of neurons and the number of training epochs resulted in a more accurate prediction and shuffling the input data gave better results in two cases. while the increase of the number of lags used to predict the next value decreased RMSE, suggesting that longer sequences used for training purposes provide better predictions. The results obtained for three steps ahead predictions indicated that the Encoder-Decoder type of network outperforms the Stacked model, such improved prediction involving, unfortunately, a longer training time. The same as for the previous rage of models, a higher number of neurons led to a better performance and a longer series of past values used to predict the future generated better results. As for the stateless and stateful approaches for the network configurations, it was ascertained that the latter drastically degrades the prediction performance.

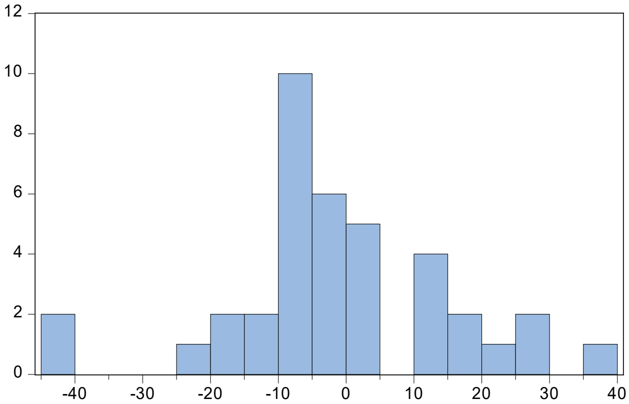
Overall, we observed an important limitation of the LSTM, namely the complexity of computations and the uncertainty regarding the accuracy of results, as compared to the econometric approach. Further research might consider the implementation of conformal machine learning techniques, so as to obtain uncertainty quantification too, including a larger number of LSTM architectures. All in all, despite the intensive utilization of machine learning techniques in the actual research, they did not generate better results than econometric models in all the cases.

The ability to anticipate fluctuations in platform participation, as mentioned earlier, can have practical applications for platform providers, especially when considering flexible paid subscription plans. For example, accurate forecasting models can guide platforms in offering dynamic subscription options, such as allowing users to temporarily suspend paid subscriptions during off-peak months like June through August, when platform activity may decrease due to vacations. This would not only improve customer satisfaction but also optimize the platform's revenue management. Such flexibility can contribute to better resource allocation and a more efficient user experience, reflecting the practical importance of forecasting in the platform economy.

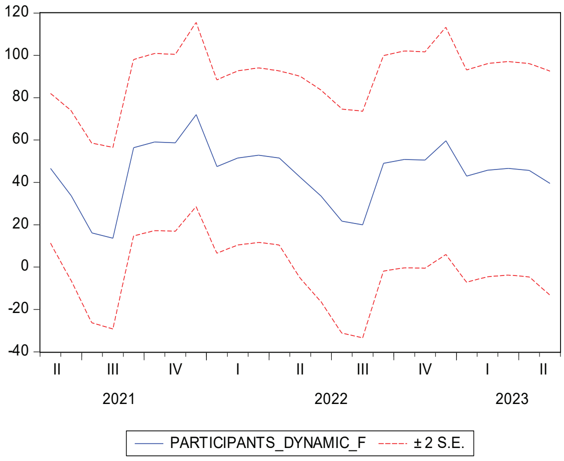
Appendix 1

Correlogram of residuals for SARMA (1,0) $(1,0)_{12}$ model

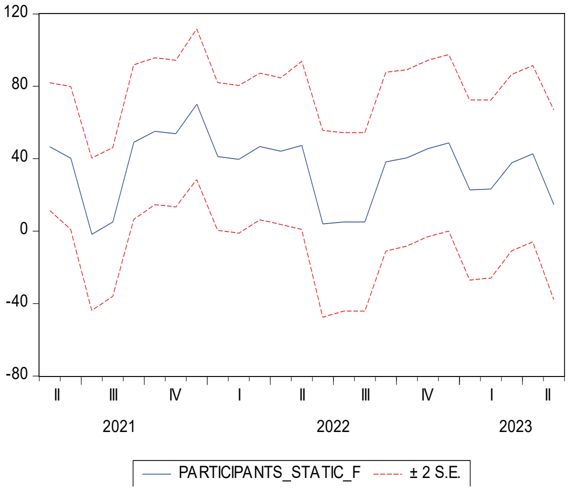
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
. | . |	. | . |	1	-0.021	-0.021	0.0182	
. | . |	. | . |	2	-0.022	-0.022	0.0380	
. |*. |	. |*. |	3	0.202	0.201	1.8027	0.179
. | . |	. | . |	4	-0.031	-0.024	1.8447	0.398
. |*. |	. |*. |	5	0.094	0.106	2.2546	0.521
. | . |	. | . |	6	-0.011	-0.053	2.2605	0.688
. |*. |	. |*. |	7	0.090	0.113	2.6613	0.752
.*| . |	.*| . |	8	-0.129	-0.185	3.5025	0.744
**| . |	**| . |	9	-0.235	-0.225	6.3962	0.494
. | . |	.*| . |	10	-0.050	-0.142	6.5319	0.588
. | . |	. |*. |	11	0.063	0.138	6.7579	0.662
. | . |	. | . |	12	-0.009	0.069	6.7628	0.748
. | . |	. | . |	13	-0.062	0.016	7.0002	0.799
. | . |	. | . |	14	-0.041	-0.065	7.1056	0.851
. | . |	. | . |	15	-0.023	0.014	7.1415	0.895
.*| . |	.*| . |	16	-0.079	-0.085	7.5761	0.910



Series: Residuals	
Sample 2020M04 2023M05	
Observations 38	
Mean	-0.905280
Median	-2.445840
Maximum	36.25251
Minimum	-42.76558
Std. Dev.	16.30154
Skewness	-0.169743
Kurtosis	3.827429
Jarque-Bera	1.266491
Probability	0.530866



Forecast: PARTICIPANTS_DYNAMIC_F	
Actual: MEETINGS	
Forecast sample: 2020M04 2023M05	
Adjusted sample: 2021M05 2023M05	
Included observations: 25	
Root Mean Squared Error	19.60209
Mean Absolute Error	15.81796
Mean Abs. Percent Error	16.94235
Theil Inequality Coefficient	0.235684
Bias Proportion	0.557119
Variance Proportion	0.143681
Covariance Proportion	0.299200



Forecast: PARTICIPANTS_STATIC_F	
Actual: MEETINGS	
Forecast sample: 2020M04 2023M05	
Adjusted sample: 2021M05 2023M05	
Included observations: 25	
Root Mean Squared Error	15.24557
Mean Absolute Error	9.900077
Mean Abs. Percent Error	12.12304
Theil Inequality Coefficient	0.200310
Bias Proportion	0.105687
Variance Proportion	0.030659
Covariance Proportion	0.863654

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Using Spatial Analysis to Assess Cohesion For Sustainable Development Goals

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ABSTRACT

Our study explores the integration of spatial analysis methodologies within the context of the Sustainable Development Goals (SDGs) at the regional level in European Union countries. The application of spatial analysis allows for a nuanced understanding of SDGs progress and obstacles within specific territorial units.

Adopted by the United Nations, the Sustainable Development Goals (SDGs) provide an all-encompassing framework for tackling global issues in the social, economic, and environmental spheres. Through the examination of geographic data, spatial analysis techniques give a distinct perspective and can provide important insights into regional inequities and localised difficulties. Spatial analysis—which includes spatial autocorrelation tools—provides a visual narrative of regional cohesion and offers a deep understanding of the distribution and connectivity of SDGs accomplishments across various territorial units.

For planners, stakeholders, and politicians, this visual aid is invaluable as it facilitates informed decision-making that leads to more integrated policies.

Furthermore, the application of spatial analysis methods makes it easier to allocate resources efficiently and track progress towards the SDGs. It allows for authorities, decision-makers, and interested parties to plan resources effectively, rank interventions in order of importance, and monitor the effects of programmes locally.

Our study extensively employs available data at the NUTS 3 level, providing a comprehensive measurement of SDGs achievements. Through a close examina-

tion of data at the NUTS 3 level, our research offers a comprehensive evaluation of SDGs accomplishments, facilitating an in-depth comprehension of advancements and discrepancies within certain territorial units. Additionally, this strategy is in line with the cohesion process strategically, making it possible to assess these goals' contributions to fair development and regional cohesion more thoroughly.

Our research emphasises the relationship between achieving the Sustainable Development Goals and regional cohesion by focusing on the cohesion process. This emphasises how important it is to accomplish not just the individual goals but also to promote inclusivity, lessen inequality, and unite people in various geographical contexts.

Thus, our research contributes to a more inclusive and unified approach to sustainable development within the European Union by enhancing our understanding of SDGs progress at a granular level and highlighting the significance of these accomplishments in fostering cohesion. Furthermore, we stress the significance of utilising spatial analytic techniques to improve the execution, observation, and assessment of plans intended to accomplish the SDGs.

Keywords: *spatial analysis, SDGs, cohesion,spill-over, NUTS3*

JEL Classifiction: *F63, R12, Q01*

1. INTRODUCTION

The main aim of this paper is to analyse the spill-over effect and regional cohesion within European Union (EU) countries at the Nomenclature of Territorial Units of Statistics (NUTS) 3 level. NUTS is a three-level hierarchical system used by the European Union for dividing up the EU territory (Eurostat, 2022).

The NUTS 3 regions are the smallest subdivisions and can provide a fine-grained geographical breakdown for spatial analysis. By examining the interactions among neighbouring regions, the study aims to provide a visual overview and spatial analysis of the available data, offering insight into spatial cohesion of sustainable development. In order to achieve this aim, we have analysed the variables available on Eurostat related to sustainable development, at NUTS 3 level for the EU-27 countries. These variables have been matched with indicators used to measure the achievement of sustainable development goals (SDGs). Thus, our analysis focused on themes corresponding to SDGs 8 and 10: decent work and economic growth, and reduced inequalities. We employ exploratory spatial data analysis and spatial autocorrelation indicators to observe the spatial interactions and spill-over effects for these two dimensions of sustainable development.

Furthermore, the study highlights the current difficulties brought about by the lack of data at the NUTS 3 regional level. This study underlines the need for improved data collection and reporting procedures while highlighting the information gaps that already exist, emphasizing the significance of reliable data for accurate analysis. By highlighting the need of data reliability and availability, this study contributes to the overall argument about EU cohesion and regional development initiatives. Precise and extensive data at the NUTS 3 level are essential for both academic research and policymakers trying to develop effective policies for stimulating the achievement of sustainable development goals across regions.

Our paper comprises four sections, each section with a distinct purpose in presenting our research. The first section presents a concise literature review with a particular emphasis on the topics related to spatial analysis of the sustainable development cohesion. The second section folds into two parts, one describing the methods involved and second describing the data employed in the analysis. In the third section we provide the results obtained through spatial analysis techniques and engage in thorough discussions. Our paper concludes with the final remark section. In this final section we stress the importance of data availability at the NUTS 3 level and the extension of the number of indicators that are measured to fine-grained geographical breakdown.

2. LITERATURE REVIEW

The literature regarding cohesion assessment and sustainable development goals is rich and covers a variety of topics (e.g., Pîrvu et al, 2019; Sommer, 2019; Badircea et al, 2021; Perez-Gladish et al, 2021, Cavalli et al, 2021; Danquah and Ouattara, 2023).

The idea of European cohesion dates back in 1957 with the Treaty of Rome, through which the European Community was originally created (Tucker, 1975; Leonardi, 2006). In 1994 in the Maastricht Treaty was introduced the Cohesion Fund aiming to support investment in the territorial cohesion for the EU countries with the gross national income (GNI) per capita below 90% of EU-27 average (Leonardi, 2006). Since cohesion includes the concepts of inclusion, decreased inequities, and shared advantages, it is typically understood to refer to social, economic, or geographical cohesion (Darvas et al, 2019). Thus, cohesion is vital to accomplishing the SDGs (Kölling, 2021).

The United Nations adopted the 17 Sustainable Development Goals (SDGs) in 2015 as a global call to action to address a variety of urgent issues and advance sustainable development globally (Easterly, 2015). A wide range of interconnected issues are covered by these goals, which must be accomplished by 2030 (SDG U, 2019). These issues include hunger, poverty, health, education, gender equality, clean water and sanitation, climate action, affordable and clean energy, sustainable cities and communities, responsible consumption and production, life below the water, life on land, peace, justice, and strong institutions (SDG U, 2019).

Territorial cohesion, which focuses on the spatial distribution of the indicators and resources (Davoudi, 2005; Kölling, 2021; Medeiros, 2016), is inextricably linked to many SDGs (Davoudi, 2005; Medeiros, 2021). Medeiros (2021, p14) considers "spatial planning as a crucial instrument to develop strategic and planned sustainable development policies at all territorial levels, and to produce appropriate policy recommendations". Thus, spatial planning is crucial for coordinating sustainable development and promoting strategic cohesion policies across all EU member countries.

The SDGs were adopted by the United Nations (UN) in order to achieve sustainable development by 2030. These goals are known as "transforming our world," reflecting an ambitious agenda (Rai et al, 2019).

The SDGs presents a vital interest for taking collective action, remaining also uncritical of the central causes of economic growth, inequality, and overconsumption. The 2030 Agenda for Sustainable Development includes the reduction of inequality, transforming this into a goal in its own right in SDG 10 (Kuhn, 2020).

SDG 10 implies reducing inequalities, both in case of income, age, sex, disability, race, ethnicity, origin, religion or economic or other status within a country, and among countries, such as regarding representation, migration and development assistance (Basnett et al, 2019).

Aiming strong sustainability, we consider SDG 8 "Decent Work and Economic Growth", being seen both as phenomena, institutions and ideologies (Kreinin and Aigner, 2022). SDG 8 considers sustainable growth, employment, and decent work for everyone (Küfeoğlu, 2022), aiming to achieve "economic growth" through "Decent Work" (Küfeoğlu, 2022).

The International Labour Organisation (ILO) defined decent work through four pillars and ten dimensions in Decent Work Agenda in 1999 (ILO, 1999). According to this, decent work implies employment opportunities, adequate earnings, decent working time, combining work and personal life, work that should be abolished, stability and security of work, equal opportunity, safe work environment, social security and social representation (Conigliaro, 2018).

According to Frey (2017), the notion of work emerged alongside discussions on sustainability and its connection with economic growth. SDG 8 encompasses workforce diversity opportunities for everyone, including people with disabilities, gender equality, and fair wages for everyone involved

(Khalique et al, 2022). This implies equal employment opportunities, both for men and women (Chigbu and Nekhwevha, 2023), thus contributing to overall economic development. Also inclusive economic growth requires decent work, decent work being represented by secure, safe, with fair wages, and equally accessible to men and women (Bello-Bravo and Lutomia, 2020). The Sustainable Development Goals are interconnected, and this aspect is evident when talking about SDG 8 and SDG 10 (Cling and Delecourt, 2022). Achieving only SDG 8 without taking account of SDG 10, will only reinforce the existing inequalities.

3. METHODS AND DATA

Spatial analysis is a powerful instrument to visualize the assessment of the cohesion for Sustainable Development Goals, especially when this analysis focuses on a granular level such as NUTS 3 level. Analysing data for the smallest subdivision of NUTS level enhances our ability to understand, monitor, and address regional disparities. Also, it contributes to a more refined and context-specific approach to spatial cohesion and sustainable development. In this section we address the methodology employed and the data available at the NUTS 3 level for EU-27 countries that can be used as proxy variables in the analysis of sustainable development cohesion.

3.1. Methods

Our aim is to capture spatial relationships, interactions and patterns for analysing the assessment of the sustainable development cohesion at European Union NUTS 3 level regions using various spatial analysis techniques, such as exploratory spatial data anal analysis and spatial autocorrelation indicators.

As a descriptive tool for the variables used, we employed spatial exploratory tools, namely the univariate graphical representations for the underlying variables. From the set of univariate graphical tools, we used standard deviation maps because they effectively capture and visualize variations in data distribution, offering a comprehensive viewpoint on spatial patterns and deviations across geographical regions. Moreover, they provide a quick an intuitive way of identifying outliers, as observations which are at three or more standard deviations above or below the mean.

For assessing the spatial autocorrelation and the spatial interactions, we used both local and global Moran's I statistics in our analytical method. The global Moran's I allow us to assess the general spatial autocorrelation using the following formula in Equation 1 (Anselin, 2022):

$$I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\left(\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}\right) \sum_{i=1}^{n} (x_i - \bar{x})^2} \text{ (Equation 1)}$$

Where:
n is the number of territorial units;

x_i and x_j represent the values of the employed variable in territorial units i and j;
$\bar{x}$ is the mean of variable x across the n territorial units;
w_{ij} is a binary weighting matrix with a value of $w_{ij} = 1$ if territorial units i and j are neighbouring, and zero otherwise.

Subsequently, Equation 2 describes the significance testing of Moran's I (Tiefelsdorf and Boots, 1995), aiding in understanding the strength and significance of spatial patterns observed in the data.

$$z_I = \frac{I - E(I)}{S_{error\,I}} \text{ (Equation 2)}$$

Where:
I is the Moran's I value;
$S_{error\ I}$ is the standard error of the Moran's I value;
E(I) is the expected value of Moran's I.

In order to assess the significance of Moran's I, a permutation test or Monte Carlo simulation (MC simulation) is commonly used to produce a distribution under the null hypothesis. The null hypothesis typically assumes spatial randomness (no spatial autocorrelation). The distribution is compared with the observed Moran's I value to ascertain its statistical significance. Therefore, if the z_I > Z α/2 the null hypothesis is rejected, meaning that the spatial autocorrelation is present.

The range of Moran's I values is from -1 to +1; a negative number denotes differences across territorial units, while a positive value denotes spatial similarities. One way to interpret the results is presented in Table 1.

Moran's I interpretation

Table 1

Strength of Association	**Positive** Spatial Similarity (high-high or low-low)	**Negative** Spatial Dissimilarity (high-low or low-high)
Small	0.1 to 0.3	-0.1 to- 0.3
Medium	0.3 to 0.5	-0.3 to -0.5
Large	0.5 to 1.0	-0.5 to -1.0

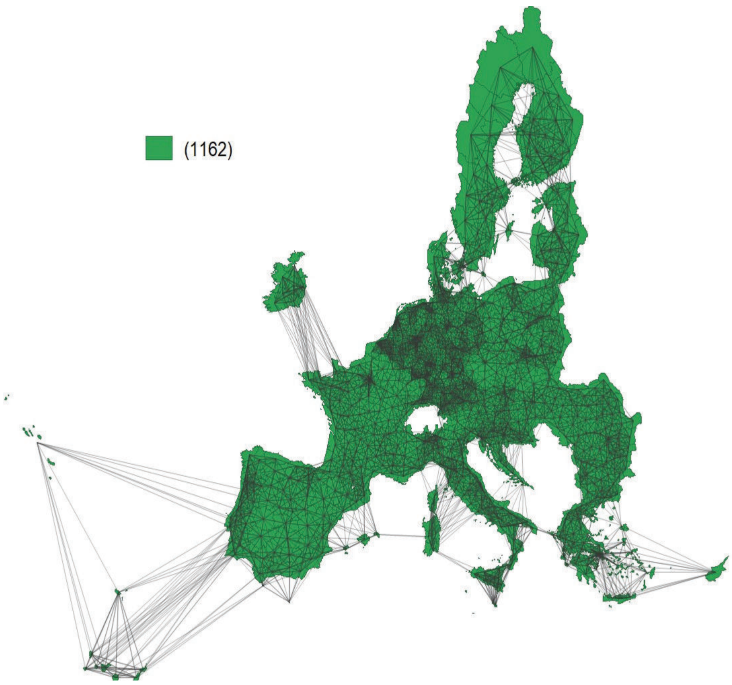
Source: Own representation based on Moura and Bráulio (2020).

To establish the spatial contiguity, the binary weighting matrix w_{ij} can be computed based on various methods such as: binary matrix contiguity (e.g., queen or rook), to certain distance limit (e.g., Euclidian distance), or based on kernel functions. Hence, we tested various contiguity matrices available in GeoDa in order to have a small number of neighbors to prevent territorial units from being all directly adjacent to each other, but an adequate number of neighbours to allow for significant spatial interactions.

Ultimately, based on the connectivity map (see Figure 1) and for the purpose of our analysis, we employed a contiguity matrix based on the kernel uniform function constraints to map out connections over this large geographic area in order to investigate neighborhood interactions.

Connectivity map in GeoDa based on kernel uniform function

Figure 1



The kernel uniform function is defined as a K(z) function where z is the ratio between the distance d_{ij} from territorial unit i to territorial unit j and the bandwidth h_{ij}. So $z = d_{ij} / h_{ij}$ which ensures that z will always be 1 and for the distance greater than the bandwidth the function K(z) will be zero. In our paper, for the bandwidth we selected the measure as the maximum k-nearest neighbors distance as this was the one assuring the optimal contiguity presented in Figure 1.

The local Moran's I is a local indicator for spatial association known as LISA and calculated based on the global Moran's I. The operational definition states that a LISA indicator is a statistic that meets two requirements. First of all, the local indicator for each observation provides information on the significance of spatial clustering for similar values around that particular observation. Secondly, adding up the LISAs for all the observations yields the global indicator for spatial association (Anselin, 1995). Locations or neighbouring locations where LISA is significant indicate local spatial clusters ("hot spots") but also local spatial outliers. In this paper, besides univariate

Local Moran's I we employ also the bivariate Local Moran's I which enables us to observe the relationship between one variable at a specific location and the average of another variable for the neighbouring locations (the spatial lag of another variable).

In a Moran Scatter Plot, the four quadrants offer a classification of the possible types of spatial autocorrelation:

- High-high (coloured in red) highlights positive spatial autocorrelation, meaning that higher than average observations have neighbours with also higher than average values for the same variable (in case of univariate LISA) or for another variable (in case of bivariate LISA)
- Low-Low (coloured in blue) refers also to positive spatial autocorrelation but with values of the variable(s) below the average
- High-Low (coloured in pink) and Low-High (light blue) suggest negative spatial autocorrelation

3.2. Data

Our data was retrieved from Eurostat for year 2021, using publicly available data for NUTS 3 level regions of the EU-27. The data selection process started with a search on Eurostat for the key words "by nuts 3 regions" which returned all available variables at NUTS 3 level.

The indicators of the Sustainable Development Goals (SDGs) served as a reference for the variables' selection. We mention that the number of variables at NUTS 3 level is extremely limited and the themes they cover are not sufficient to be able to link them to sustainable development indicators. Thus, we have selected the variables covering SDG 8: decent work and economic growth, but with the methods used in this research we can say that we also reach SDG 10: reduced inequalities. Considering that part of the labour resources is employed in companies, the variables that correspond to SDG 8 are *The number of enterprises with at least one employee* and *The total number of enterprises regardless of the number of employees*. Since the reducing inequalities, which is the purpose of SDG 10, can be observed through data visualization, we can say that the methods employed in this paper are a way to analyse this aspect.

The number of enterprises with at least one employee and *The total number of enterprises regardless of the number of employees* are two variables are two variables that describe economic activity from the perspective of the entrepreneurial environment. The difference between the two variables lies in the presence or absence of employees within the enterprises. Since not all enterprises have employees and the data is available in this regard, we considered that a comparison between the two variables is useful for our study. In Table 1, it can be observed that the dimension of variable *Number of enterprises with at least one employee* is approximately two times smaller than that of variable *Total number of enterprises*.

Variables employed

Table 1

Variable name	Gross Domestic Product (GDP)	Number of enterprises with at least one employee	Total number of enterprises
Code	lgGDP	lgEmpl_Ind	lgEnt
Definition	Gross Domestic Product expressed as Purchasing Power Standard (PPS, EU27 from 2021), per inhabitant	The number of enterprises with at least one employee	The total number of enterprises regardless of the number of employees
Mean (log)	30027.2 (4.44)	100024.1 (3.79)	27454.3 (3.79)
S.D. (log)	13961.9 (0.17)	15593.4 (0.40)	45232.1 (0.40)
Median (log)	27700 (4.44)	5845.5 (3.77)	13458 (3.77)
Min-Max value (log)	9000-143300 (3.95-5.16)	332-230060 (3.95-5.16)	630-537752 (2.52-5.36)
Missing values	14	106	106

Source: Eurostat, logarithm values in parentheses

The final dataset contained 1162 territorial units for the Eu-27 countries for NUTS 3 granulation level. Despite the large number of observations, the dataset contained a series of missing values, which are presented for each variable in Table 1. According to the results of the descriptive statistics for the non-logarithmic variables, it is observed that reveal heterogeneity. In order to assess comparability, but also to control for normal distribution of the variables we applied log transformation. The results were estimated using GeoDa version 1.20.

4. RESULTS AND DISCUSSIONS

The analysis presented in our paper is divided into three phases. To begin, we used standard deviation maps for each variable to visually examine spatial spill-over and cohesion. Further, to verify general cohesion, we carried out an analysis of global spatial autocorrelation for all variables using univariate global Moran’s I and univariate Local Moran’s I. Finally, we explored whether the factors affect and interact locally, which is the reason why we conducted a local spatial autocorrelation analysis. While global spatial autocorrelation analysis was used to demonstrate overall cohesion, standard deviation maps and univariate Local Moran's I allowed for a visual assessment of spatial spill-over and cohesion for each variable.

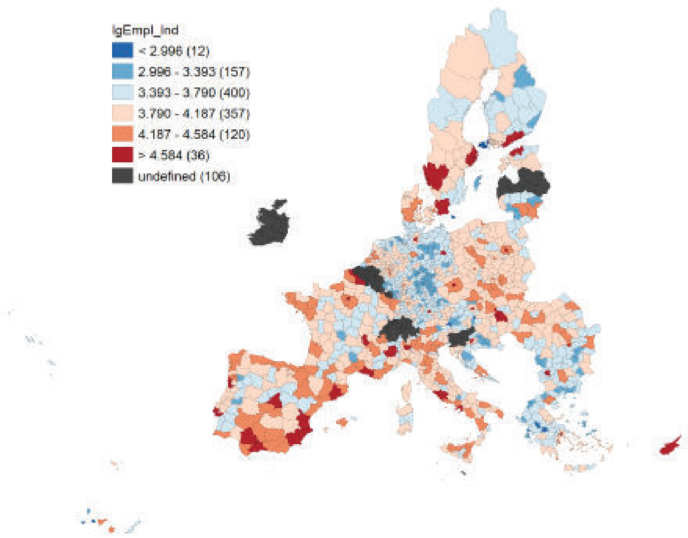
Using standard deviation maps, we began our study by attempting to visualize spatial cohesion for the variables that were being investigated. The findings show notable patterns in spatial spill-over for the variables employed.

These results provide important information on how the data is distributed and varies over various geographic areas, laying the path for a deeper investigation of the underlying causes affecting the patterns that are seen.

Regarding the number of companies (Figure 2 and 3) the distribution result may seem slightly counter-intuitive, but it can be correlated with the GDP distribution. On this basis, we can argue that in developed regions the markets have covered most of their needs through companies located in third countries and not necessarily in their country of origin (Narula and Dunning, 1999; Penrose, 2013).

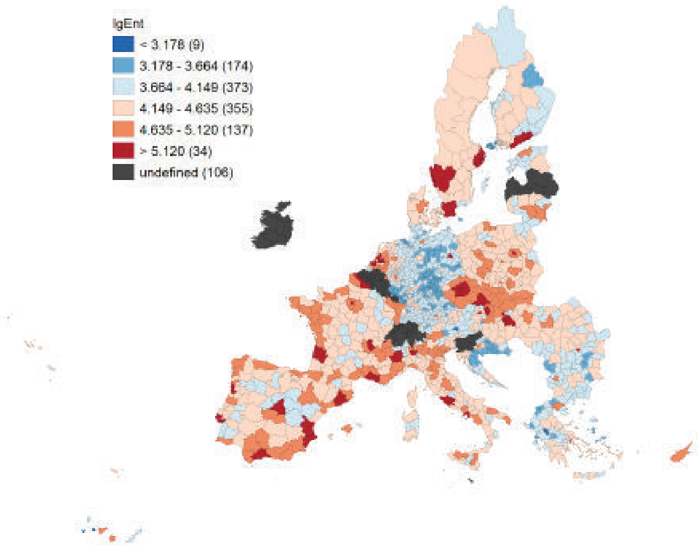
Standard deviation map in GeoDa for variable "*Number of enterprises with at least one employee*"

Figure 2



Standard deviation map in GeoDa for variable “*Total number of enterprises regardless of the number of employees*”

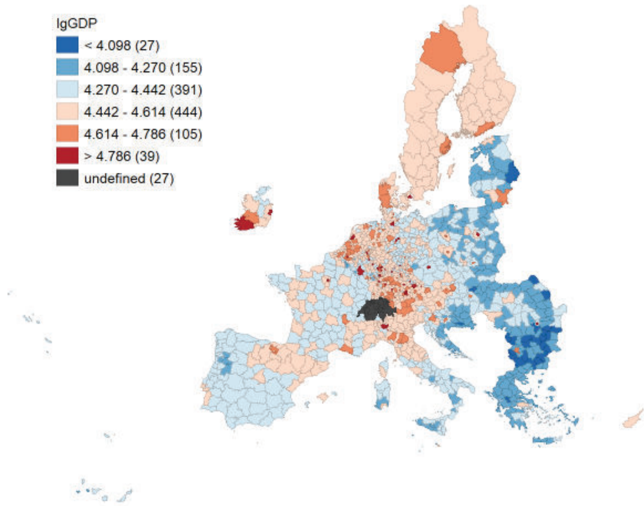
Figure 3



Even though the variables related to the number of enterprises are essentially similar, they represent two different concepts. Since not all established enterprises create jobs to absorb a part of the unemployment we considered that a comparison between the two variables: *The number of enterprises with at least one employee* and *The total number of enterprises regardless of the number of employees* is useful to observe the spatial interactions with GDP

Standard deviation map in GeoDa for "Gross Domestic Product (GDP)"

Figure 4



In the case of GDP (Figure 4), a delimitation according to the geographical position of the territorial units is evident. Thus, the countries that have a GDP at two standard deviations to the left of the mean value are the in the Eastern European part. However, the spill-over effect of central European countries is also observed, with the GDP of neighbouring countries tending towards the mean value.

The Global univariate Moran's I values for the variables employed are statistically significant (according to the pseudo p-value), positive and above 0.5, which shows spatial similarities at the level of NUTS 3 territorial units. This implies that if the value of that variable is high in one region, neighbouring regions will have the same trend. This correlation is called high-high, but there is also a low-low correlation which implies low values in a region with neighbouring regions having the same trend. Therefore, the spill-over effect is confirmed for the three variables analysed (see Table 2).

Global univariate Moran's I

Table 2

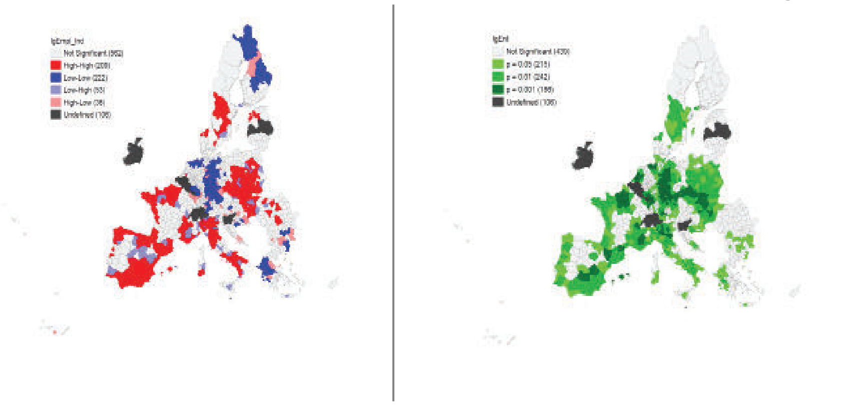
Sample	Moran's I values	Z_I	pseudo p-value
Gross Domestic Product	0.499	43.56	0.001
Number of enterprises with at least one employee	0.351	28.09	0.001
Total number enterprises	0.526	42.48	0.001

Source: GeoDa results

LISA univariate results (Figures 5 to 6) show a clear spill-over effect in the case of the three variables included in the analysis: regions where the number of enterprises is high are surrounded by regions with a high number of enterprises, while regions with a low number of enterprises are surrounded by regions with a low number of enterprises.

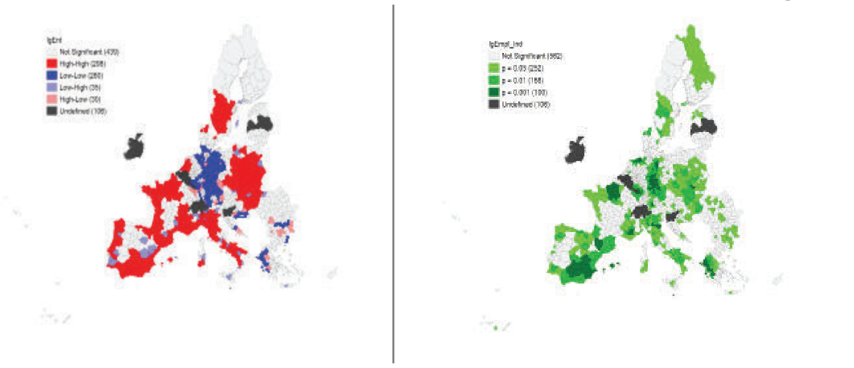
Univariate local spatial autocorrelation of "*Number of enterprises with at least one employee*" (left: LISA, right: statistical significance of LISA test)

Figure 5



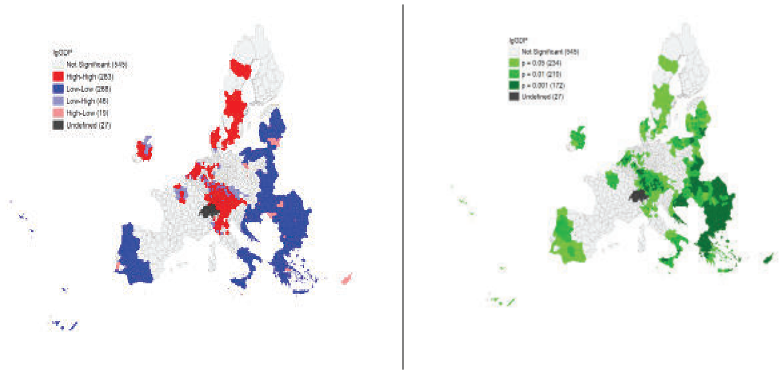
Univariate local spatial autocorrelation between of "*Total number of enterprises regardless of the number of employees*" (left: LISA, right: statistical significance of LISA test)

Figure 6



Univariate local spatial autocorrelation of "Gross Domestic Product"
(left: LISA, right: statistical significance of LISA test)

Figure 7

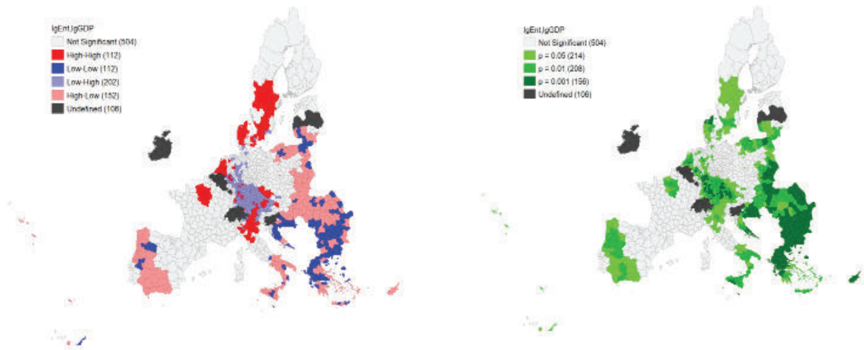


The spill-over effect is even more clear in the case of the GDP variable (Figure 7). In this case, regions with high GDP are concentrated in the centre of European Union.

The third step of our analysis involves bivariate local spatial correlation analysis, where we used the GDP as a spatial lag variable in respect to the variables corresponding to the number of enterprises (see Figure 8 and Figure 9).

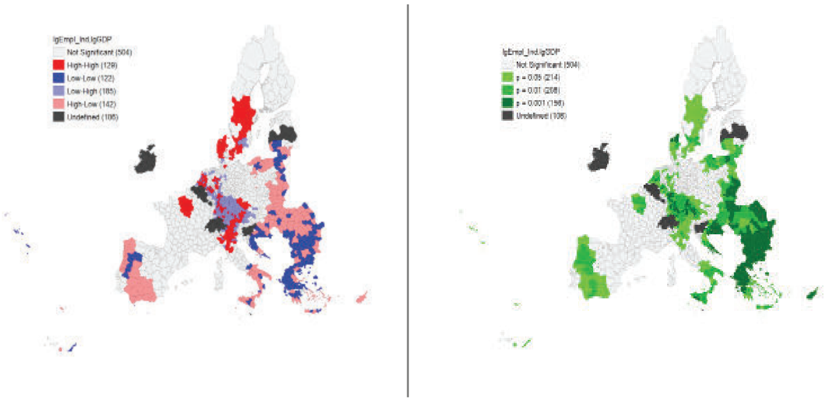
Bivariate local spatial autocorrelation between The "Total number of enterprises regardless of the number of employees" and the "Gross Domestic Product" (left: LISA, right: statistical significance of LISA test)

Figure 8



Bivariate local spatial autocorrelation between the "Number of enterprises with at least one employee" and the "Gross Domestic Product" (left: LISA, right: statistical significance of LISA test)

Figure 9



The LISA analysis presented in Figure 8 and Figure 9, provides a detailed picture of territorial cohesion in terms of the relationship between GDP and the number of enterprises. The spill-over effect is also visible in this case especially in the case of the relationship between GDP and the number of enterprises with at least one employee (see Figure 9). Strong low-low associations are recorded in South-Eastern Europe (parts of Romania, Bulgaria, Greece), but also in Baltic states, parts of Poland and Croatia. These clusters of regions are thus characterized by a significant association between a low number of enterprises and a low GDP. However, although the relationship is significant for these particular regions, it is not significant for wide areas in Western Europe like most of Germany, France or Spain. This difference in behaviour suggests the perpetuation of the East-West divide in terms of the analysed variables.

The link between GDP and the number of enterprises illustrated by the LISA analysis, highlights the fact that low-GDP areas frequently have a low number of businesses. This is relevant to SDG 8 which promotes sustained economic growth and productive employment. Therefore, a region's economic activity and employment opportunities are generally lower in areas with fewer enterprises. Also, the presence of low-low associations in certain regions suggests that those regions require targeted financial support in order to promote economic development. This is essential to ensure that all regions can benefit from economic opportunities in order to reduce inequality (SDG 10).

5. FINAL REMARKS

Our results showed that the spill-over impact from central European states is evident, as nearby countries tend to gravitate toward the mean values of the variables employed. Strong spatial correlations highlight the cohesion of regional economic trends, as seen by statistically significant Global univariate Moran's I values at the NUTS 3 level.

The verified spill-over impact encompassing all variables highlights the interdependent dynamics that define the economic terrain in the examined regions. This pattern underscores the need for targeted economic policies that promote entrepreneurship. By creating a favourable environment for business development and job creation we can have obvious results to achieve SDG 8—decent work and economic growth—and address the pressing inequalities promoted by SDG 10.

Our results are similar with the ones found in the literature in the field. Skvarciany and Astike (2022) applied the COPRAS approach, the results indicating the most vital indicator is the annual growth rate of real GDP per employed person. Basil et al (2021) studied economic growth, education and decent work, the results indicating that computing education and employment opportunities have a significant impact on economic growth.

The decent work presents a critical role in fostering economic growth, the fair employment practices and financial inclusion significantly influencing the economic growth (Zehri et al, 2024). Sustainable development and inclusive growth are the path for improving welfare and quality of life. Economic well-being represented by economic growth must include an increase in real per-capita income. Sustained and inclusive economic growth drives development by providing more resources for education, health, consumption, transport, and water and energy infrastructure, leading to new and better employment opportunities (Hasseen, 2023).

Unfortunately, the data availability is a real problem in our quest to achieve consistent results. Through this analysis we want to draw the attention on the importance of the data availability at NUTS 3 level. The issue of data availability at the granular level needs to be considered by all stakeholders involved in the assessment of the European cohesion for the sustainable development. Although there is a lot of data at NUTS 2 level, a view at a more detailed level such as NUTS 3 highlights weak areas that would otherwise be absorbed by strong areas when the level of geographical breakdown increases. Therefore, the main limitations of this research are primarily due to the lack of data at territorial level on fine geographical breakdown, such as NUTS 3 level.

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A Bottom-Up Approach for Estimating the Size Of Rural Tourism in Romania

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ABSTRACT

Purpose

The purpose of this research is to present some estimates regarding the size of rural tourism in Romania based on the existing data from official tourism statistics provided by the National Institute of Statistics (INS).

Design/Methodology/approach

A bottom-up approach was used by aggregating INS data from more than 1,000 - 1,200 rural localities (ro. comune) in Romania that have tourism statistics in the period 2019-2023. Based on the assumption that rural tourism occurs in these rural localities, some statistical indicators were calculated for the rural area of Romania: accommodation capacities (existing capacity and functioning capacity), arrivals, overnight stays, length of stay and bed-places occupancy. However, as a limitation, due to the fact that in Romania some urban localities comprise also villages where rural tourism might occur, some adjustments are possible to be made in the estimates to include agro-tourism boarding houses (ro. pensiuni agroturistice) of the urban localities.

Main findings

The results show that even rural area concentrates half of the accommodation establishments and over 30% of the accommodation capacity in Romania it attracts only 21-22% of total tourists registered in accommodation establishments. This illustrates a lower capacity of the rural area to constitute a real driver to boost Romanian tourism.

Originality/value

This paper proposed a new method to unveil statistics on rural tourism in Romania based on data aggregation from Local Administrative Units (LAUs) in a pragmatic approach to define rural space based on the classification of localities (ro. UAT-uri – comune, orașe, municipii) as used in the official statistics in Romania.

Conclusions/Recommendation

Within accommodation statistics, National Institute of Statistics might start publish data with the breakdown Rural vs. Urban localities (out of which, agritourist boarding houses from urban localities).

Keywords: *rural tourism, tourism statistics, rural area, Romania*

JEL Classification: *Z30, C81*

1. **INTRODUCTION**

Measuring tourism as an economic activity is most commonly made at the sectorial level since tourism is from supply-side seen as a set of economic activities that are providing goods and services to visitors be it overnight visitors (tourists) or day-visitors (with no overnight stays). However, when different types of tourism (i.e. cultural tourism, ecotourism, rural tourism, urban tourism, mountain tourism, coastal tourism, business tourism, health tourism etc.) are subject to statistical measurement, the approach should be somehow different.

Rural tourism is entirely related to the rural space which has its own particularities and characteristics. But the rurality concept is a complex one with different approaches in Europe and also worldwide. The distinction between rural and urban areas is not easy to be made especially when small localities and/or periurban areas are involved. In these circumstances, it is necessary to have a pragmatic approach to define rural areas. So, in the case of Romania, in order to delineate the rural area one can use the classification of localities as used by official statistics which is provided by the National Institute of Statistics (INS). Measuring tourism in rural area can be therefore related to this national classification of localities and this is what this paper tries to propose as practical approach based on existing official data.

United Nations World Tourism Organization, UNWTO (2024) posts the following definition of rural tourism as ‘a type of tourism activity in which the visitor’s experience is related to a wide range of products generally linked to nature based activities, agriculture, rural lifestyle / culture, angling and sightseeing’. Moreover, it is stated that rural tourism occurs in non-urban (rural areas) with the three characteristics: low population density, landscape and land-use dominated by agriculture and forestry and traditional social structure and lifestyle. However, this definition is far from being straightforward since the concept of rurality is not easy be defined and it differs from country to country.

At European level, in the field of tourism statistics Eurostat disseminates data for some variables with the breakdown called <degree of urbanisation – abbreviation DEGURBA>. According to this approach, Local Administrative Units (LAUs) (which is the lowest administrative level for a country) are classified into three categories: Cities, Town and suburbs and Rural areas and are “based on a combination of geographical contiguity and population density, measured by minimum population thresholds applied to 1 km^2 population grid cells” (Eurostat, 2024a). In other words, LAUs are used to divide up the territory of the EU for the purpose of providing statistics at a local level (Eurostat, 2024b).

More precisely, with reference to tourism statistics, at European level, data on capacity and occupancy is presented broken down by the following three categories: Cities, Towns and suburbs and Rural areas. However, referring to the later, an in-depth investigation on Eurostat (2024c) data regarding the lists of LAUs for Romania for the year 2021 revealed that not all localities in Romania titled as communes (ro. comune) were included in the category the rural area. According to Eurostat (2024c) there were 2,740 LAUs defined as DEGURBA code 3 for rural areas. At the same time, 81 towns in Romania were allocated to DEGURBA code 3 for rural areas while 204 communes were allocated to the DEGURBA 2 for towns and suburbs. This is in contrast with MDLPA (2024) data that accounts for 2,862 localities as communes (rural localities) which might have an impact of tourism statistics in Romania's rural space.

Also some studies carried out at EU level emphasize the modest position of Romania as regards tourism in the rural area. For instance, it is stated that Romania, together with Hungary, part of Poland, Germany, Finland and Lithuania have low rural accommodation capacity (Barranco et al., 2021). More, some anomalies were obtained when clustering some destinations in Romania, particularly in defining Mountain and nature category for some regions (i.e. Ialomita county as part of this category) as in the paper of Batista et Silva et al. (2021).

In Romania, when quantifying the size of rural tourism, traditionally some types of accommodation units have been used namely agritourist boarding houses (and in the past rural boarding houses – but now agritourist boarding houses include also rural boarding houses (INS, 2024a). The approach of using types of accommodation for rural tourism is more recently found in Bogdan and Simon (2019) when presented data on tourism flows in the rural areas in Romania. But this approach is far from being accurate since agritourist boarding houses as types of accommodation units could also be found in the urban localities.

Moreover, when referring to rural areas there are also other types of accommodation units besides agritourist boarding houses. Therefore, if considering only agritourist boarding houses, a significant under-evaluation would occur. This is the reason why aggregating tourism data for 1,000 - 1,200 communes (rom. comune) for the rural area was considered a much better option in order to precisely identify the tourism in the rural area.

As a personal contribution, this paper proposes a new method to unveil statistics on rural tourism in Romania based on data aggregation from LAUs defined as communes. This method can be embraced also in the official tourism statistics in Romania and National Institute of Statistics can start to regularly publish data on tourism in the rural areas in Romania. A new category can be created when disseminated tourism statistics considering the urban vs. rural dichotomy thus tourism in communes vs. tourism in town and cities (rom. turismul din comune vs. turismul din orașe și municipii) or more commonly being labelled as tourism in the rural areas vs. tourism in the urban areas.

2. METHODOLOGY

The main assumption of this paper is that rural tourism is defined as being tourism that occurs in the rural areas as defined by the official status of the locality as commune (ro. comună) according to the national regulations in Romania. There is also an official act endorsed by the Ministry of Agriculture, Forests and Rural Development and the Ministry of Administration and Internal Affairs in 2005 that define rural space as being those areas belonging to communes as well as to periurban areas of towns and municipalities (MAPDR and MAI, 2005). The lowest territorial entity in Romania is represented by village that can be either part of commune (the most common situation) or part of a town or a municipality (ro. oraș sau municipiu). In some cases, some periurban areas of towns or municipalities can form a village, but this cannot be always the case. At the same time, it is important to mention that in Romania there are no official data at the level of villages that are part of towns or municipalities. In 2023 according to INS (2024a) there were 467 villages that belong to towns or cities representing 3.6% of total villages in Romania.

Therefore, in a practical manner, rural area could be defined as localities represented by communes (rom. comune). These represent local administrative units (LAUs) and are compatible with NUTS classifications (Eurostat, 2024b). NUTS which is the Nomenclature of Territorial Units for Statistics is a classification developed in the European Union. In fact, LAUs are a subdivision of NUTS 3 regions covering the EU's whole economic territory. An aggregation of data for all the communes in Romania that have tourism statistics has been carried out. Data were collected from between 1,000 - 1,200 localities (ro. comune) that have data on tourism statistics. Data was extracted from Tempo database in the period March-April 2024 (INS, 2024). For each county in Romania (there are 41 counties), data in the Tempo database are available at the locality level (at LAUs level). It is important to say that in Romania in total there are 2,862 communes according to Ministry of Development, Public Works, and Administration, MDLPA (2024).

The following statistical indicators have been aggregated to cover the evolution of tourism in the rural area in Romania in the last 5 years (2019-2023), covering both the pre-pandemic period (2019) and also pandemic and post-pandemic years (2020-2023):

- Number of tourist accommodation units (number of establishments)
- The existing accommodation capacity (number of bed-places)
- The functioning accommodation capacity (number of days bed-places)
- Number of arrivals (number of tourists)
- Number of overnight stays (nights spent at tourist accommodation establishments)
- Average length of stay
- Occupancy rate (of bed-places) (ro. indicele de utilizare netă a capacității de cazare în funcțiune)

It is important to note that these indicators are produced by INS monthly and annually and are collected from accommodation establishments that are authorized (classified) by the national competent authority namely Ministry of Economy, Entrepreneurship and Tourism. There are two surveys from which data are collected by INS: the survey entitled "The occupancy of accommodation establishments in Romania (ro. Frecventarea structurilor de primire turistică cu funcțiuni de cazare turistică)" – a monthly and yearly survey and the survey entitled "Existing accommodation capacity at 31st of July (ro. Capacitatea de cazare existentă la 31 iulie)" – a yearly survey. In addition, from another survey carried out by INS, a relevant indicator from demand side was analysed namely "Number of trips taken by residents for holidays and business purposes (having rural area as main destination of the trip)" for illustrative purposes. This indicator is derived from the survey entitled "Tourism demand of residents in Romania (ro. Cererea turistică a rezidenților)".

However, it has to be admitted that considering only communes as localities for defining rural area in Romania has some obvious limitations since there are also towns or cities that includes also villages as subcomponent territorial unit. Since tourism occurs also in these villages that are part of urban area, rural tourism would be underrepresented if it is limited only to communes. But the highest level of data disaggregation at territorial level is at municipality level (LAUs level) in Romania (not at the level of subcomponents of LAUs). Therefore, as a practical solution, it was possible to extract also data on agritourist boarding houses from urban localities under the assumption that all these agritourist boarding houses are all located in villages that are officially part of town and cities. This assumption is based also on the law provisions (MAPDR and MAI, 2005) that stipulate that tourism and rural leisure services are activities occurring also in the periurban area of towns and cities as part of the rural space. Moreover, according to the Romanian legislation, agritourist boarding houses must have at least one activity related to agriculture, fish farming, fishing, reed harvesting, animal husbandry, cultivation of different types of plants, orchards of fruit trees or a craft activity, with a workshop, from which various handicraft items result (National Authority for Tourism, 2013).

To sum up, data on rural tourism in Romania are added from two sides, on the one hand from communes (defines by the national law as rural localities) and on the other hand, from agritourist boarding houses from towns and cities (rom. orașe și municipii). In this way, it is considered that a better quantification of the size of rural tourism in Romania is undertaken. Not the least, a comparison with Eurostat data is provided in order to outline the differences for some indicators where data is available.

3. RESULTS

3.1. *Accommodations statistics*

In this section accommodation statistics refer to data obtained from accommodation establishments in a supply-side perspective.

In the last 5 years, the number of accommodation establishments from the rural area in Romania has constantly increased from 4,003 in 2019 to 6,445 in 2023. The same is the case of the share of these units from rural area in the total number of accommodation establishments at national level (an increase from 47.6% in 2019 to 50.8% in 2023). Thus, it is evident that rural area accounts for little more than a half of total number of accommodation establishments in Romania (table 1).

Number of accommodation establishments in the rural area and at national level, 2019-2023

Table 1

Indicator	2019	2020	2021	2022	2023	+/- 2023 vs. 2019 (%)
Number of accommodation establishments from communes	3,842	4,033	5,663	5,967	6,253	+62.8
Number of agritourist boarding houses from towns and municipalities	161	182	168	174	192	+19.3
Total rural area	**4,003**	**4,215**	**5,831**	**6,141**	**6,445**	**+61.0**
Number of accommodation establishments at national level	8,402	8,610	11,736	12,201	12,697	+51.1
Share of rural area	47.6%	49.0%	49.7%	50.3%	50.8%	-

Source: INS (2024a) and own calculations

One can note also the growth rate (2023 as compared with 2019) which is higher in the case of rural area in comparison with the national level (61.0% vs. 51.1%) denoting a greater appeal of rural area for investments in accommodation establishments. However, in both cases, this high rate is explained also by some methodological issues, more precisely the data coverage starting with 2021 with the new accommodation typology named “rooms and apartments for rent”, that was not included in 2019.

If we refer to accommodation capacity, namely number of accommodation bed-places, in 2023, rural area in Romania accounts for little less than 30% of total bed-places in the country. It is important to mention that at the European Union (EU27) level this percentage was even higher reaching to 43.9% (own calculations based on Eurostat data).

In absolute values, over 135 thousand accommodation bed-places were allocated to rural area in Romania, increasing with 38.6% as compared with 2019. Not surprisingly, this growth rate is superior to the growth rate registered at national level (+21.6%) in the same period. This impacts also the share of rural area in total accommodation capacity in Romania which increases with four percentage points in 2023 compared with 2019 (from 27.4% in 2019 to 31.2% in 2023) (table 2).

Existing accommodation capacity (number of bed-places) in the rural area and at national level, 2019-2023

Table 2

Indicator	2019	2020	2021	2022	2023	+/- 2023 vs. 2019 (%)
Number of bed-places from communes	94,312	97,809	120,630	126,879	131,545	+39.5
Number of bed-places in agritourist boarding houses from towns and municipalities	3,287	3,279	3,163	3,470	3,748	+14.0
Total rural area	**97,599**	**101,088**	**123,793**	**130,349**	**135,293**	**+38.6**
Number of bed-places at national level	356,562	358,119	410,291	422,114	433,487	+21.6
Share of rural area	27.4%	28.2%	30.2%	30.9%	31.2%	-

Source: INS (2024a) and own calculations

It is important to note that the existing accommodation capacity did not decline in the first pandemic year neither in the rural area nor at la national level. But one has to admit that this is due strictly to the nature of the indicator which measures the physical existence of a capacity (in Romania, at 31st of July) which is the peak tourism season. In both cases (both for rural areas and at national level), one can note a continuous growth of the existing accommodation capacity from year to year which denotes a development of the sector from the accommodation supply perspective.

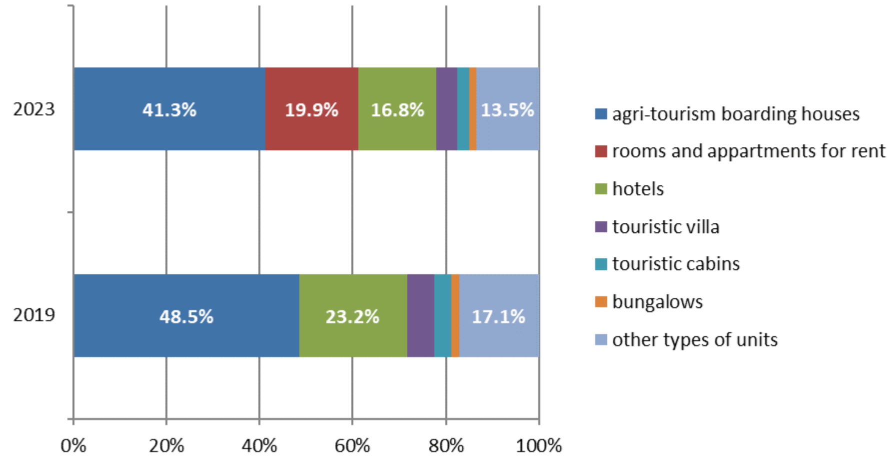
Also in this case, data comparability 2023 vs. 2019 is affected by the coverage since starting 2021 introduction of the accommodation typology named “apartments and rooms for rent” obviously influenced the data series. For example, in 2021 there are added more than 52 thousand bed-places at national level and more than 22 thousand in the rural area.

From this perspective, it is important to see also the distribution of accommodation capacities by typologies in 2019 as compared with 2013, in other words, in a pre-pandemic and post-pandemic year (figure 1).

One can see that in the pre-pandemic year 2019, almost a half (48.5%) of accommodation capacities was located in agritourist boarding houses. However, due to inclusion of rooms and apartments for rent category, the share of agritourist boarding houses is lower in 2023 as compared with 2019 (41.3%); Rooms and apartments for rent occupies the second position with a share of almost 20% but also hotels have also important shares (23.2% in 2019 and 16.8% in 2023). Touristic villas account for around 5% and the rest of accommodation typologies from rural area accounts together for below 20% in 2023 and a little above 20% in 2019. Overall, it is to be noted the dominance of agritourist boarding houses as type of accommodation both in 2019 and 2023.

Number of bed-places in the rural area by typologies in 2019 and 2023

Figure 1



Source: own calculations based on INS (2024a)

As regards functioning accommodation capacity, rural area had almost 32 million days-bed-places in 2023, representing little over 30% (30.6%) from the total functioning accommodation capacity in Romania. What is significant is the growth rate of functioning accommodation capacity in rural area in 2023 compared with 2019 which is more than double than the similar growth rate at national level (36.4% vs. 17.5%). This means that the accommodation offer in the rural area has constantly increased at a rate superior to the national level. Also, to note that in the rural area, in the pandemic year 2021 more accommodation offer is put on the market than compared with the pre-pandemic year 2019. In other words, a return of the tourism offer in the rural area occurs in 2021 in contrast with the return of the tourism offer at national level that occurs only in 2022 when the pre-pandemic levels are exceeded. Also, starting 2021 the share of rural area in total functioning accommodation capacity in Romania constantly grows from 27.8% in 2021 to 29.2% in 2022 and 30.6% in 2023 (table 3).

Functioning accommodation capacity (number of days-bed-places) in the rural area and at national level, 2019-2023

Table 3

Indicator	2019	2020	2021	2022	2023	+/- 2023 vs. 2019 (%)
Number of days-bed-places from communes	22,550,679	15,798,497	23,329,536	26,213,148	30,893,563	+37.0
Number of days-bed-places in agritourist boarding houses from towns and municipalities	877,285	658,364	935,013	942,066	1,058,971	+20.7
Total rural area	**23,427,964**	**16,456,861**	**24,264,549**	**27,155,214**	**31,952,534**	**+36.4**
Number of days-bed-places at national level	88,789,656	64,040,595	87,217,823	93,007,230	104,348,563	+17.5
Share of rural area	26.4%	25.7%	27.8%	29.2%	30.6%	-

Source: INS (2024a) and own calculations

At the same time, due to sanitary restrictions in 2020, the accommodation supply (functioning accommodation capacity) declined in the rural are with almost 30% compared with 2019 which is with more than 2 percentage points lower than the same decline rate at national level. This proved a lower capacity of the accommodation establishments in the rural area to adapt to the new pandemic realities.

The size of tourism flows in the rural area of Romania in the period 2019-2023 is represented in absolute values between 1.4 and 2.8 million tourists (arrivals) which represents around 19-23% from the total number of tourists registered in Romania (table no. 4). The first pandemic year (2020) is characterized by a sharp decline of arrivals as compared with the previous year (-43%) but still lower than the decline registered at country level (-52%) which shows a slightly better position than the one of rural tourism.

One has to note that the pandemic years 2020 and 2021 are characterized by an increase of the share of rural area with 2 percentage points compared with 2019, a share that is moderating in 2022. In other words, undoubtedly there was a relative increase of tourist preferences for rural area in Romania after 2020. In absolute values, in 2023, over 2.8 million tourists were registered in accommodation establishments in rural area, increasing with 12.7% compared with 2019 while at national level a decline was posted in the same period (-2.9%). One has to note the continuous growth of number of tourists in rural area starting 2021 onwards.

More, starting with 2022, tourism in the rural area has exceeded the level before pandemics (2019) showing a better resilience capacity as compared with the evolution of tourism at national level which did not completely recovered after the pandemic period not even in 2023 (table 4).

Number of tourists (arrivals) in accommodation establishments in the rural area and at national level, 2019-2023

Table 4

Indicator	2019	2020	2021	2022	2023	+/- 2023 vs. 2019 (%)
Number of arrivals from communes	2,436,567	1,388,561	2,273,302	2,610,893	2,759,003	+13.2
Number of arrivals in agritourist boarding houses from towns and municipalities	89,893	52,374	86,167	84,696	87,789	-2.3
Total rural area	**2,526,460**	**1,440,935**	**2,359,469**	**2,695,589**	**2,846,792**	**+12.7**
Number of arrivals at national level	13,374,943	6,398,642	10,205,322	12,588,333	12,852,156	-2.9
Share of rural area	18.9%	22.5%	23.1%	21.4%	22.2%	-

Source: INS (2024a) and own calculations

The same characteristics as in the case of arrivals can be seen also in the case of overnight stays (nights spent at tourist accommodation establishment) having in mind that the growth rate in 2023 as compared with 2019 is less than a half compared with the one for arrivals (+5.4% versus 13.2%), while at national level, the same rate is two times higher (-8,4% versus -2.9%). In absolute terms, in rural area in 2023 more than 6 million overnight stays have been registered compared with 5.8 million in 2019. Starting 2020, rural area in Romania concentrates around 21-22% from the total number of overnight stays registered in Romania (table 5).

Number of overnight stays in accommodation establishments in the rural area and at national level, 2019-2023

Table 5

Indicator	2019	2020	2021	2022	2023	+/- 2023 vs. 2019 (%)
Number of overnight stays from communes	5,702,286	3,077,781	5,035,771	5,709,790	6,011,427	+5.4
Number overnight stays in agritourist boarding houses from towns and municipalities	151,493	87,665	142,986	138,828	143,854	-5.0
Total rural area	**5,853,779**	**3,165,446**	**5,178,757**	**5,848,618**	**6,155,281**	**+5.2**
Number of overnight stays at national level	30,086,091	14,579,140	22,747,562	27,044,372	27,565,092	-8.4
Share of rural area	19.5%	21.7%	22.8%	21.6%	22.3%	-

Source: INS (2024a) and own calculations

As regards the average length of stay in the rural area, there are no significant changes in the period 2019-2023. This is relatively similar starting 2020 at around 2.2 days, registering a slow decline compared with 2019 (-6.7%). At national level, the average length of stay is oscillating around 2.1 - 2.3 days in the period 2019-2023. One can see that there are no significant changes between length of stay in the rural area and length of stay at national level (table 6).

Average length of stay in accommodation establishments in the rural area and at national level, 2019-2023

Table 6

Indicator	2019	2020	2021	2022	2023	+/- 2023 vs. 2019 (%)
Average length of stay in the rural area	2.3	2.2	2.2	2.2	2.2	-6.7%
Average length of stay at national level	2.2	2.3	2.2	2.1	2.2	-4.7

Source: INS (2024a) and own calculations

Known as the indicator of the relation between tourism demand (overnight stays) and tourism supply (functioning accommodation capacity), the occupancy of accommodation establishments in the rural area is lower than occupancy at national level, generally this difference ranging between over 3 percentage points in 2020 to over 8 percentage points in 2019. In both situations (at rural level and at national level), the evolution of this indicator is similar in 2023 as compared with 2019. In other words, one can see that the occupancy rate in 2023 is still far behind the level reached in 2019, being with 23% lower in the case of rural area and with 22% lower for total accommodation units in Romania. For rural area, the occupancy drops below 20% in 2023 being somehow similar with the level registered in 2020. At national level, however, the occupancy registered in 2023 is superior to the level registered in 2020 with almost 4 percentage points (table 7).

Occupancy (of bed-places) in accommodation establishments in the rural area and at national level, 2019-2023 (%)

Table 7

Indicator	2019	2020	2021	2022	2023	+/- 2023 vs. 2019 (%)
Occupancy (of bed-places) in the rural area	25.0%	19.2%	21.3%	21.5%	19.3%	-22.9
Occupancy (of bed-places) at national level	33.9%	22.8%	26.1%	29.1%	26.4%	-22.0

Source: own calculations based on INS (2024a)

3.2. ***Tourism demand of residents for the rural area in Romania***

From a different perspective, that of tourism demand of residents (for trips for holidays and business purposes), one can see that rural area accounted for around 23-28% from the total number of trips undertaken by residents in Romania. Also in this case, the pandemic years 2020 and 2021 are characterized by an increase with some percentage points of the share of rural area in total Romania as compared with 2019 while in the period 2022-2023 this share is around 25%. One can see that in all period 2019-2023, the rural area ranks third in the destination options of Romanian tourists travelling inside the country after cities and mountain area. Also, in all this period the rural area is better represented compared with the seaside area.

In absolute terms, in the period 2019-2023 the highest number of trips in the rural area is registered in 2021 (4.17 million), at the opposite end being year 2020 with almost 3.2 million trips in the rural area. Not the least, it is to note that the first pandemic year brings a significant decline also in the rural area but the rate of decline is lower than the national level (-19% compared with 34.2%), in other words, rural area has been affected to a lesser extent as compared with other regions such as cities, seaside and mountain area. Moreover, one has to note that the pandemic year 2021 brings a full recovery of the tourism demand for the rural area in Romania which was not the case at national level where the pre-pandemic levels were not exceeded yet. Also to note, in 2023 there is a decline of tourism demand for domestic trips both for rural areas and at national level due to removal of travel restrictions and increase preference of Romanians to travel abroad (table 8).

Number of domestic trips taken by residents for holidays and business purposes by destination area, 2019-2023

Table 8

Destination in Romania	2019	2020	2021	2022	2023	+/- 2023 vs. 2019 (%)
Total	16,863,013	11,087,663	16,044,913	16,261,236	14,501,236	-14.0
Cities	5,343,296	3,241,753	4,524,374	4,637,966	3,903,058	-27.0
Seaside	2,693,903	1,354,477	2,471,592	2,662,009	2,264,318	-15.9
Rural area*	**3,895,855**	**3,155,442**	**4,165,158**	**4,136,982**	**3,727,128**	**-4.3**
Cruise	12,846	-	13,481	4,906	1,031	-92.0
Mountain area	4,871,541	3,272,349	4,812,718	4,792,738	4,575,617	-6.1
Other areas	45,572	63,642	57,590	26,635	30,084	-34.0
Share of rural area	23.1%	28.5%	26.0%	25.4%	25.7%	-

* “Including lakes and rivers” – this is the terminology used by National Institute of Statistics in its survey

Source: INS (2019, 2020, 2021, 2022, 2023) and own calculations

If we compare the share of rural area from table 8 (from demand side) with the share of rural area obtained from accommodation statistics (table 4) one can see a higher share in the case of demand side with at least almost 3 percentage points in each year in the period 2019-2023. This difference might be explained by the perception of tourists (from demand) for the rural area. In addition, from supply-side, other factors might be envisaged as well for this difference such as underreporting of accommodation providers in order to avoid taxes or lack of proper coverage of the rural space defined in this case only through communes and agritourist boarding houses in towns and municipalities.

3.3. ***Eurostat statistics on tourism in the rural areas***

As mentioned before, the European Statistical Office Eurostat is using the classification of local administrative units (LAUs) by degree of urbanization using three categories:

• Cities

• Towns and suburbs

• Rural areas

Obviously, the last category has been considered for identifying the rural areas in Romania respectively of rural tourism.

Unlike national statistics, European statistics is providing complementary a breakdown of the tourism activity (namely number of overnight stays – number of nights spent) by residents (Romanian tourists) and non-residents (foreign tourists). According to Eurostat data, the rural area of Romania accounts for low shares in total number of overnight stays of non-residents registered in Romania (7-8% in 2017-2019 and 5-6% in 2020-2021). Also in case of resident tourists, the share of rural area (in total overnight stays of residents in Romania) is one more significant (26-28%) (table 9).

Number of overnight stays in the rural area in Romania by types of tourists, 2019-2023

Table 9

Destination in Romania	2019	2020	2021	2022	2023	+/- 2023 vs. 2019 (%)
Total number of overnight stays						
Rural area	7,221,157	3,758,224	5,480,655	6,894,428	7,627,581	5.6%
Total Romania	29,889,894	14,454,464	20,657,965	26,614,221	29,205,568	-2.3%
Share of rural area	24.2%	26.0%	26.5%	25.9%	26.1%	-
Number of overnight stays of foreign tourists						
Rural area	378,759	50,994	112,233	207,088	310,799	-17.9%
Total Romania	5,269,053	996,134	1,828,443	3,638,152	4,467,102	-15.2%
Share of rural area	7.2%	5.1%	6.1%	5.7%	7.0%	-
Number of overnight stays of residents						
Rural area	6,842,398	3,707,230	5,368,422	6,687,340	7,316,782	6.9%
Total Romania	24,620,841	13,458,330	18,829,522	22,976,069	24,738,466	0.5%
Share of rural area	27.8%	27.5%	28.5%	29.1%	29.6%	-

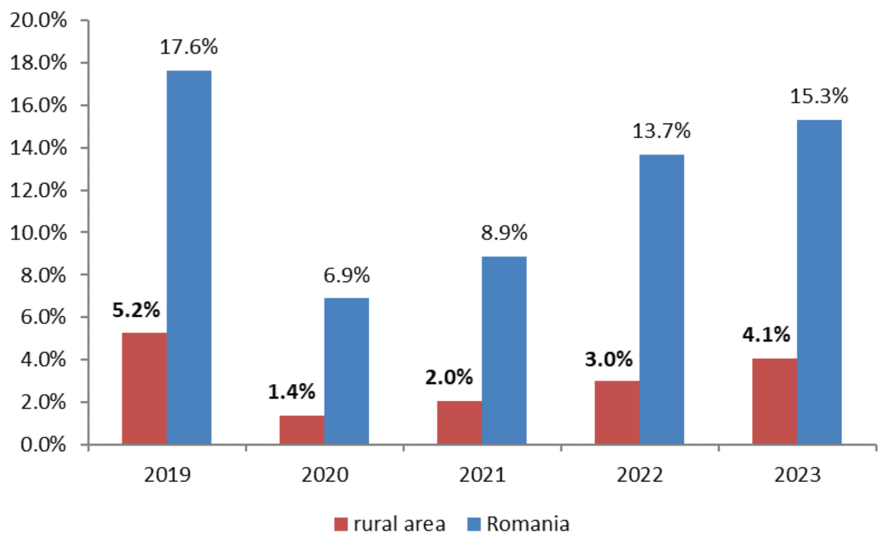
Source: Eurostat (2024d) and own calculations

In the first pandemic year (2020), only little than 50,000 thousand overnight stays of non-residents were registered in the rural area, while for Romanian tourists, in the same year over 3.7 million of overnight stays in the rural area were registered. The second pandemic year (2021) brings a double number of overnight stays of foreign tourists compared with 2020, while in the case of Romanian tourists the number of overnight stays increases with 49% in the rural area. One has to note the rate of decline in the first pandemic year for the number of overnight stays of foreign tourists which is much higher (-86.5%) as compared with the number of overnight stays of Romanian tourist in the rural area (-45.8%).

Due to the fact that foreign tourists choose in large extent cities as their main destination (including for business related purposes), the Romanian rural area attracted in the pre-pandemic period only 5.2% from the total number of overnight stays of foreign tourists in Romania. In the pandemic period, this share becomes extremely low (1.4% in 2020, 2% in 2020) due to travel restrictions that occurred at that time; in 2022 and 2023 this share increase up to 3% and respectively 4.1%. At national level, the share of non-residents in the total number of overnight stays in accommodation establishments in Romania is one much higher, both in the pre-pandemic period (17.6%) but also in the pandemic period (6.9% in 2020 and 8.9% in 2021); in 2023 one can see an increase of this share to 15.3%. These figures demonstrate a low capacity of rural area to attract foreign tourists despite its great potential and tourist attractions that are found in the rural space (figure 2).

Share of non-residents (foreign tourists) in total overnight stays in the rural area and in total Romania, 2019-2022

Figure 2

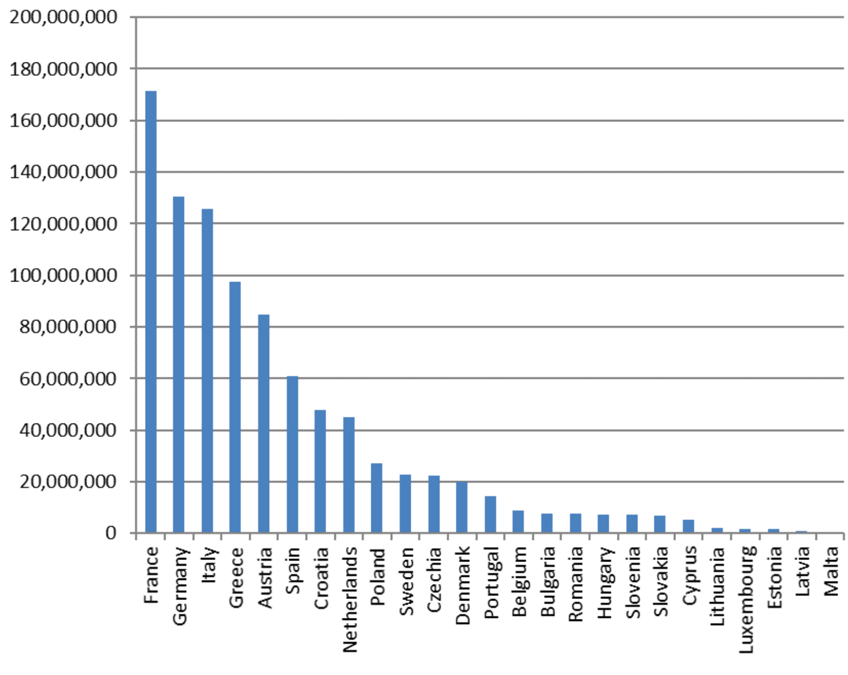


Source: Eurostat (2024d) and own calculations

At the same time, Eurostat data allows also the comparability of Romania with the other EU countries. In this endeavour we will take into consideration year 2023 (the last year with available data). Out of 27 EU member states, Romania ranks 16th, ahead of Hungary, but after Bulgaria in terms of absolute number of overnight stays in the rural areas. By far, France ranks first followed by Germany and Italy. Indeed, some rural regions from France, Italy and Spain have a considerable capacity to accommodate visitors (Barranco et al, 2021). At the opposite end, the lowest number of overnight stays in the rural area was recorded by Malta followed by Latvia and Estonia (figure 3). Overall, one can see that small countries are occupying the last position in this ranking, but considering its territory and its tourism resources, Romania should have been at least in the first part of this ranking of the EU countries. There is high potential for Romania to go ahead in this ranking of the EU countries from this perspective.

Overnight stays of the rural areas in the EU countries in 2023

Figure 3

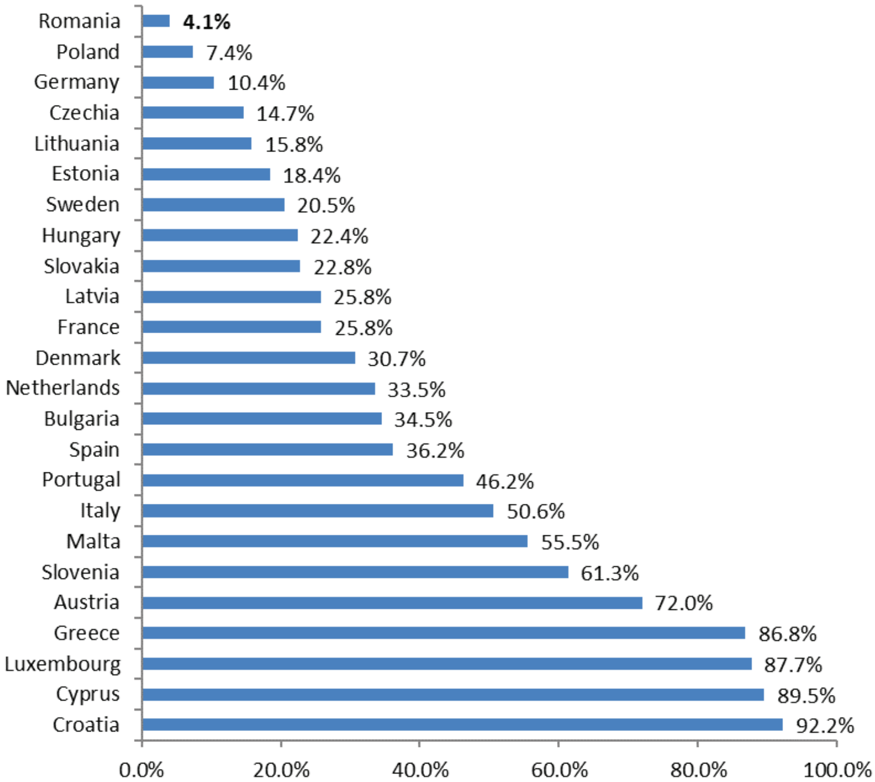


Source: Eurostat (2024d) and own calculations. No data for Finland and Ireland

Unfortunately, Romania is the EU country with the lowest share of its tourism based on foreign tourists (share of non-residents in total overnight stays) in the last year with available data (2023): it was only 4.1% which is far below the EU average of 40.2%. Along with our country in this hierarchy, there are also Poland (7.4%) and Germany (10.4%), also with relatively small percentages of overnight stays by foreign tourists in the rural areas. At the opposite pole, Cyprus, Croatia and Greece, in their rural areas, rely to a very large extent (over 80%) on foreign tourists. Overall, there are eight EU countries that have rural areas with a predominance of inbound tourism (share of foreign tourists in total number of overnight stays higher than 50%). At the same time, for 6 EU countries, located most of them in the Central and Eastern Europe, the predominance of domestic tourism in their rural areas is more than evident since the share on foreign tourists in the total number of overnight stays is below 20% (figure 4).

Share of non-residents (foreign tourists) in the total number of overnight stays in the rural areas in the EU countries, in 2023

Figure 4



Source: Eurostat (2024d) and own calculations. No data for Belgium, Finland and Ireland

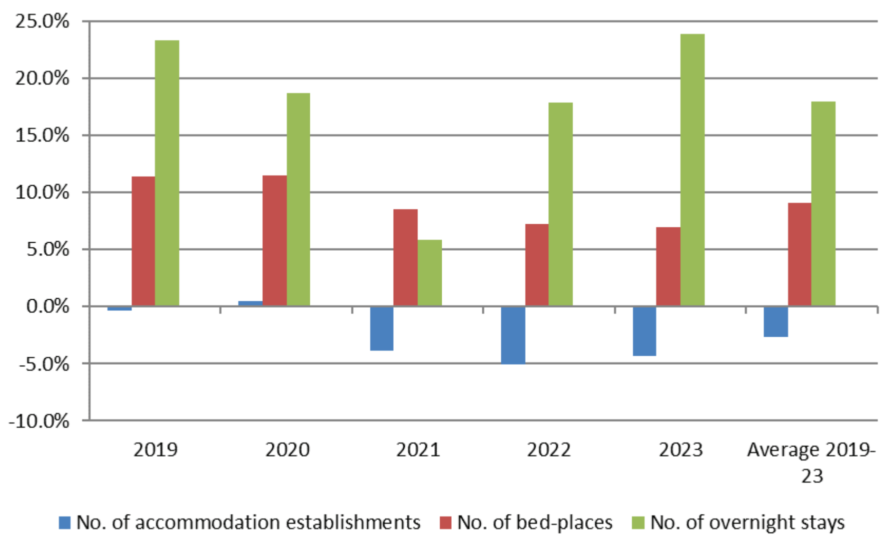
3.4. ***A comparison with Eurostat statistics on tourism in the rural areas***

Comparing the proposed approach in this paper (subsection 3.1.) with Eurostat statistics on tourism in the rural areas is possible only for three statistical indicators: number of establishments, number of bed-places and number of overnight stays (nights spent at tourist accommodation establishments) since only for these indicators, Eurostat disseminates data on degree on urbanization. In order to have a common approach for all these three indicators, relative figures of measuring this difference have been used.

This comparison gives mixed results: while in the case of number of establishments Eurostat data provided lower figures (in average with -2.6% in the period 2019-2023), for the number of bed-places and number of overnight stays Eurostat data are higher in average with 9.1% respectively 17.9% (figure 5).

Differences (in percentage) between Eurostat data and the proposed approach in quantifying tourism in the rural area in Romania

Figure 5



Source: own calculations based on Eurostat (2024d) and INS (2024a)

In explaining these differences, it should be reminded that Eurostat (2024d) included a number of 81 LAUs as part of Rural areas category even if these LAUs are seen as towns according to Romanian national regulations. In contrast, the approach proposed in this paper (subsection 3.1) was to include only communes (thus excluding towns with the exception of agritourist boarding houses). Moreover, some of the towns (as in Romanian legislation) that according to Eurostat (2024d) were part of rural area have the official national status of tourist resorts where tourism activity is very well represented (e.g. Azuga, Băile Govora, Băile Herculane, Băile Olănești, Băile Tușnad, Borsec, Buziaș, Geoagiu, Ocnele Mari, Ocna Sibiului, Slănic Moldova).

5. CONCLUSIONS

Even the pandemic period was characterized by a sharp decline of tourism both at national level and in the rural areas, the latter (rural area) experienced higher dynamics as compared with the national level, with 2022 being the year in which the pre-pandemic levels (2019) were exceeded. Instead, at national level, in 2023, tourism still has not recovered the levels reached in 2019 (-2.9% at arrivals and -8.4% at overnight stays).

The better performances recorded by tourism in the rural area in Romania can be explained indeed by the increase of tourist's preferences for these destinations (the growth of demand) but, at the same time, one cannot neglect the positive developments from the supply side perspective. Thus, both functioning accommodation capacity and existing accommodation capacity in the rural area grew at a double respectively almost double rate compared with the national level in the period 2019-2023.

Another important characteristic from the supply perspective is given by the usually low size of accommodation establishments in the rural area (having an average number of 21 beds in 2023), and this kind of establishments has been preferred to a greater extent particularly in the pandemic years 2020-2022. One has to note that rural area had in 2023 a half of total number of accommodation establishments in Romania, and regarding the existing accommodation capacity (number of bed-places), rural area concentrates over 30% of the total number of bed-places in the country in the same year; however, the rural area attracted only 21-22% from the total number of tourists and overnight stays in Romania. This proves a lower appeal and performance of rural area as compared with other destinations in Romania which has some strategic impacts at the level of tourism forms in Romania illustrating a lower capacity of the rural area to constitute a real driver to boost Romanian tourism.

As regards the typology of tourists (residents vs. non-residents), Eurostat data for the rural areas in Romania shows an over-predominance of resident tourists in the rural area both in the period before the pandemics (almost 94%) but also during pandemic years (98-99%). Of course, the travel restrictions from 2021-2022 greatly influenced these figures but even so, it is undoubtedly that domestic tourism strongly supported the tourism demand in the rural area.

Another important characteristic showed by Eurostat data is given by fact that rural area in Romania attracts foreign tourists to a lesser extent compared with the national level, the difference being over 12 percentage points in the pre-pandemic years and 5-7 percentage points in the pandemic years. The explanation is given by the fact that urban area, especially cities usually attracts important foreign tourist flows due to their accessibility and great events but also for business purposes while rural area by its nature is less profiled on this tourism segment (business tourism also known as MICE tourism – Meetings, Incentives, Conferences and Events).

Not the least, one has to outline the nature of aggregated data (number of accommodation establishments, their capacity, number of arrivals and overnight stays, length of stay) for tourism in the rural area of Romania (data provided by the National Institute of Statistics through Tempo database) which refers exclusively to localities that have the administrative status of communes and do not separately account for rural area that be part of small towns and municipalities (more precisely villages that are part of town and municipalities). The lack of data for this level (villages) – it should be noted that the territorial level for data breakdown of INS is just at LAUs level namely municipality, town and commune – constitutes a major limitation to have a more accurate demarcation of the Romanian rural space and consequently of tourism in the rural area. In order to overcome this major limitation, the solution proposed in this paper was to add a supplementary component namely the agritourist boarding houses located in municipalities and towns considering the hypothesis (which is highly likely) that all agritourist boarding houses are located in villages (and thus in the rural area) that belongs to towns and municipalities. However, one has to admit that this proposed approach does not solve the issue of other types of accommodation units that can be located in villages that belong to towns and municipalities and that can as well constitute an important component of rural tourism.

As a future perspective, using geo-referential data of accommodation units where the location of each establishment can be clearly allocated (for instance to rural areas) in combination with existing tourism statistics seems to be a promising future solution. In this regard the approach proposed by Batista e Silva et al (2018) that derived geographic coordinates from online booking services (as big data source) and used Eurostat's tourism statistics seems to be a feasible approach but still, also in this case, there are some evident limitations that should be overcome in time.

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The Romanian Consumer's Perspective on the Integration of Artificial Intelligence in E-Commerce

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ABSTRACT

This study examines Romanian consumers' perceptions of AI chatbots in e-commerce, focusing on factors influencing acceptance and user behavior impact. Using the Technology Acceptance Model, it analyzes determinants such as perceived usefulness, ease of use, trust, and risk perception, while considering demographic variables like age, gender, and urban/rural background. Statistical methods, including Confirmatory Factor Analysis and Structural Equation Modeling, highlight perceived usefulness and ease of use as primary drivers of chatbot acceptance, with age playing a significant role—showing younger generations (Generation Z and Y) as more open to AI compared to older ones (Generation X and Baby Boomers), who demonstrate hesitation. Gender and environment do not significantly impact familiarity or usage. By extending Technology Acceptance Model to include demographic factors, the study provides a deeper understanding of AI acceptance in Romania's e-commerce sector and contributes to limited Eastern European research on AI adoption. Findings suggest that e-commerce platforms should emphasize chatbots' practical benefits and ease of use to engage consumers, with tailored strategies for generational preferences further enhancing acceptance and consumer interaction.

Keywords: *artificial intelligence, chatbots, e-commerce, consumer perception, technology, user behavior, demographic differences.*

JEL Classification: *C10, C12, C38, C51, C83, C87, D03, D11, D12, D91, L81, M31, O33.*

1. INTRODUCTION

In recent decades, artificial intelligence (AI) has significantly evolved, transitioning from a theoretical concept to an omnipresent technology profoundly influencing various economic sectors. This transformation is particularly evident in e-commerce, a field that greatly benefits from AI's applicability through technologies such as machine learning, natural language processing, and intelligent conversational interfaces (Greenberg, 2017; Ikhasari & Faturohman, 2021). These technological advancements not only automate processes but also enhance digital experiences through personalization, thereby increasing operational efficiency and customer satisfaction (Pillarisetty & Mishra, 2020; Boutaba et al., 2018)

A notable example of AI implementation in e-commerce is the use of chatbots, programs designed to simulate human conversations and provide real-time personalized support. Studies show a continuous rise in the use of these chat interfaces, driven by users' preference for fast and intuitive interactions (Adam et al., 2021; Shawar & Atwell, 2007). Chatbots not only enhance consumer-retailer relationships but also influence decision-making processes through personalized recommendations and prompt responses, contributing to a more efficient shopping experience (Marjerison et al., 2022; Barolli et al., 2019).

In Romania, the adoption of these technologies is still in its early stages, yet the rapid growth of digital commerce underscores the need for a detailed analysis of consumer perceptions regarding the use of chatbots in the online purchasing process. Theoretical models such as the Technology Acceptance Model (TAM) provide a conceptual framework to understand the factors influencing the acceptance of emerging technologies, including external variables and specific consumer characteristics such as perceived usefulness and ease of use (Davis, 1989; Venkatesh & Davis, 1996).

This paper aims to investigate Romanian consumers' perceptions of chatbot use in e-commerce, exploring demographic and behavioral factors that influence the acceptance of AI-based technologies. Furthermore, the research contributes theoretically by extending the TAM framework to the specific context of the Romanian market. By doing so, the study seeks to identify both the benefits and challenges associated with integrating AI into e-commerce, offering valuable insights for optimizing digital interactions and enhancing user experiences.

2. LITERATURE REVIEW

Bloomberg (2020) highlighted that the COVID-19 pandemic has accelerated the migration of consumers from physical to online shopping, thereby increasing the demand for artificial intelligence-based solutions in retail. These solutions contribute to personalizing and optimizing the shopping experience by analyzing consumer behavior and providing tailored recommendations. According to Thanh et al. (2024), AI enhances user satisfaction and supports predictive analytics, enabling retailers to anticipate market trends effectively.

Klopfenstein (2017) notes that chatbots represent one of the most visible applications of AI, playing a crucial role in online interactions. They employ advanced algorithms to simulate human conversations, thus facilitating rapid and efficient engagement with users. Available 24/7, chatbots such as Alexa, Siri, and ChatGPT transform the shopping experience by offering personalized solutions and saving company resources. Li et al. (2021) emphasizes that over 85% of customer interactions in 2020 involved chatbot technologies, showcasing their growing relevance in the digital landscape.

Moreover, alongside their evident advantages, Johannsen et al. (2020) emphasize the challenges related to transparency and the quality of interactions with chatbots. Their success hinges on the balance between technical capabilities and user needs, and continuous improvements are essential for maximizing efficiency and customer satisfaction. Hu et al. (2022) further highlight the role of chatbots in Industry 4.0, demonstrating how digitalization amplifies their functionality through AI-driven technologies like Big Data and cloud computing.

The Technology Acceptance Model (TAM), developed by Fred Davis in 1986, is grounded in the Theory of Reasoned Action (Fishbein & Ajzen, 1975) and emphasizes two essential variables: Perceived Usefulness (PU) and Perceived Ease of Use (PEU). Davis (1986) posits that users are more likely to adopt technologies that they perceive as both useful and easy to use. According to Davis et al. (1989), PU reflects the belief that a system enhances performance, while PEU pertains to the perception that the system is straightforward to use. Shawar (2007) suggests that the acceptance of chatbots is contingent upon users' perceptions of their usefulness. Haller et al. (2020) suggest that consumer trust in chatbot recommendations directly correlates with their ease of use, further validating TAM's applicability in digital adoption.

Bickley et al. (2022) note that, in times of economic instability, these technologies can provide rapid and effective solutions. Thus, TAM provides a crucial theoretical framework for understanding the adoption of chatbots. Mehrotra (2019) expands this framework by linking it to machine learning advancements, which significantly enhance AI's perceived usefulness in consumer-facing applications.

E-commerce continues to solidify its dominant position, driving companies to gain a deeper understanding of consumer behavior in the current digital landscape. According to Cătoiu et al. (1997), this understanding is crucial for optimizing user experiences and ensuring business success. Artificial intelligence-based chatbots represent an innovation that radically transforms how companies interact with customers, offering exceptional opportunities to enhance customer satisfaction and sales while simultaneously reducing costs. Radziwill et al. (2017) emphasize that chatbot adoption aligns closely with consumer expectations, particularly in industries prioritizing automation and responsiveness.

Hussain et al. (2019) assert that a detailed analysis of consumer behavior is fundamental for the effective implementation of chatbot and AI technologies. This analysis is critical for optimizing the utilization of chatbots in the online purchasing process. By examining the elements that influence consumers' purchasing decisions, companies can create a personalized and relevant experience. Cohen (2019) suggests that chatbots are not only effective for external customer service but also valuable tools for internal corporate communication, streamlining operations like training and recruitment.

Consumer behavior constitutes a fundamental aspect of individuals' economic activities. According to Cătoiu et al. (1997), it refers to the behaviors and choices made by individuals during the acquisition and consumption of goods and services. Philip Kotler and his collaborators (1999) describe this behavior as the result of inputs received and processed by consumers, often referred to as a "black box." Within the consumer decision-making process, both inputs and outputs are influenced by a diverse array of information derived from various sources. Marshall posits that the acquisition of goods and services results from conscious rational and economic evaluations (Cretoiu et al., 2011). Consequently, consumer behavior is characterized by a series of essential traits, including the interdependence of its manifestations and motivations (Stanciu, 1999).

Consumer behavior is influenced by a multitude of factors. Dubois and Alain (1994) categorize these factors into two main groups: individual factors, which encompass personality and lifestyle, and environmental factors, including socio-demographic aspects. This complex diversity of consumer behavior underscores the importance of detailed analysis for understanding the decision-making process in purchasing and consumption. Kotler et al. (1998) classify influencing factors into cultural, social, and personal dimensions, encompassing various aspects that affect consumer behavior. Thus, Gries & Naudé (2020) confirm that AI solutions, particularly chatbots, play a role in adapting consumer purchasing behavior, reflecting the increasing integration of these technologies across demographic groups.

3. THEORETICAL BACKGROUND AND METHODOLOGY

This research explores consumer perceptions regarding the utilization of artificial intelligence and chatbots in online shopping, grounded in the Technology Acceptance Model. This model serves as a theoretical framework for analyzing the adoption and acceptance of these technologies by Romanian consumers. The study aims to validate hypotheses concerning the influences of key variables defined by TAM within the context of online shopping. The primary research questions address the perceived advantages and disadvantages of utilizing chatbots, the factors influencing the intention to use them, and the demographic differences in their acceptance. The study builds upon the adjustments of a theoretical model proposed by Nagy and Hadjú (2021), which incorporates relevant statistical dimensions of the TAM model alongside external variables such as trust and risk, all of which are presented in Table 1. All variables were measured using a 7-point Likert scale, ranging from 1 ("Strongly Disagree") to 7 ("Strongly Agree").

Dimensions and measurement instruments

Table 1

VARIABLE	ACRONYM	ITEM
Perceived Ease of Use (PEU)	PEU1 PEU2 PEU3 PEU4	Artificial Intelligence-powered applications are easy to use because they provide me with a personalized experience. Shopping does not require much mental effort on my part when supported by Artificial Intelligence. Shopping is not as complicated when I use Artificial Intelligence because it offers me products that suit my preferences. It is easy to become proficient in using Artificial Intelligence for the online shopping process.
Perceived Usefulness (PU)	PU1 PU2 PU3 PU4	Using artificial intelligence in the online shopping process allows me to find the best deals. Using artificial intelligence in the online shopping process improves my efficiency in the purchasing process. Using artificial intelligence in the online shopping process is useful for me. Using artificial intelligence in the online shopping process saves me time.

Consumer Attitude (CA)	CA1 CA2 CA3	Shopping is more fun and enjoyable when Artificial Intelligence helps me find the most suitable products for my needs. Online shopping with the help of Artificial Intelligence is a good choice. I have a positive attitude toward using Artificial Intelligence in the online shopping process.
Behavioral Intention (BI)	BI1 BI2 BI3	I intend to use artificial intelligence more frequently in the online shopping process in the future. I intend to recommend to others to use Artificial Intelligence in the online shopping process. I am willing to spend a certain amount of money to be able to use Artificial Intelligence in the online shopping process..
Trust (T)	T1 T2 T3 T4	I am convinced that using Artificial Intelligence in the online shopping process provides me with the best product deals. I trust applications/websites that use Artificial Intelligence because they offer me a personalized experience. I trust that Artificial Intelligence, through chatbots, provides a much more detailed and relevant overview than the information I could find myself. I trust that the information provided by Artificial Intelligence, through chatbots, is always accurate, offering clear and correct answers.
Risk (R)	R1 R2 R3	I am concerned that my personal data may not be secure when using Artificial Intelligence. Artificial Intelligence, through chatbots, collects too much private information. Artificial Intelligence makes it impossible to keep my personal data safe.

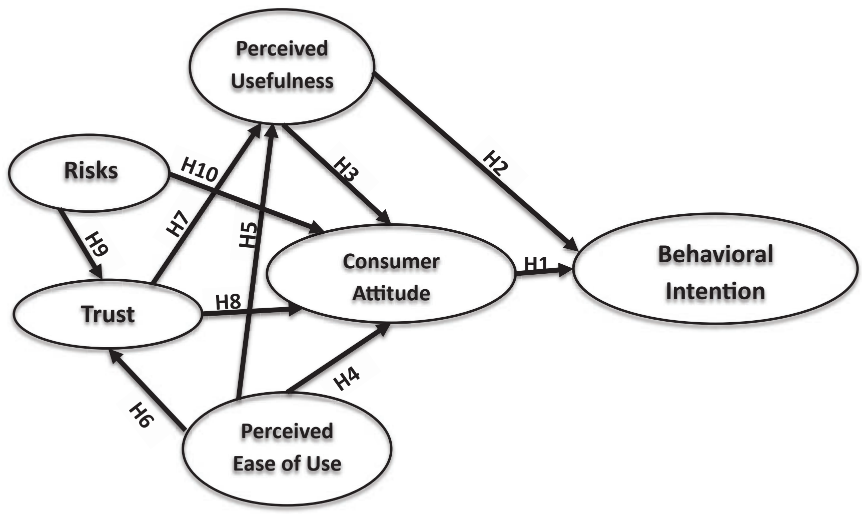
The variables were taken and adapted from the work of Nagy, S. and Hadjú, N. (2021), with the aim of specifically evaluating the perceived role of artificial intelligence in the context of online shopping. Therefore, the arrows connecting the dimensions in Figure 1 represent the hypothetical causal relationships in the direction of the arrows. These hypothetical causal relationships become the research hypotheses to be studied in this research, thus forming the conceptual model:

- ***H1: Consumer attitude has a positive effect on behavioral intention.***
- ***H2: Perceived usefulness positively affects behavioral intention.***
- ***H3: Perceived usefulness has a positive effect on attitude.***
- ***H4: Perceived ease of use positively influences attitude.***

- ***H5: Perceived ease of use positively influences perceived usefulness.***
- ***H6: Perceived ease of use has a positive impact on trust.***
- ***H7: Trust has a positive effect on perceived usefulness.***
- ***H8: Trust positively influences attitude.***
- ***H9: Risk perception negatively affects trust.***
- ***H10: Risk perception negatively affects attitude.***

The conceptual model

Figure 1



3.1. DATA ANALYSIS AND TECHNIQUES IMPLEMENTED

In order to investigate perceptions regarding the role of artificial intelligence in online shopping more thoroughly, a quantitative analysis method was adopted, using a questionnaire as the main research instrument. Therefore, the data source used is primary. This approach allowed for the analysis of a statistically significant sample and the collection of quantitative data, thus facilitating the rigorous and precise evaluation and interpretation of the results. During the methodological stage of this research, several statistical-econometric techniques were implemented to examine consumer perceptions regarding the use of artificial intelligence in online shopping, emphasizing the statistical aspects of the analyses performed using RStudio - version 4.1.2. having MASS, moments, psych, lavaan, and lavaanPlot as relevant packages. Two essential analytical methods were employed to assess consumer perceptions of AI in online shopping: Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM).

Confirmatory Factor Analysis was used to evaluate and validate measurement models for latent variables, focusing on their adequacy with the empirical data collected. In his 2015 work, Rex B. Kline explains that CFA examines constrained measurement models, which include specifying the number of factors, the correlation between factors and indicators, and the model of error correlations (if applicable). These models assume a reflective measurement, where the factors influence the indicators, and include continuous indicators, each with a unique dependence on a factor and independent errors. This configuration defines unidimensional measurement and allows for testing hypotheses of convergent and discriminant validity in models with two or more factors. According to Kline (2015), CFA requires the fulfillment of key assumptions, such as an adequate sample size and data normality. The sample size must be at least ten times the number of observed items in the model to ensure the stability and reliability of the estimates. Additionally, data normality is verified by measuring skewness and kurtosis, with acceptable values between [-2, 2] for skewness and [-7, 7] for kurtosis. Moreover, the internal consistency of the items is evaluated through the Cronbach's Alpha test, where a value above 0.7 is considered acceptable, indicating that the items coherently measure the latent construct. In the context of Confirmatory Factor Analysis and Structural Equation Modeling, the Average Variance Extracted (AVE) is an essential metric for assessing convergent validity. An AVE value greater than 0.5 indicates that the construct accounts for more than half of the variance in its indicators, demonstrating that the indicators reliably measure the intended construct. This is critical for ensuring the distinctiveness and accuracy of each construct within the model, thereby enhancing the model's overall validity and reliability. Consequently, AVE contributes significantly to the robustness of CFA and SEM analyses, confirming the soundness of the measurement instruments used in the study (Cheung et. al., 2023).

Structural Equation Modeling was also used to validate and evaluate complex theoretical models, exploring the causal relationships between observed and latent variables. In her 2012 work, Barbara M. Byrne explains that Structural Equation Modeling is a complex statistical method that combines Confirmatory Factor Analysis with structural regression models. SEM allows for the evaluation of causal relationships between latent and observed variables, as well as testing the congruence of the proposed model with empirical data. This method facilitates the testing of convergent and discriminant validity hypotheses, offering a more in-depth understanding of the causal relationships between key variables. However, the identification of the factor and the limitation of predictive utility can blur the estimates of correlations between a factor and external variables (Rigdon, 2014). To evaluate the adequacy of measurement and structural models in the context of Structural Equation Modeling, indicators such as Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR) will be used, following Kline's (2015) recommendations. Acceptable values for these indicators are: CFI and TLI above 0.9, RMSEA below 0.08, and SRMR below 0.08. These values indicate an adequate fit of the theoretical model to the empirical data, ensuring the validity of the results.

Additionally, the study used the chi-square independence test to identify associations between demographic variables such as gender, age, and location, according to Kline (2015). The test compared the observed and expected frequencies, and if the p-value was less than 0.05, the null hypothesis was rejected, indicating significant differences between the observed and expected distributions. Otherwise, it was concluded that no significant differences existed.

These analytical methods were essential for reaching solid and relevant conclusions in the statistical study regarding consumer perceptions of AI use in the online shopping sphere.

3.2. DATABASE DEVELOPMENT

The data for this study was collected via an online structured questionnaire, distributed to a convenience sample of 250 respondents from Romania, during the period from December 2023 to March 2024. The questionnaire, designed to capture both demographic details and evaluative opinions, comprised 35 questions in total, of which 21 were evaluative items excluding demographic questions. To measure respondents' attitudes and perceptions, the questionnaire employed a seven-point Likert scale for the evaluative questions. The ideal sample size is calculated as 210 (21 * 10 = 210). With this in mind, the sample of 250 respondents fits within the recommended range (Kline, 2015). The data was initially centralized in Microsoft Excel and later analyzed using RStudio, where statistical techniques provided insights into the patterns and trends within the sample.

The sample includes a diverse demographic profile, with 62.8% women and 37.2% men, and an average respondent age of 25.8 years, which aligns with a younger, digitally engaged population. Most respondents (80.8%) reside in urban areas, reflecting the concentration of internet connectivity and technological adoption in cities. Notably, 50% of the respondents are students, of whom 32.8% are also employed, suggesting a sample that is highly involved in both academic and professional settings.

In terms of educational background, there is a strong representation from applied and technical fields. A significant 46% of respondents are studying in applied sciences, including disciplines such as mathematics and computer science, followed by 24.8% in economic sciences. Engineering students account for 8% of the sample, while social sciences are represented by 7.2% of respondents. Other fields include biological and biomedical sciences (4.4%), humanities and arts (3.6%), legal sciences (3.2%), and sports science and physical education (2.8%). This distribution suggests that the sample is largely composed of students from STEM and economic fields, which may influence their perspectives on technology use in e-commerce.

The income distribution among respondents reveals economic diversity. The largest proportion, 25.2%, reports a monthly income of less than 500 RON, while 22.4% earn over 5000 RON. Other income brackets are also represented, with 20% earning between 3000 and 4999 RON, 19.6% between 1000 and 2999 RON, and 12.8% between 500 and 999 RON. This wide range of income levels indicates that the sample includes respondents from varied economic backgrounds, which can provide insights into how financial resources impact e-commerce preferences and technology adoption.

When it comes to the devices used for online shopping, the data shows a strong preference for mobile devices, with 71.2% of respondents primarily using their mobile phones to make online purchases. Laptops are the second most popular choice, used by 18.8% of respondents, followed by PCs (8.4%) and tablets (1.6%). This tendency toward mobile usage highlights the convenience and accessibility of mobile commerce, particularly among younger and urban respondents who may rely on their phones for a range of daily activities.

Overall, this dataset reflects a technologically adept, young, and urbanized sample with a solid representation in applied sciences and economic fields. The demographic and income diversity within the sample allows for a comprehensive analysis of various factors influencing e-commerce behavior and attitudes toward technology, particularly within the context of mobile commerce and AI-driven interactions, such as chatbots, in Romania.

4. RESULTS

4.1. DEMOGRAPHIC ANALYSIS

A variety of demographic factors, such as age, gender, and background influence consumer perception of the use of artificial intelligence in online shopping. This research analyzes how these variables affect consumers' perceptions of AI in online shopping, with a particular focus on the young segment. A detailed age group analysis provides a deeper understanding of how young people perceive this technology. Additionally, gender is an important factor, along with the respondents' background, as digital infrastructure and access to technology can vary between urban and rural areas, influencing the adoption of modern technologies. Thus, the chi-square analysis will assess significant differences based on these aspects to obtain a balanced view of consumer perceptions.

To examine whether respondents' gender and their environment (rural or urban) are associated with their level of experience in online shopping and artificial intelligence usage a chi-square analysis was performed. The Chi-square test results showed p-values greater than 0.05, leading to the acceptance of the null hypotheses. This indicates that there is no significant difference between genders regarding online shopping experience and no significant influence of rural or urban background on the level of artificial intelligence usage among respondents.

The study also investigates the relationship between age and openness to using artificial intelligence, focusing on generational differences in technology adoption. Based on a sample of 250 participants divided into Generation Z (178), Generation Y (36), Generation X (29), and Baby Boomers (7), the analysis employed a chi-square test, which yielded a p-value of 0.0007, indicating a significant influence of age on AI usage. These findings emphasize distinct behavioral and attitudinal patterns across generations, consistent with prior research highlighting generational variations in interacting with emerging technologies (Dhanapal et al., 2015).

4.2. FRAMEWORK AND LINKAGES IN THE TECHNOLOGY ACCEPTANCE MODEL: A STRUCTURAL EQUATION MODELING APPROACH

Following the demographic analysis, Confirmatory Factor Analysis and Structural Equation Modeling will be employed to validate and test the relationships between the studied variables. Figure 1, which illustrates the Technology Acceptance Model, and Table 1, detailing the analyzed dimensions, serve as the foundation for hypothesis testing.

This methodological approach allows for a rigorous examination of the interactions between variables and provides empirical support for validating the hypotheses. By applying CFA, the fit of the proposed models to the collected data will be assessed, ensuring the validity of the measurement instruments. Subsequently, SEM will be used to test and validate the theoretical models, examining the causal relationships between variables. Additionally, to verify whether the dataset follows a normal distribution, two relevant statistics will be analyzed: skewness and kurtosis. Interpreting the skewness data reveals values ranging between -2 and 2, with most values close to zero. A skewness value near zero suggests a symmetric distribution. Therefore, the data exhibit significant symmetry, indicating that the distribution is normal. Similarly, the kurtosis values, which fall within the specified range of [-7, +7], mostly between +2 and +3, indicate that the distribution is close to normal. The kurtosis values suggest that the data's height and fullness are similar to those of a normal distribution. This similarity supports the validity of the confirmatory factor analysis and the interpretation of results.

In CFA and SEM, it is crucial to assess the consistency of the items that make up the measurement scales. This is typically done using Cronbach's Alpha and Average Variance Extracted coefficient to ensure reliability and internal consistency across items.

The results of the Cronbach's Alpha test and AVE test for each dimension, source: own processing in RStudio

Table 2

VARIABLE	Cronbach's Alpha	AVE
Trust (T)	0.86	0.609
Consumer Attitude (CA)	0.9	0.762
Perceived Usefulness (PU)	0.93	0.772
Perceived Ease of Use (PEU)	0.86	0.614
Behavioral Intention (BI)	0.86	0.678
Risk (R)	0.8	0.579

The findings illustrated in the Table 2 reveal that each variable exhibits a high level of internal consistency, as evidenced by Cronbach's Alpha values surpassing the 0.8 threshold, thereby affirming the reliability of the constructs. Furthermore, the Average Variance Extracted (AVE) values for all variables exceed the 0.5 criterion, which substantiates their convergent validity.

Thus, the results obtained in this study confirm the robustness and reliability of the measurement instruments employed in the confirmatory factor analysis and structural equation modeling. Given that all the conditions and assumptions required for CFA are met and that the items show good internal consistency as evaluated by Cronbach's Alpha and AVE, the next phase of the analysis can proceed. Consequently, the analysis will continue with structural equation modeling to investigate the relationships between the identified latent constructs.

The fit indicators according to SEM, source: own processing in RStudio

Tabel 3

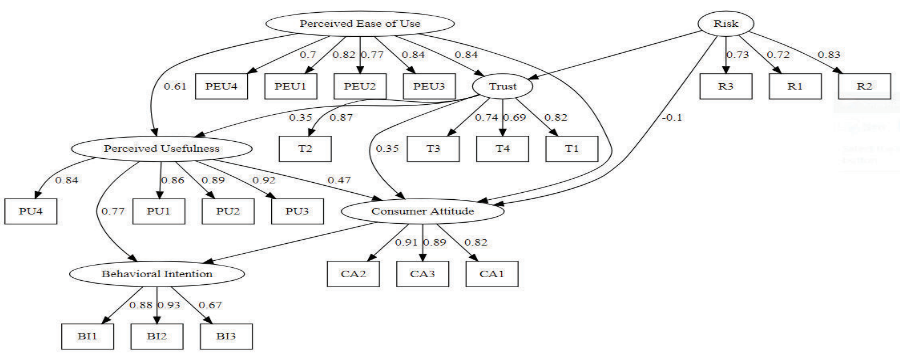
Comparative Fit Index (CFI)	Tucker-Lewis Index (TLI)	Root Mean Square Error of Approximation (RMSEA)	Standardized Root Mean Square Residual (SRMR)
0.953	0.945	0.067	0.044

The model fit indicators for the SEM, presented in Table 3, provide a detailed assessment of the quality of the proposed model's fit. The Comparative Fit Index (CFI) is 0.953, and the Tucker-Lewis Index (TLI) is 0.945, both exceeding the threshold of 0.90, indicating a very good fit. The Root Mean Square Error of Approximation (RMSEA) has a value of 0.067, which is below the 0.08 limit, suggesting an adequate fit of the model to the data. Additionally, the Standardized Root Mean Square Residual (SRMR) is 0.044, and being below 0.08, it reflects an excellent fit, highlighting minimal discrepancies between the observed and estimated data. In conclusion, the high values of the CFI and TLI indices, along with RMSEA and SRMR within their reference ranges, provide strong evidence for an excellent model fit to the observed data, thereby confirming its statistical validity.

The analysis of the results begins with the evaluation of indicator loadings. For each latent variable, the indicator loadings (factor loadings) indicate the extent to which each indicator appropriately represents the respective latent variable. Higher loading values suggest a stronger correlation. As can be observed in Figure 2, which presents the results of the conceptual model, the standardized loadings range between 0.6 and 0.8, representing a moderate-to-strong correlation.

The final modeling of the conceptual model, source: own processing in RStudio

Figure 2



The next analysis focuses on the regression relationships between latent variables, as presented in Table 4. The regression coefficients highlight the strength and direction of the relationships between latent variables, while the "p" values reflect the statistical significance of these relationships. The analysis reveals that Perceived Ease of Use (PEU) significantly influences both Perceived Usefulness (PU) ($\beta = 0.643$, $p < 0.001$) and Trust (T) ($\beta = 0.786$, $p < 0.001$), indicating that systems perceived as easy to use are more likely to be seen as useful and trustworthy. However, the effect of PEU on Consumer Attitude (CA) is not statistically significant ($\beta = 0.174$, $p = 0.137$), suggesting that ease of use alone does not directly shape users' attitudes.

Perceived Usefulness (PU) stands out as a key factor, showing strong positive effects on both Behavioral Intention (BI) ($\beta = 0.907$, $p < 0.001$) and Consumer Attitude (CA) ($\beta = 0.489$, $p < 0.001$). This underscores the central role of usefulness in fostering positive attitudes and motivating users to engage with a system.

Similarly, Trust (T) has a significant positive influence on both Perceived Usefulness (PU) ($\beta = 0.348$, $p < 0.001$) and Behavioral Intention (BI) ($\beta = 0.350$, $p < 0.001$), highlighting the importance of building trust to enhance perceived value and intention to use. Conversely, Risk (R) negatively impacts Behavioral Intention (BI) ($\beta = -0.112$, $p = 0.003$), illustrating that perceived risks act as a deterrent to user engagement, although risk does not significantly affect Trust ($\beta = -0.049$, $p = 0.299$).

In summary, Perceived Usefulness and Trust emerge as the most influential predictors of Behavioral Intention, while Perceived Ease of Use indirectly contributes by shaping perceptions of usefulness and trust. At the same time, reducing Risk is crucial to fostering stronger behavioral intentions, making it essential to address potential concerns users may have regarding system adoption.

The regression relationships between latent variables

Tabel 4

VARIABLE	DIRECT EFFECTS					
	Perceived Ease of Use (PEU)	**Perceived Usefulness (PU)**	**Consumer Attitude (CA)**	**Behavioral Intention (BI)**	**Trust (T)**	**Risk (R)**
Perceived Ease of Use (PEU)	-	0.643*** (p<0.001)	0.174 (p=0.137)	-	0.786*** (p<0.001)	-
Perceived Usefulness (PU)	-	-	0.489*** (p<0.001)	0.907*** (p<0.001)		-
Consumer Attitude (CA)	-	-	-	0.133 (p=0.391)	-	-
Behavioral Intention (BI)	-	-	-	-	-	-
Trust (T)		0.348*** (p<0.001)	0.350*** (p<0.001)	-	-	
Risk (R)	-	-	-0.112** (p=0.003)	-	-0.049 (p=0.299)	-

* - $p < 0.05$; ** - $p < 0.01$; *** - $p < 0.001$
Source: own processing in RStudio

5. DISCUSSION AND CONCLUSIONS

The first objective was to determine the degree of acceptance of chatbots among Romanian users and to identify the influencing factors. Structural equation modeling revealed that perceived usefulness and ease of use are essential factors that positively influence the intention to use chatbots. Additionally, trust in technology proved to be crucial in shaping a positive attitude and increasing the frequency of use (Venkatesh & Davis, 1996).

The second objective involved applying the Technology Acceptance Model (TAM) to understand the advantages and disadvantages of chatbot usage. The findings confirmed the validity of TAM in the context of e-commerce in Romania, demonstrating that perceived usefulness and ease of use are strong predictors of attitude and behavioral intention. These findings emphasize the importance of these factors in the adoption of AI technologies (Davis, 1989).

The third objective aimed to extend the TAM model to include the impact of demographic differences on chatbot acceptance. Demographic analysis revealed that age is a significant factor, with younger generations being more open and familiar with artificial intelligence. In contrast, gender and background (urban/rural) did not have a significant impact, suggesting a relatively uniform acceptance of AI technology across these groups (Philip Kotler et al., 1999).

The demographic analysis revealed that age plays a pivotal role in shaping consumer perceptions of AI in online shopping. The results show significant generational differences in the accessibility and attitudes toward artificial intelligence. Younger generations, such as Generation Z and Generation Y, demonstrate greater familiarity and openness to AI technologies, largely due to their early and sustained exposure to digital innovations (Hu et al., 2022). In contrast, older generations, including Generation X and Baby Boomers, display more hesitation, often stemming from unfamiliarity with these technologies or resistance to change. However, gender and environment did not show a significant influence on AI usage, suggesting that differences between men and women, as well as between urban and rural environments, are not substantial in terms of familiarity with AI technology in the context of online shopping (Cătoiu et al., 1997).

Moreover, the analysis tested several hypotheses regarding the relationships between latent variables, such as perceived usefulness, ease of use, trust, risk perception, and consumer attitudes. These hypotheses were assessed using confirmatory factor analysis and structural equation modeling. The resulting conclusions highlight the complexity and multidimensional nature of AI's influence on consumer behavior in Romania. Thus, the study emphasizes the importance of trust as a crucial determinant of consumers' acceptance of artificial intelligence in online shopping. Without trust, consumers may view AI-powered stores or applications as less useful and develop negative attitudes, resulting in lower online traffic (Marjerison et al., 2022). Thus, Table 5 below summarizes the research hypotheses along with their respective results.

The results after the tested hypotheses

Tabel 5

HYPOTHESIS	RESULT	EXPLANATION
H1: Attitude has a positive effect on behavioral intention.	Not confirmed	Although a positive relationship was observed, it was not statistically significant, indicating that other factors might have a stronger influence on behavioral intention than attitude. This suggests the need to investigate additional variables that could play a decisive role in shaping behavioral intention.
H2: Perceived usefulness positively affects behavioral intention.	Confirmed	This indicates that users' perception of the usefulness of AI and chatbots has a direct and significant impact on their intention to use these technologies. This result aligns with the Technology Acceptance Model (TAM), highlighting the importance of perceived usefulness in the adoption of new technologies.
H3: Perceived usefulness positively affects attitude.	Confirmed	This suggests that perceiving AI and chatbots as useful leads to a more positive attitude toward these technologies. The result reflects the importance of demonstrating clear benefits of AI technologies to improve user perception.
H4: Ease of use positively affects attitude.	Not confirmed	Although a positive relationship was observed, it was not statistically significant, suggesting that ease of use does not have a major impact on consumer attitude in this context. This may be due to users expecting modern technologies to be intuitive, so ease of use is not a decisive factor in shaping attitude.
H5: Ease of use positively affects perceived usefulness.	Confirmed	This highlights the importance of developing user-friendly and intuitive interfaces to enhance the perception of usefulness.
H6: Ease of use positively affects trust.	Confirmed	This indicates that technologies that are easy to use enhance users' trust in them, underlining the importance of trust in adopting new technologies.
H7: Trust positively affects perceived usefulness.	Confirmed	This suggests that users' trust in AI positively influences their perception of its usefulness, reflecting the importance of building and maintaining trust.
H8: Trust positively affects attitude.	Confirmed	This suggests that improving users' attitude requires promoting security practices and transparency that strengthen trust.
H9: Risk perception negatively affects trust.	Not confirmed	Although a negative relationship was observed, it was not statistically significant, suggesting that risk perception does not significantly affect trust in this context.
H10: Risk perception negatively affects attitude.	Confirmed	This indicates that risks and uncertainties negatively influence consumers' attitude toward AI. The result underscores the importance of effectively managing and communicating risks to maintain a positive attitude.

This analysis offers valuable insights for retailers, emphasizing the importance of age as a determinant of AI adoption. Understanding these demographic distinctions allows for the development of more tailored strategies to enhance user experience, ultimately leading to more personalized online shopping interactions and improved consumer satisfaction. The study highlights the importance of trust in consumers' acceptance of artificial intelligence in online shopping. Trust is crucial; without it, consumers are likely to view AI-powered stores or applications as less useful and develop negative attitudes, resulting in lower online traffic.

Future research recommendations include replicating the study in multicultural contexts and testing Parasuraman's (2000) Technology Readiness Index model for comparative analysis. Increasing the sample size would enhance the robustness and statistical power of the findings. Additionally, employing more comprehensive measurement tools, controlling for confounding variables, and examining other relevant factors—such as technical characteristics, performance, and pricing—would provide deeper insights into the factors influencing users' attitudes and behaviors toward modern technologies.

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