A GIS-Based Spatial Evaluation Model for Planning Urban Regeneration Investments

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Abstract. In recent years, the attention towards the use of artificial intelligence techniques, applied across various sectors (from logistics to urban planning, from healthcare to real estate valuation), has highlighted two divergent aspects in the implementation of these tools: on one hand, the advantages that can arise from their intrinsic ability to process big data, in order to enhance efficiency, innovation, and precision, providing strategic benefits to those involved in decision-making processes; on the other hand, the issues related to the possibility of controlling the generated outputs, when it comes to managing and interpreting black boxes that are difficult to be verified. In the field of territorial intervention valuation, the use of "rapid" estimation models, easily replicable even by less experienced users, represents an added value in identifying the best design solutions, especially in public/private partnership operations, so as to define win-win paths for the involved parties. Borrowing from the economics the principles of the urban rent, a procedure for evaluating the temporal evolution of area incidence factors, applied to the city of Rome (Italy), has been proposed. The results, geo-referenced in a GIS environment, provides for an easy-to-consult graphical interface to identify urban areas to be prioritized. The integration of the proposed method with an elastic net regression analysis has allowed the identification of the socio-economic variables that have most influenced the appreciation/depreciation of territorial areas, serving as a useful support for investment decisions (both public and private) and for urban intervention planning choices.

Keywords: Urban rent · GIS · Valuation · Urban regeneration · elastic net regression · spatial analysis · temporal analysis

1 Introduction

At European level, the New Urban Agenda [1] and the Sustainable Development Goal (SDG) No. 11 consider the urbanization the main territorial development policy [2, 3], by recognizing a predominant role to regeneration initiatives able of pursuing the targets of sustainable and resilience development and to bridge the gap between the different zones

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of the cities in terms of social and urban quality. In line with the continuous social and productive changes that have been characterizing the cities' dynamicity, the importance assumed by regeneration within the urban governance justifies the cogence to develop effective tools for the preliminary assessment of territorial interventions and for their monitoring [4]. These tools are expected to be capable of supporting decision-making processes, by adequately taking into account the locational factors of the project site and the local community needs [5]. In the current context, the economic measures introduced by governments within the National Recovery and Resilience Plan require the elaboration of new operational guidelines at the territorial, urban and architectural scale for the urban requalification, in order to support the decision-making processes of the Public Administrations and to effectively manage the obtained funding [6]. Therefore, the definition of evaluation techniques through which the project solutions can be appropriately analyzed has become fundamental, in order to avoid the failure of the provided investments.

In recent years, the potential and the opportunities arising from the application of artificial intelligence techniques have been universally acknowledged: in all sectors — from logistics [7, 8] to urban planning [9], from healthcare [10] real estate appraisal [11] — the advantages that have been derived from the intrinsic capacity to process big data have been correlated with the possibility of raising the levels of efficiency, innovation, and precision, providing those involved in decision-making processes with strategic benefits [12, 13].

On the other hand, the issues related to the risk of losing control over the generated outputs remains open, as well as the perplexities related to the complexity of managing and interpreting black boxes that are difficult to be verified. In the context of evaluating territorial interventions, the development of "rapid" estimation models, i.e. clear, transparent and easily replicable even by less experienced users, undoubtedly represents an added value in identifying optimal design solutions, especially in public/private partnership operations [14, 15], in order to define *win-win* paths for the actors involved, enabling the monitoring of project progress, as well as its flexibility in adapting to the dynamics associated with changes in the needs and the demands of the local communities [16].

2 Aim

The research presents a twofold objective.

In primis, borrowing the economic prodromes of the urban rent principles [17–21], a procedure for assessing the temporal evolution of area incidence factors has been proposed, by employing this economic parameter as a *proxy* for the locational preferences of the community in a specific territorial context. The increase/decrease of this factor over time, represented in a GIS environment in order to provide a simple and quick-to-consult graphical interface, has allowed for the identification of urban areas that have experienced an appreciation over time and, simultaneously, those that have been affected by a reduction in market attractiveness.

The simplicity of calculating the area incidence factors will allow, through their updating in a GIS environment, to ensure transparency, clarity, and continuity in the analysis of changes in preferences within the considered urban context, thus enabling the

rapid identification—also through feedback from the needs and the demands expressed by the local communities following surveys in the reference territory — of the areas requiring the most attention and monitoring.

Then, by integrating the georeferenced outputs with an appropriate econometric analysis, it has become possible to highlight the socio-economic variables that have most influenced the appreciation/depreciation of the urban areas examined. The final results from the integration of the two phases described — *i)* estimation of temporal area incidence factors and their georeferencing, *ii)* identification of the socio-economic variables most relevant to the evolution of the area incidence factors and, therefore, the locational appreciation of the community — provide a valuable support for decision-making in territorial investment, by assisting the stakeholders (both public and private) involved in the planning processes of urban regeneration interventions.

The research is structured as follows. Section 3 describes the developed method, constituted by the two steps i) and ii) described above. Section 4 illustrates the application of the method to the case study of the city of Rome (Italy): taking into account the temporal period between the years 2015 and 2023, the evolution of the annual values of the area incidence factors is outlined and represented in thematic maps in GIS environment; then, through the implementation of an elastic net regression, the most significant socio-economic variables on the area incidence factors (i.e. on the market appreciation of the local communities) are identified. Finally, in Sect. 5 the conclusions of the work are discussed.

3 Method

The developed method consists of two phases:

i). estimation of temporal area incidence factors and their georeferencing in a GIS environment;
ii). analysis of the socio-economic variables that influence the phenomena of evolution of the area incidence factors and, therefore, the locational appreciation of the community.

Phase i). With reference to the Italian territory, the determination of the area incidence factors is carried out at the "microzone" municipal level, replicating the methodology proposed by Guerrieri [22] and applied on the entire national territory by Tajani et al. [23]. According to the Italian Presidential Decree 138/1998 and ensuing the Regulation issued by the Economy and Finance Ministry, a "microzone" is defined as «a portion of the municipal territory […] that is homogeneous in terms of location, urban-style, historical-environmental, socioeconomic characteristics, as well as the endowment of urban services and infrastructures»: therefore, the "microzone" is a macro-area of the territorial municipality in which the locational factors (i.e. accessibility, presence of services, building characteristics, green areas, pedestrian zones, etc.) contribute to the market price formation in a uniform manner. For each microzone of the entire national

territory, the Italian Revenue Agency determines and half-yearly updates and publishes the average market values (i.e. quotations) for each intended uses.

Assuming that, within a municipal territory, the minimum quotation for the residential intended use ($V_{m,min}$, expressed in €/m^2) which has been recorded among all the microzones contributing to forming the municipal area, represents the threshold amount at which it has become profitable to build new housing units (i.e., coinciding with the absolute rent, equal to the cost of production gross of a normal profit expected by an ordinary investor [24–26]), the differential rent generated in microzones with higher market quotations (V_m, measured in €/m^2) is an expression of the incidence of the area, i.e. its weight in the determination of the market value of the built property.

Therefore, for the *i-th* microzone of the *j-th* municipality under investigation, the area incidence factor ($INC_{(i,j)}$, measured in %) has been evaluated using Eq. (1):

$$INC_{(i,j)} = \frac{V_{m(i,j)} - V_{m,\min(j)}}{V_{m(i,j)}} \tag{1}$$

Once the *INC* coefficients have been determined for different time periods and represented in a GIS environment, it has become possible to analyse the temporal evolution of the appreciation/depreciation of the examined territorial areas, as well as to calculate and graph the differentials (ΔINC) in the value of the area incidence factors, in order to quickly identify the areas that have increased in value and those that, due to substantial depreciation, require the most attention.

Phase ii). Following the outputs obtained in phase i) and based on the available data within the urban context under analysis, an econometric analysis can be developed to identify the socio-economic variables that may have had the most significant impact on the changes in zonal preferences by local communities. The outputs of this analysis will be able to provide useful indications on the needs that, more than the others, have been perceived as cogent by the community that will be affected by possible investments on the territory, and therefore will allow to guarantee a support to the decision-makers in the planning processes of urban interventions.

4 Case Study

The developed method as been implemented for the microzones of the city of Rome. Since the analysis aims to elucidate the locational preferences of urban communities, for the calculation of the area incidence factors through Eq. (1) the published quotations for residential use have been taken into account, in order to detect the appreciation/depreciation due to the purchase choices of the subjects who, prevalently, buy for direct use (and therefore not for investment purposes). The time frame for analysing the evolution of the area incidence factors has been from 2015 to 2023. Overall, the analysed microzones — those for which quotations related to residential use are published — are 169. In order to provide a tool that can be easily and quickly consulted and interpreted, the outputs obtained from the application of Eq. (1) for each microzone and each year

of the investigation have been georeferenced in a GIS environment (Figs. 1, 2, 3, 4, 5, 6, 7, 8 and 9), whereas Fig. 10 displays the map of the differentials of the area incidence factors between 2023 and 2015.

The results obtained have led to interesting considerations. While between 2015 and 2019, there has been a general increase in the area incidence factors within the municipal territory — characterized by an average value of approximately 45% in 2015, 47% in 2016, 52% in 2017, 53% in 2018 and 55% in 2019 —, between 2020 and 2021 the coefficients have experienced a decline — from 54% to 50% —, evidently caused by the effects of the COVID-19 pandemic. In the years 2022 and 2023, the area incidence factors have increased once again, although they have not reached the values recorded in the pre-pandemic years. Observing the graph in Fig. 10, which shows the differential of the coefficient values between 2023 and 2015, it has emerged that, while the historic centre of Rome has maintained its appreciation over the years, the peripheral areas, benefiting from *i)* the effects of smart working, *ii)* public municipal investment policies aimed at improving service quality in less central areas, and *iii)* the absence of the current overtourism phenomenon — which has led many potential buyers to prefer locations further from the historic city —, have mainly experienced a significant increase in the market attractiveness. At the same time, the graph in Fig. 10 allows for the identification of areas — all suburban ones — that require attention, where a significant reduction in the value of the area incidence factors has been observed, due to the lack of infrastructure and services and/or social issues.

In order to outline possible intervention strategies for the municipal territory based on the temporal-spatial outputs obtained, and by consulting the data available from the National Institute of Statistics (ISTAT) [27] and the Urbistat website [28], eleven socio-economic indicators (Table 1) have been identified for each of the 169 study microzones in the city of Rome, with reference to the year 2023. These indicators have been used as explanatory variables for the area incidence factor (*INC*) in the year 2023 through the implementation of a regression analysis.

Specifically, the variables are:

- disposable income per capita (R), which represents the ratio between the gross disposable income of consumer households and the total number of people residing in the reference area, expressed in euros;
- unemployment rate (U), defined as the ratio of the number of individuals seeking employment to the total labour force, expressed as a percentage;
- population density (D), expressed as the ratio between the number of people residing in a specific area and the surface area of that area, measured in inhabitants per square kilometers;
- presence of foreigners (F), referring to the population composed of individuals with non-Italian citizenship or stateless persons habitually residing in Italy, calculated as a percentage of the total population;
- housing maintenance expenses (M), representing the average annual amount allocated to the maintenance and improvement of private housing and residential buildings, expressed in euros per capita per year;
- ambulatory service expenses (A), representing the annual cost incurred for access to territorial ambulatory health services, expressed in euros per inhabitant per year;

- hospital service expenses (H), measuring the annual amount spent on hospital services, expressed in euros per inhabitant per year;
- transport service expenses (T), including costs for both public and private transportation, such as buses, trains, and other modes used for daily or specific journeys, expressed in euros per capita per year;
- leisure and cultural service expenses (C), which include expenditures for recreational, cultural, and entertainment activities, such as cinema, theatre, museums, and other cultural events, expressed in euros per capita per year;
- education expenses (E), relating to costs for education, such as tuition fees for schools and universities, educational materials, and other learning activities, expressed in euros per capita per year;
- social protection expenses (P), which include financial resources allocated to services such as unemployment benefits, pensions, support for individuals with disabilities, and other welfare programs, expressed in euros per capita per year.

In Table 2, the main descriptive statistics — mean value, minimum value, maximum value, and standard deviation — of the variables of the model to be defined have been reported, while in Table 3, the correlation matrix of the variables has been presented. Analyzing the Pearson indices in Table 3, a high positive correlation of the dependent variable (i.e. *INC*) with all considered explanatory variables is observed, except for the indicators unemployment rate (U), population density (D) and presence of foreigners (F): therefore, these three indicators can be excluded from the development of the regression model. Furthermore, it has been observed that the socio-economic variables are characterized by a significant correlation among themselves, a phenomenon that could lead to collinearity problems. In order to prevent overfitting in the analysis data, an elastic net regression [29, 30], has been implemented, optimized through a ten-fold cross-validation which has been aimed at minimizing prediction error while ensuring an appropriate balance between model complexity and generalizability. This approach has been employed to reduce the effect of each predictor in the model and, consequently, to stabilize the regression function, as it is particularly suitable for datasets affected by multicollinearity.



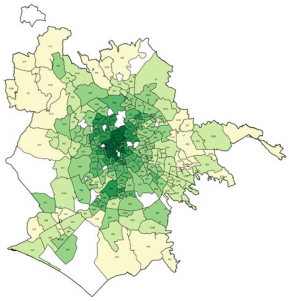


Fig. 1. INC - year 2015.

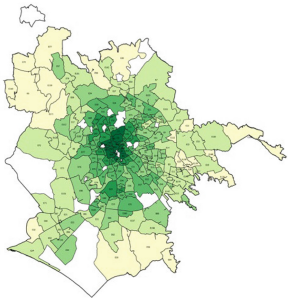


Fig. 2. INC – year 2016.

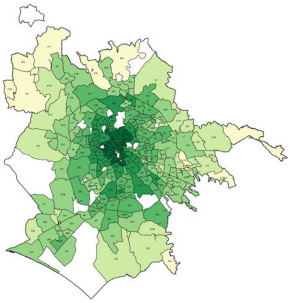


Fig. 3. INC – year 2017.

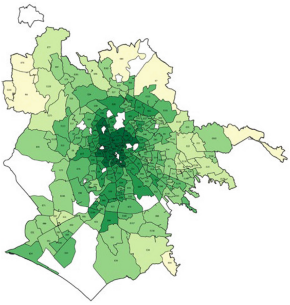


Fig. 4. INC – year 2018.

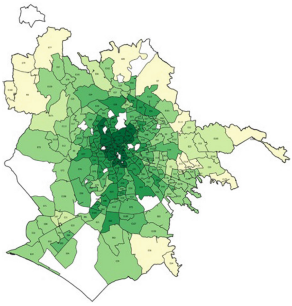


Fig. 5. INC – year 2019.

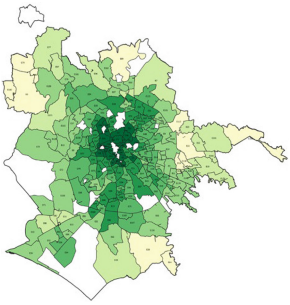


Fig. 6. INC – year 2020.

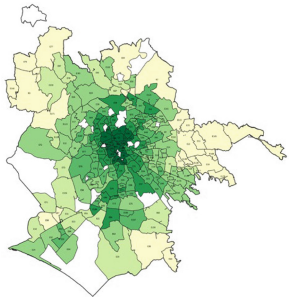


Fig. 7. INC – year 2021.

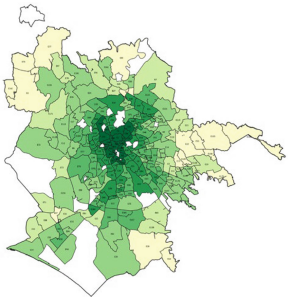


Fig. 8. INC – year 2022.

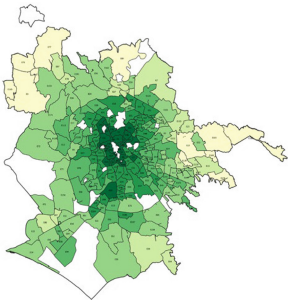


Fig. 9. INC – year 2023.

The output obtained is reported in Eq. (2), where the regression has identified the following relevant variables: the disposable income per capita (R), the leisure and cultural service expenses (C), the education expenses (E) and the social protection expenses (P).

$$INC = 24.857 + 0.000279 \cdot R + 0.007229 \cdot C + 0.023206 \cdot E + 0.136194 \cdot P \qquad (2)$$

The determination coefficient R^2 of the Eq. (2) is equal to 0.89, indicating a high statistical significance of the determined model. The function obtained thus shows that, based on the socio-economic indicators recorded, four variables have been identified as the most influential on the locational preferences of local communities. Among them, the decisive

contribution has been provided by the social protection expenses (82.53%). The weights of the education expenses (12.78%) and the leisure and cultural service expenses (4.51%) are smaller, while the influence of the disposable income per capita on the area incidence factors is nearly negligible (0.17%).

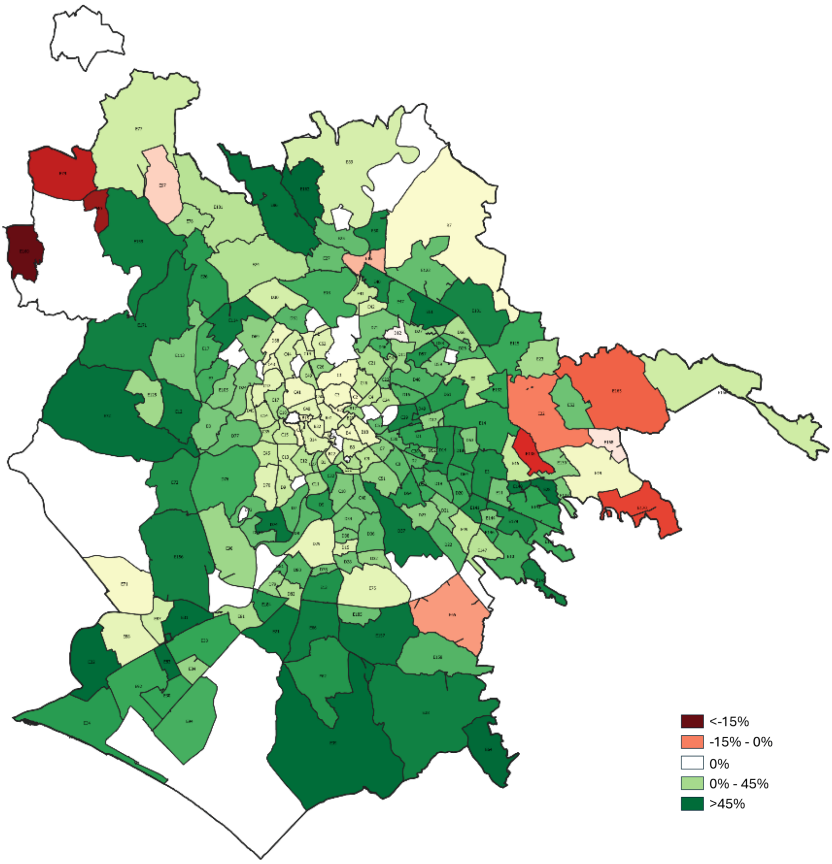


Fig. 10. ΔINC 2015–2023.

Table 1. Socio-economic variables for the regression analysis.

Variable	Acronym	Measurement unit
Disposable income per capita	R	€
Unemployment rate	U	% of the total population
Population density	D	inhabitants/km^2
Presence of foreigners	F	% of the total population
Housing maintenance expenses	M	€ per capita/year
Ambulatory service expenses	A	€ per capita/year

(*continued*)

Table 1. (*continued*)

Variable	Acronym	Measurement unit
Hospital service expenses	H	€ per capita/year
Transport service expenses	T	€ per capita/year
Leisure and cultural service expenses	C	€ per capita/year
Education expenses	E	€ per capita/year
Social protection expenses	P	€ per capita/year

Table 2. Descriptive statistics of the variables.

Variable	Average	Min.	Max	Stand. dev.
INC [%]	56.00	10.00	85.00	15.07
R [€]	25,241.00	9745.00	65,398.00	8849.29
U [%]	8.78	1.20	43.10	6.46
D [inh./km^2]	5843.00	1.50	97,037.00	8217.97
F [%]	13.55	2.70	35.70	6.72
M [€/year]	180.00	43.47	540.50	79.38
A [€/year]	397.00	195.00	924.00	115.90
H [€/year]	112.00	23.74	342.89	50.79
T [€/year]	340.53	168.60	787.00	98.15
C [€/year]	632.63	24.03	2208.74	347.25
E [€/year]	204.00	3.21	784.11	126.50
P [€/year]	127.00	93.27	214.39	19.19

Table 3. Correlation matrix.

	R	U	D	F	M	A	H	T	C	E	P	**INC**
R	1	0.06	0.31	0.09	0.98	0.99	0.99	0.99	0.99	0.99	0.99	**0.83**
U	0.06	1	−0.25	0.57	0.06	0.07	0.07	0.06	0.06	0.05	0.06	**−0.18**
D	0.31	−0.25	1	−0.05	0.32	0.31	0.31	0.31	0.31	0.31	0.31	**0.31**
F	0.09	0.57	−0.05	1	0.08	0.10	0.11	0.10	0.09	0.08	0.09	**0.01**
M	0.98	0.06	0.32	0.08	1	0.98	0.98	0.98	0.98	0.97	0.97	**0.81**
A	0.99	0.07	0.31	0.10	0.98	1	0.99	0.99	0.99	0.98	0.99	**0.82**
H	0.99	0.07	0.31	0.11	0.98	0.99	1	0.99	0.99	0.98	0.99	**0.82**
T	0.99	0.06	0.31	0.10	0.98	0.99	0.99	1	0.99	0.99	0.99	**0.83**
C	0.99	0.06	0.31	0.09	0.98	0.99	0.99	0.99	1	0.99	0.99	**0.83**
E	0.99	0.05	0.31	0.08	0.97	0.98	0.98	0.99	0.99	1	0.99	**0.83**
P	0.99	0.06	0.30	0.09	0.97	0.99	0.99	0.99	0.99	0.99	1	**0.83**
INC	**0.83**	**−0.18**	**0.31**	**0.01**	**0.81**	**0.82**	**0.82**	**0.83**	**0.83**	**0.83**	**0.83**	**1**

5 Conclusions

According to the current and global aim to pursue the diffusion of smart cities, the importance to provide effective preliminary assessment tools for urban planning policies constitutes a relevant focus of attention. Although the potential and opportunities that can arise from the use of artificial intelligence techniques have been recognized in the field of real estate valuation and urban planning support [31], the risk associated with the loss of control over the outputs generated by big data processing has been acknowledged,

as well as the perplexity related to the complexity of managing and interpreting black boxes that are difficult to verify.

In this context, a user-friendly and easily replicable valuation model has been developed and tested in the present research, thanks to the graphical representation of outputs in a GIS environment, which are also intelligible to less experienced users. The methodology underlying the illustrated model borrows the prodromes of the urban rent theory for the assessment of the area incidence factors, i.e. the coefficients that express the importance that the local communities attribute to the set of the locational factors that characterize a homogeneous market area. Applied to the microzones that define the municipal territory of the city of Rome, the determination of the differential urban rent (i.e. of the different area incidence factors) has allowed for the explicit identification of the temporal variations in the appreciation of different areas by the local communities, and thus for the quick identification — also through the visualization on maps — of the territorial areas that, more than others, demonstrate the need for urban regeneration initiatives.

The developed model for the city of Rome could serve as a useful reference for both public and private operators in urban intervention planning priorities: the analysis conducted reveals that, between 2015 and 2023, on one hand, there has been a decline in preference for the suburban areas of the city (such as the Tor Bella Monaca neighbourhood), due to insufficient infrastructure and/or services and/or social inclusion issues; on the other hand, many peripheral areas, compared to the central ones where no relevant variations in the appreciation have been recorded, have experienced significant increases in desirability, as consequence of the widespread adoption of smart working following the COVID-19 pandemic and, therefore, a greater preference for areas that offer better livability, both in terms of available services and the absence of the overtourism phenomenon that inevitably affects the central areas.

The implementation of an elastic net regression, using the area incidence factors as the dependent variable alongside eleven socio-economic variables collected for the studied micro-zones, has allowed for the identification of the indicators that most influence, in the year 2023, the area incidence factors, which serve as proxies for the housing choices of local communities. The final regression model selects only four socio-economic variables as those that are truly explanatory of the formation of the area incidence factor values: the disposable income per capita, the leisure and cultural service expenses, the education expenses and the social protection expenses.

By comparing the contribution of each of these four indicators, it had been observed that, in the city of Rome, the areas that had been most economically valued have been primarily associated with higher expenditure on social protection, followed by spending on education and leisure and cultural services: this output can provide for a valuable support in the planning of upcoming urban regeneration interventions in the city of Rome, highlighting the imperative need to include, in the various proposed and to-be-implemented design solutions, the programming of services that would meet the needs revealed by the carried out analysis.

Therefore, the results could support the choice processes for effective strategic lines of territorial development, constituting a further point of view for the investigation of the urban territory, which could integrate a context analysis for an overall exam of the strengths and the criticalities of the considered case study.

Although the model has been tested in the specific context of Rome, it demonstrates strong potential for transferability to other urban settings, insofar as it is grounded in standardized socio-economic indicators and GIS-based spatial analysis. Its practical application in different contexts, however, may be constrained by the availability, quality, and consistency of the pertinent territorial data.

Future research insights may concern the application of the method to other (national and/or international) case studies, in order to test its reliability and to deepen its potentialities in terms of practical implications. In this sense, comparative analysis could be carried out, in order to verify the obtained results and investigate the outputs within the specific territorial context.

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