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Does City Smartness Improve Urban Environment and Reduce Income Disparity? Evidence from an Empirical Analysis of Major Cities Worldwide

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1 ABSTRACT

Urban policymakers often advertise their cities as smart, emphasizing the wide–scale adoption of internet technologies, innovation activities, and the number of universities the city hosts as proof of successful transition towards greater smartness. Question, however, remains whether the accumulation of these attributes results in tangible benefits for local residents. To answer this question, we compare different metrices of city smartness with several indicators of intra–urban income disparity and environmental performance, using data available for 100+ major cities worldwide. As the analysis indicates, the proliferation of internet technologies and the number of universities the city hosts, i.e., popular ways of advancing "smartness", are not related to either intra–urban income disparity or environmental performance of cities per se. We thus suggest that the transition of cities towards greater smartness should be focused on people's needs and ICT-using skills, not on ICT proliferation per se. To the best of our knowledge, this study is the first that links the level of city smartness with intra–urban income inequality and environmental performance of cities and substantiates these links empirically. By accumulating this knowledge, the study helps to understand better the smart city phenomenon and its impact on urban development.

Keywords: smart cities, social inequalities, environmental quality, planning, worldwide

2 INTRODUCTION

The emergence of the smart city (SC) concept in the early 1970's resulted from a wide–spread dissatisfaction with traditional urban planning models that dominated decision–making at the time (Hall, 1988; Stübinger & Schneider, 2020). According to these models, cities are designed as high–density buildings and transportation hubs (Garde, 2020; Stübinger & Schneider, 2020), rather than places that serve residents' needs (Girardi & Temporelli, 2017). The introduction of the SC concept was aimed to change this paradigm by integrating information and communication technologies (ICTs) into the city management in order to improve urban services and the quality of life (QoL) of local residents (Hall, 1988; Marsal–Llacuna et al., 2015; Komninos, 2018; Mokarrari & Torabi, 2021; Sharif & Pokharel, 2022).

A common expectation is that, as cities become smarter, they can expectedly offer more effective solutions to various urban issues, such as poverty (Klevchik, 2019), societal inequality (Sampson, 2017; Martin et al., 2018; Richmond & Triplett, 2018), and environmental degradation (Katz & Bradley, 2013; Shelton et al., 2015; Cui & Cao, 2022). To achieve these objectives, cities deploy diverse ICT solutions that accumulate inputs from various sensors to monitor ongoing changes in the urban environment. The most prominent examples of smart ICT systems include the "The LuxTurrim5G Ecosystem" in Espoo, Finland that provides ultra–fast Internet connectivity, and the "SensorWebBike" system that helps to assemble air quality information in Syracuse, Italy (Lebrusán & Toutouh, 2020). In addition, various ICT tools are deployed to address vital urban challenges, such as online traffic management, and security issues. For instance, municipal authorities can use smart information systems to receive and accumulate information and respond quickly to disasters and emergencies, such as extreme weather events, fires, floods, landslides, etc. (Gath-Morad et al., 2017).

Establishing places of higher learning and encouraging innovations are two other popular strategies of advancing city smartness (Rinaldi et al., 2018; Masik et al., 2021). As Ardito et al. (2019) point out, cities ranked high on the urban smartness scale, often host numerous universities and colleges, and provide tens of thousands of well–paid high–tech jobs (Manville et al., 2014).

Prominent SC examples are London in the UK, Tel Aviv–Yafo in Israel, Barcelona in Spain, Dubai in the UAE, and Singapore. These cities employ a range of ICT tools and solutions that offer individually–tailored information and services to their residents (Stratigea, 2012; Novotný et al., 2014; Lee et al., 2016), increase resource use efficiency (Mingay & Pamlin, 2008; Aletà et al., 2017; Wendling et al., 2018), monitor air pollution remotely (Estrada et al., 2019; Ranjith Reddy, 2019), and help to optimize road traffic (Bubel & Szymczyk, 2016; Mitchell et al., 2018; Ameer et al., 2019). Examples of such smart innovations are gondolas and electric stairs in Medellin, Colombia that not only improve urban commuting but have also been a source of pride for the local community (Eberlein, 2014).

The TransMilenio and Bus Rapid Transit (BRT) systems in Bogotá, Columbia and Rio de Janeiro in Brazil, are two other examples of smart urban innovations that provide fair access to intra-urban mobility for people of different socio-economic strata (Peraertz, 2016). The multi-disciplinary information center in Rio de Janeiro is another prominent example of smart-city functioning that receives, processes and coordinates information from various sources, such as surveillance cameras, traffic lights, and medical response teams, helping to respond to ongoing events and save lives (Gath-Morad et al., 2017).

Previous studies of the SC phenomenon investigated the effect of smart technologies on QoL in urban areas (Navarro et al., 2017; Stanković et al., 2017); inclusivity problem (Giffinger & Lu, 2015; Meijer & Thaens, 2018; Lee et al., 2022); energy use (Nagy et al., 2019); job creation (Barba-Sánchez et al., 2019), and preservation of the natural environment and its resources (Cavada et al., 2016; Evans et al., 2019; Asteria et al., 2021). However, one important question seems to have escaped the research attention almost entirely:

Do smart cities actually make life better for their residents, by improving environmental conditions and reducing intra–urban income disparity?

The present study is aimed to answer this question, by examining 100+ major cities worldwide, using the most recent data, available for the year 2020 collected from different sources, including databases maintained by the World Bank, OECD, the World Meteorological Organization (WMO) and others. The cointegrated dataset that was formed during the study consists of 23 indicators, reflecting socio–economic, environmental, and technological aspects of the urban development, such as population size, per capita gross domestic product, environmental performance metrics, various innovation indices, e–government development index and others. To the best of our knowledge, the study is the first that looks into the association between city smartness, on the one hand, and intra–urban income inequality and environmental conditions in cities, on the other, and investigates these links empirically.

The results of the present analysis demonstrate that a city's progress towards greater smartness does not necessarily translate into more intra-urban income equality or tangible environmental benefits for the local residents. The main reason is that not all the tools and strategies, adopted by cities to advance "smartness," help to achieve these objectives. In particular, we found no evidence that popular ways of advancing "city smartness", such as proliferation of internet technologies and increasing the number of universities the city hosts, are associated with either smaller intra–urban income disparity or better environmental conditions in cities per se. As we conclude, in order to be successful, transition of cities towards greater smartness should focus on people's needs and enhancement of human skills, such as e.g., improving proficiency of ICTs use, and not on a simple accumulation of ICTs features in cities per se. As we suggest, the knowledge, gained in this study, can help decision-makers to develop informed policies focusing on people's needs and skills of using ICTs, instead of promoting the spread of ICTs in cities as a goal in itself.

This chapter is an abridged version of the paper published by these authors in Sustainable Cities & Society (2023(96): 104711). The remainder of this chapter is organized as follows: In Section 3 our methodological approach is presented, and the data collection method is described. In Sections 4 and 5, the study's key findings are reported and discussed. Conclusions and recommendations are formulated in Section 6, and this section also outlines the study's limitations and discusses directions for future research.

3 MATERIALS AND METHOD

3.1 Cities under study

The present analysis was carried out using data on 100+ cities worldwide (see Figure 1) thta are frequently mentioned by previous studies as localities with smart attributes (Caragliu et al., 2011; Anthopoulos, 2017; Komninos, 2018; Ameer et al., 2019; Sánchez–Corcuera et al., 2019; Luo et al., 2020; Ozkaya & Erdin, 2020; Hajduk, 2021).

The cities in question range in size from 100K to 31M residents and are located on six continents – Asia (22), Africa (1), North America (27) and South America (14), Europe (33), and Australia (4), – thus representing all the regions of the world.

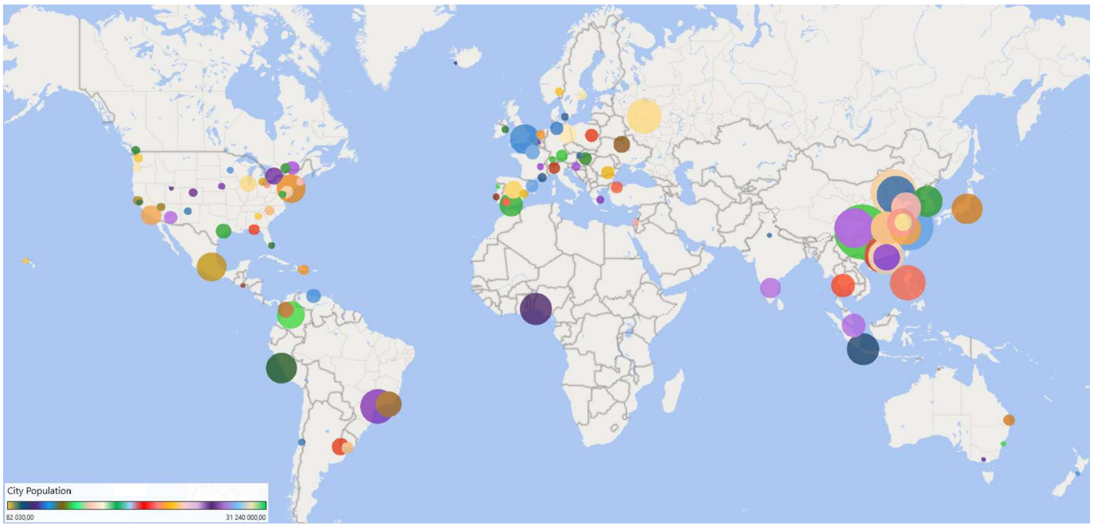

Fig. 1: Geographic location of the cities under analysis graded according to their population size, residents

3.2 Performance measures

The following three performance indicators – plume air quality index (AQI), urban green cover (UGC), and GINI inequality index, – are used in the analysis as dependent variables. Each of these performance metrics is important in its own right, as discussed in brief below.

AQI is an important measure of environmental performance, due to its ability to estimate the overall air quality in cities, by weighing concentrations of different air pollutants and accounting for combined effects (Li et al., 2017; Karavas et al., 2021; Suman, 2021). Importantly, the index converts concentrations of different air pollutants into a single value that simplifies analysis (Joshi & Mahadev, 2011; Suman, 2021). For the present study, the values of the index in question were obtained from the Plume Labs database (Plume Labs, 2021), in which it is estimated by combining information on the following five commonly monitored air pollutants: ozone (O3), nitrogen dioxide (NO2), sulfur dioxide (SO2), particulate matter of under 10 µm diameter (PM10) and particulate matter of under 2.5 µm in diameter (PM2.5) (Plume, 2019).

UGC provides city dwellers with a variety of products and ecosystem services that contribute to climate-change mitigation and adaptation, improve human health and well-being, contribute to biodiversity conservation, while reducing the disaster risk (Salbitano et al., 2016). UGC is a widely used measure of urban environmental performance due to its ability to estimate the level of greenery per an areal unit (or per capita) using remote sensing imagery and spatial analysis tools (Van de Voorde, 2017). For the present study, the values of the UGC index for individual cities were obtained from the Landsat database (U.S. Geological Survey, 2021b) and processed using the MultiSpec system (Purdue Research Foundation, 2021) and the EarthExplorer tool (U.S. Geological Survey, 2021a).

GINI is one of multiple measures of intra–urban income inequality. Other commonly used inequality indices include the Dahl Index, the Hirschman–Herfindahl Index, the Theil Index, the Atkinson Index, the Kolm Index, and others (Coulter, 2019). In this study, we opted for the GINI index, due to its ease of interpretation (Sitthiyot & Holasut, 2020) and the availability of the index calculates for different geographic units, including major cities (Osberg, 2017). The values of the index in question vary from 0 to 1, with 0 standing for perfect equality and 1 indicating utter inequality (Morton & Blair, 2015; Hejduková & Kureková, 2017; Sitthiyot & Holasut, 2020). In previous studies, GINI was found to be closely associated with societal fairness (Klevchik, 2019), and QoL in general (Marsal–Llacuna et al., 2015).

3.2.1 Measures of city smartness

The selection of specific SC performance indicators for the present analysis was based on a systematic analysis of previous studies, in which various SC metrics were used (Lombardi et al., 2012; Albino et al., 2015; Silva et al., 2018; Marchetti et al., 2019; Lim et al., 2019; Li et al., 2019). In our previous study

(Dashkevych & Portnov, 2022), these indicators were classified and systematized, helping us to identify 48 most commonly used SC empirical metrics, grouped into three main categories – economy and technology, environment, and society, – with the indices being ranked according to the frequency of their use in empirical literature (see Table 1).

To simplify the data collection and analysis, we selected nine most frequently used metrics, marked in Table 1 by asterisks. As sustainable development explicitly assumes a balance between social, economic, and environmental objectives (de Jong et al., 2015), the selected metrics chosen evenly represent the three main dimensions of sustainability – economy/technology, environment, and society, – by including three categorization criteria into each group. In previous studies, these measures have been used, alone or in combination, to estimate the level of city smartness and to measure urban performance in general (Lombardi et al., 2012; Aelenei et al., 2016; Mohanty et al., 2016; Liu et al., 2020; Ozkaya & Erdin, 2020; Hajduk, 2021).

Empirical metrics		Data source	Keywords
Economy and Technology	Access to public free Wi–Fi (the number of wireless access points)*; Number of startups*; Innovation cities index*; Broadband subscriptions per 100 inhabitants; Percentage of households with access to Internet; Web Index; Share of people who order goods or services over the internet; Number of users of sharing economy transportation per 100 000; Percentage of public parking spaces equipped with real–time availability systems; Percentage of public transport lines equipped with a real–time information system; Labor productivity; GDP per capita; Change in gross household income; Hourly wage; Purchasing power parity; Number of jobs created; Unemployment rate	Scopus, Web of Science Core Collections, ScienceDirect	city; urban area*; settlement*; urban region*; metropoli*; township*; smart; sustainable; criteria*; measure*; index*; metric*; parameter*
Society	Number of universities in the city (or number of students per 1,000)*; Happiness index*; E–Government development index*; Proportion of population with secondary and higher education; Expenditure on education per capita; Expenditure on leisure and recreation per capita; Corruption perceptions index; Share of residents participating in online platforms; Number of online government services; Extent to which public amenities are available within 500m; Decrease rate in travel time; Access to basic health care services /waiting time; Percentage of the city area covered by digital surveillance cameras; Emergency service response time; Number of transportation fatalities per 100,000; Number of violence, annoyances and crimes per 100,000; Access to public outdoor recreation space – public outdoor recreation spaces (m2) within a 500m radius from homes; Increase in ground floor space for commercial or public use; Life expectancy; Morbidity and mortality; Social inequality (GINI index or similar)	Scopus, Web of Science Core Collections, ScienceDirect	city; urban area*; settlement*; urban region*; metropoli*; township*; smart; sustainable; green; criteria*; measure*; index*; metric*; parameter*
Environment	The number of real–time remote air quality monitoring stations*; Environmental health and ecosystem vitality (Environmental Performance Index)*; The number of electric vehicles charging stations per registered electric vehicle *; Share of the city water distribution network monitored by smart water systems; Percentage of rain and grey water re–used to replace potable water; Percentage of the city population that has a door–to–door garbage collection with an individual telemetering of household waste quantities; Proportional share of the wastewater pipeline network monitored by a real–time data tracking sensor system; Percentage of street lighting remotely managed by light management systems; Percentage of buildings (or housing units) with smart energy or water meters; Proportional share of public buildings equipped for indoor air quality monitors	Scopus, Web of Science Core Collections, ScienceDirect	city; urban area*; settlement*; urban region*; metropoli*; township*; smart; sustainable; green; criteria*; measure*; index*; metric*; parameter*

Table 1: Empirical metrics commonly used by empirical studies for measuring the level of city smartness

3.2.2 Control variables

Population size is one of the most important indicators of urban development (Yamagata & Seya, 2013; Luo et al., 2020), because largest cities are often most productive due to intense competition (Kötter & Friesecke, 2009; Hummel, 2020) and knowledge spillover (Glaeser et al., 1992; Abel et al., 2012), but often lag in environmental performance, due to high volumes of traffic and elevated concentration of production facilities (Lin & Egerer, 2020). GDP per capita is another important measure of urban development since higher incomes are associated with QoL, as well as with better environment performance (Carli et al., 2018; Li et al., 2019; Azizalrahman & Hasyimi, 2020). We thus included these two measures as potential predictors for AQI, UGC, and GINI values in the study cities. Additional variables, used in the analysis as controls, were capital city status, city area, population density, democracy index, average temperatures, elevation above the sea level, precipitation, and latitude. As previous studies show, these variables, alone or in combination, help to explain urban performance (Roy & Yuan, 2009; Heider et al., 2018; Romano et al., 2020; Gough, 2021; MacManus et al., 2021), which justify their inclusion as predictors into the present analysis.

3.3 Data sources

The availability of data for a cross-city comparison is an important consideration due to the fact that the dataset for the analysis needs to be not only inclusive but also comprehensive. To ensure that the performance indicators used in the present study are fully reliable and comparable, the data from the present analysis were assembled from international databases, including the World Bank (The World Bank, 2021) and Organization for Economic Co–operation and Development (The Organisation for Economic Co–operation and Development, 2021) databases. The data for the analysis were collected for the year 2020, which were the most recent data available in these databases, at the time of the analysis's initiation. Concurrently, environmental and physical data, such as average temperatures, elevation above the sea level, precipitation, air pollution, and latitude, used in the present analysis as control variables, were obtained from the World Meteorological Organization (World Meteorological Organization, 2021), Climate–data.org (Climate–data.org, 2021), GeoDataSource (GeoDataSource, 2021), Aqicn.org (The World Air Quality Index project, 2021), and the Yale University environmental health and ecosystem vitality (environmental performance index) database (Yale University, 2021). The complete list of indicators, covered by the analysis, and their data sources are specified in Table 2.

Indicator		Description
Econ. and Techn.	Access to public free Wi–Fi	Number of wireless access points, from 0 (lowest) to 1 (highest)
	Startups	Global cities ranking of startups (0 to 235)
	Innovation cities index	Innovation index (0 to 100)
Society	Higher education	Number of universities or other higher education institutions with BA, MA and PhD programs (from 0 (lowest) to 1 (highest))
	Happiness index	Evaluation scale running from 0 (very unhappy) to 10 (very happy)
	E–Government development index	From 0 to 1, with 1 corresponding to the highest–rated online services provision and 0 to the lowest
Environment	Real–time remote air quality monitoring stations	Number of real–time remote air quality monitoring stations in the city, from 0 (lowest) to 1 (highest)
	Environmental health and ecosystem vitality	Environmental performance index, from 0 (worst) to 100 (best)
	Electric vehicles charging stations (EVCSs)	Number of EVCSs, from 0 (lowest) to 1 (highest)
Response variables:		
Environmental conditions		Overall air quality index, which brings together the concentration values of different air pollutants, measured from 0 to 300 (extreme pollution peaks – over 200)
		Urban green cover per capita, m2/person
Income inequality		GINI inequality index is from 0 to 1, with 0 representing perfect equality and 1 representing perfect inequality
Control variables:		
GDP		GDP per capita, $US (ln)
Population		Population size residents, residents (ln)
Geographical location		Latitude, dd

Table 2: Empirical criteria used in the study for the SC classification and analysis

3.4 Research hypothesis

As established by empirical studies, SCs help to advance economic development and improve transportation (Ismagilova et al., 2019), provide better health care and reduce resource consumption (Muktiali, 2018). Yet empirical evidence, accumulated to date, is rather contradictory regarding whether SCs lead in environmental performance and show less intra–urban income disparities, compared to cities with fewer attributes of smartness (Graham, 2002; Hollands, 2008; Becchio et al., 2016; Mundoli et al., 2017; Chamoso et al., 2018). Therefore, the following operational hypothesis was posited for empirical verification in this study:

H0: Cities that incorporate multiple "smart attributes" do not exhibit, ceteris paribus, less income inequality, or better environmental conditions, compared to cities with fewer attributes of smartness. Alternatively:

H1: City smartness is significantly associated with less income inequality and better environmental conditions in urban areas.

If H1 is correct, different metrics of city smartness should emerge as statistically significant predictors of the dependent variables under analysis – i.e., GINI, AQI, and UGC, – upon controlling for potential confounders (see Subsection 3.2.2). Otherwise, we shall reject this hypothesis.

3.5 Statistical analysis

To validate H1, we analyzed the integrated dataset in three consecutive steps (see Figure 2). First, we estimated bivariate correlations between SC different metrics, to determine the degree of collinearity between them. As several SC metrics (e.g., "innovation index", "e–government development index", "number of startups" and the "number of air quality monitoring stations"), were found strongly collinear (r>0.6, p<0.05), the principal component analysis (Jolliffe & Cadima, 2016) was used, to extract “orthogonal,” i.e., uncorrelated, components for subsequent analysis. The principal component analysis (PCA) and multiple regressions are frequently employed analytical tools, suitable for the analysis of large, multi-variable datasets with multiple, often collinear predictors (Portnov et al., 2018; Burton, 2021), such as that used in the present study. To facilitate comparison, all the metrics were converted into categorical variables in the IBM SPSS v.27 software, using its “Transform” module (IBM, 2021).

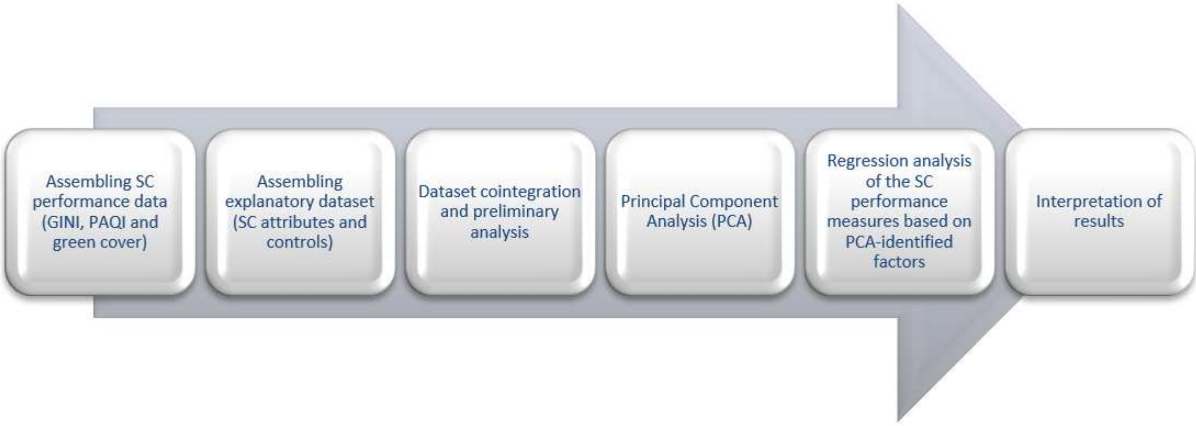

Fig. 2: Study flowchart

The PCA analysis is a multivariate statistical technique that helps to identify the smallest number of hypothetical constructs, also known as factors, that can parsimoniously explain the covariation observed among a set of original variables (Watkins, 2018). By defining orthogonal (i.e., uncorrelated) factors, this transformation helps to facilitate the use of standard regression techniques, in which strongly collinear variables can lead to an estimation bias (Jolliffe & Cadima, 2016). In particular, the analysis was run next, using the following generic regression equation:

Pik = $\boldsymbol{b_0 + \beta_0 \cdot SCF_{il} + \lambda_0 \cdot CONTR_i + \varepsilon_i}$, (1)

where Pik is vector of k–performance measures of city i (k=1, 2, 3; GINI inequality index, k=1; k=2: AQI; k=3: UGC); SCFil is vector of SC attributes of city i, represented by l–orthogonal factors extracted; $\boldsymbol{CONTR_i}$ is vector of control variables, including GDPpc ($US, ln), latitude (dd), population size (residents, ln), capital status (yes/no), etc.; b0, β, λ are regression coefficients and ε is a random error term.

In the initial stages of the analysis, additional variables, such as city area, population density, elevation above sea level, average temperatures in summer/winter, democracy index, monthly average rainfall days, and monthly average precipitation, were also considered. However, none of them emerged as statistically significant and were eventually dropped from the analysis.

The 5% probability level (p<0.05) was set as the acceptable level of statistical significance (Gowda et al., 2019). During the analysis, the normality of regression residuals, as well as multicollinearity and heteroscedasticity were monitored (Ainiyah et al., 2016; Abdullah, 2018), and the principal component analysis was applied, as previously mentioned, to substitute the original components by the factors extracted, when the multicollinearity assumption was violated (p<0.05). In addition, the normality of regression residuals was examined using P–P plots and the results were found to be satisfactory. The analysis was performed in the IBM SPSS v.27, software using its descriptive statistics, factor analysis, and multiple regression analysis modules (IBM, 2021).

4 RESULTS

4.1 General trends

As several metrics appear to be strongly collinear, -- viz.: “innovation index” and “e–government development index” (r=0.811; p<0.01); “happiness index” and “environmental health and ecosystem vitality” (r=0.764; p<0.01); “e–government development index” and “environmental health and ecosystem vitality” (r=0.732; p<0.01); “happiness index” and “e–government development index” (r=0.710; p<0.01); “the number of startups” and “the number of air quality monitoring stations” (r=0.569; p<0.01); “innovation index” and “happiness index” (r=0.548; p<0.01); “number of wireless access points” and “number of universities” (r=0.480; p<0.01). Considering these correlations, we extracted uncorrelated components (i.e., factors), as detailed in the next subsection, to be used in subsequent regression analysis.

4.2 Factor analysis

The results of the factor analysis, performed using the PCA method (Jolliffe & Cadima, 2016), are reported in Table 5. As evidenced by Table 5, three separate factors were extracted as underlying dimensions of the nine original SC metrics (see Table 2). The first factor (F1) is strongly and positively correlated with the “innovation index”, “happiness index”, “e–government development index”, and “environmental health and ecosystem vitality” (r=0.770÷0.919; P<0.01) but does not correlate significantly with any technology adoption measures analyzed (p>0.2).

Variable	Rotated Component Matrix		
	F1	F2	F3
Number of wireless access points	–0.157	0.052	0.864
Number of startups	0.076	0.887	–0.024
Innovation index	0.766	0.214	–0.217
Number of universities	–0.145	0.135	0.797
Happiness index	0.851	0.017	–0.186
E–government development index	0.917	0.075	–0.067
Number of air quality monitoring stations	0.067	0.854	0.189
Environmental health and ecosystem vitality	0.867	0.030	–0.061
Number of electric vehicles charging stations	0.512	0.487	0.357
Rotation Sums of Squared Loadings			
Total	3.222	1.826	1.636
% of Variance	35.804	20.292	18.177
Cumulative %	35.804	56.095	74.272

Table 3: Factor analysis of the SC metrics. Notes: Extraction Method: Principal Component Analysis; Rotation Method: Varimax with Kaiser Normalization.

This factor can thus be termed “innovativeness, smart government, and ecosystem vitality.” The second factor (F2) correlates strongly with the “number of startups” and the “number of air quality monitoring stations” (r=0.850÷0.879) and can be thus termed “startups and air quality monitoring”. The third factor (F3) has strong positive correlations with the “number of wireless access points”, and the “number of universities” (r=0.791÷0.860) and can thus be termed “higher education and internet access.” These three factors jointly explain ~74% of the original variables' variation, with F1 capturing 36% of that variation, F2 – 20%, and F3 – 18% (see Table 3).

4.3 Regression analysis

The results of the regression analysis of the factors influencing intra–urban income disparity (GINI) and environmental conditions in cities (AQI and UGC) are reported in Table 4 for statistically significant variables only, as identified by the stepwise regression analysis procedure.

Variable		Model 1A			Model 2A			Model 3A		
		ba	tb	VIFc	ba	tb	VIFc	ba	tb	VIFc
(Constant)		0.73	3.95**	–	44.05	14.55**	–	15165.14	2.90**	–
SC factor	Factor 1 (Innovativeness, smart government, and society)	–0.10	–5.57**	1.22	–18.90	–6.21**	1.00	0.20	1.96*	1.13
	Factor 2 (Startups and ecology)	–	–	–	–	–	–	–	–	–
	Factor 3 (Internet access and education)	–	–	–	–	–	–	–	–	–
Population size residents (Ln)		–0.32	–2.50*	1.22	–	–	–	–883.96	–2.47*	1.00
GDPpc, $ (Ln)		–	–	–	–	–	–	–	–	–
Latitude		–	–	–	–	–	–	–53.47	–2.64*	1.00
No of obs.		101			101			101		
R2		0.24			0.28			0.11		
R2 – adjusted		0.23			0.27			0.09		
Fd – stat		15.53**			38.60**			6.20**		

Table 4: Factors affecting the income inequality and air qualities in the cities under analysis (Method – stepwise regression; only statistically significant variables (P<0.05) are included). Notes: see comments to Table 6. Model 1A: GINI inequality index as dependent variable; Model 2A: Plume Air Quality Index as dependent variable; Model 3A: Green cover per capita as dependent variable.

As evidenced in Table 4, Factor 1, “Innovativeness, smart government, and ecosystem vitality”, is negatively and significantly associated with the dependent variables under analysis (Model 1A: b = – 0.102; t = – 5.600;

P<0.01 and Model 2A: b = – 18.781; t = – 6.157; P<0.01), while in Model 3A, estimated for UGC, it is positively associated with the dependent variable under analysis (Model 3A: b = 0.205; t = 1.955; P<0.05). In particular, as Table 4 shows, this factor tends to reduce, all other factors kept constant, income inequality and air pollution in the study cities (measured by GINI and AQI, respectively) and increase UGC. Notably, neither Factor 2, "Startups and air quality monitoring" nor Factor 3, "Higher education and internet access", emerge as statistically significant predictors of either GINI, AQI, or UGC (p>0.05). Concurrently, population size is statistically significant in Model 1A (GINI: b = – 0.33; t= – 2.517; p<0.05; Table 7), while GDPpc (UGC: b = 1408.220; t= 2.366; p<0.05; Table 7) and latitude (UGC: b = –74.448; t= –2.954; p<0.01; Table 7) are statistically significant in Model 3A.

5 DISCUSSION

The main objective of the study was to investigate the relationship between the level of city smartness, on the one hand, and intra–urban income inequality and environmental conditions in cities, on the other, which have been largely overlooked by previous studies. Our conclusion is that a city's progress towards greater smartness does not necessarily translate into more intra-urban income equality or tangible environmental benefits for local residents. An apparent reason is that not all the tools and strategies, adopted by cities to advance "smartness", help to achieve the above objectives. In particular, we found no evidence that popular ways of advancing "city smartness", such as proliferation of internet technologies and increasing the number of universities the city hosts, are associated with either smaller intra–urban income disparity or better environmental conditions in cities per se. This result thus leads us to reject H1. As we conclude, in order to be successful, transition of cities towards greater smartness should be focused on people's needs and enhancement of human skills, such as e.g., improving proficiency of ICTs use, and not on a simple accumulation of ICTs features in cities per se.

The absence of significant links between intra–urban income inequality and environmental performance of cities, on the one hand, and the scope of Internet proliferation and air pollution monitoring, on the other, is rather an unexpected outcome. The matter is that decision–makers, in an attempt to make their cities smarter, often place an emphasis on the proliferation of internet technologies, by providing e.g., city–wide broadband Internet access and installing multiple sensors for urban management and monitoring (Mitton et al., 2012; Zanella et al., 2014; Bibri & Krogstie, 2020; Syed et al., 2021). According to Kenny (2003), who examined the impact of Internet on economic growth and QoL in the OECD countries, Internet access has a long–term positive impact on economic development and QoL. As also noted by García–Mora & Mora–Rivera, (2021), Internet access is an effective mechanism that contributes to decreasing poverty and inequality. Yet the present evidence–based study supports none of these expectations. In particular, our study detects no significant association between either GINI, AQI, or UGC and the number of air quality monitoring stations or the number of wireless access points, that is, performance metrics, incorporated into Factors 2 and 3 extracted by the factor analysis. An apparent reason is that cities might actually become more unequal through the use of ICTs, because the poor always have less access to such technologies and are less skilled in their use (Graham, 2002). In other words, the availability of new technologies does not necessarily lead to their adoption, and the pace of ICT adoption by different population groups is not always uniform or fair. By the same token, "packing" cities with ICT tools do not necessarily have a positive impact on the environment either. As noted in several previous studies (cf., inter alia, Slob & Lieshout, 2002), additional space created, or resources saved with the help of ICTs, are eventually absorbed by new activities that lead to more energy consumption, and thus might adversely impact the environment in the long run. That is typical especially for less-developed countries, where urban economic development and population growth accelerate energy consumption substantially upward (Li et al., 2021).

As the present study thus reveals, a popular belief that "packing" cities with ICT tools can help generate positive environmental externalities and reduce intra–urban income inequality is apparently wrong. Therefore, to achieve a real improvement in environmental performance and to reduce urban inequality in cities, ICT tools that cities employ need to offer effective solutions to specific urban issues that a particular city faces (Katz & Bradley, 2013; Shelton et al., 2015), and to increase the efficiency of specific urban services that are identified as wasteful or inefficient (Bibri, 2019).

To facilitate the adoption of ICTs, it is also necessary to provide more equal access to such technologies for all population groups, including the elderly, lower–income population strata, and people with disabilities, through community programs and bespoke training (Muriithi et al., 2016; Kassongo et al., 2018). Increased user confidence in ICTs can also be achieved through providing 24/7 technical support (Muriithi et al., 2016) and encouraging grassroot–level citizen initiatives aimed at environmental monitoring, interactive problem–reporting, and enabling online conferencing with the city management (Kassongo et al., 2018).

The smart city government might also involve initiatives that make professional training and education more affordable through municipal subsidies or grants for the underprivileged, especially for children from low–income families and people with disabilities (Coe et al., 2001; Garg et al., 2017). Thus, for example, the City of Chicago in the USA successfully launched an education municipal initiative, which builds a pipeline from high school to college, and applies this innovative through the Technology–Early–College–High–School Pathway (Klett & Wang, 2014).

Citizen participation is another objective, achieving which might help to reduce inequality and improve environmental performance of cities. As an example, the city of Namyangju in South Korea offers its residents an interactive participation platform that makes it possible to share information about local issues, by sending on–line reports to the city mayor and the city government (Myeong et al., 2020).

6 CONCLUSIONS

The present study demonstrates that reduction in income inequality and air pollution in cities is associated with several performance metrics, linked to innovativeness, smart government, and ecosystem vitality. Yet we find no evidence that the proliferation of Internet technologies and the number of universities the city hosts, i.e., popular ways of advancing "city smartness", are related to either intra–urban income disparity or environmental performance of cities per se. By way of empirical analysis, the present study also demonstrates that unless a specific ICTs feature, used to advance city smartness, is directly relevant to human welfare, such a feature is unlikely to contribute to city resilience and achieving environmental sustainability goals.

We thus recommend that transition of cities towards greater smartness should be focused on people's needs and skills in using ICTs, not on ICTs per se. This transition might include facilitating ICT access to all, including the elderly, lower–income population strata, and people with disabilities. Additional measures might include providing 24/7 technical support, enabling citizens to report urban problems in real–time, and encouraging grassroots–level citizen initiatives in environmental monitoring, by making such reporting options more accessible and affordable to all.

Several limitations of the present study analysis should be mentioned. First and foremost, as previously mentioned, we found no evidence of a significant association between either GINI, AQI, or UGC and several urban performance measures, such as e.g., the number of air quality monitoring stations and the number of wireless access points. This conclusion is based on the analysis of specific variables and may not necessarily be relevant to other SC indicators. Follow-up studies should thus attempt to analyze more SC performance measures, linking them to intra-urban income inequality, air quality, and other SC outcomes, using the analytical approach employed in this study or similar analytical tools. Such analyses would help to understand better which SC features actually foster population welfare, increase social resilience, and improve QoL in cities overall.

While the data we analyzed are fairly representative of different regions and reflect potential development confounders (such as, capital status, city area, etc.), the analysis covered only one year (2020) and involved 101 cities with available and comparable data. Further studies should thus attempt to expand the scope of the cities under analysis and the study's timeframe. Another important topic for future research is technological, economic, and environmental competencies of people living in SCs. Finding of such a study might help to foster urban competitiveness and improve QoL in cities overall.

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