Volume 9, Issue 4, April – 2024 International Journal of Innovative Science and Research Technology
ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24APR504

Smart Cities: Boosting Economic Growth through Innovation and Efficiency

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Abstract:- This master's thesis, entitled "Smart Cities: Boosting Economic Growth through Innovation and Efficiency," embarks on an exploration of the transformative potential of smart urbanization in the face of global challenges. Envisioning cities as dynamic ecosystems fueled by technology, sustainability, and effective governance, the research delves into historical roots and theoretical frameworks across urban planning, technology, economics, and governance. The thesis invites readers on a journey through smart infrastructure, digital connectivity, and data-driven governance, illustrating how smart cities function as both innovation hubs and catalysts for economic dynamism. The conclusion draws insights from a comprehensive exploration spanning six countries from 2000 to 2021, interpreting data as a narrative that unveils the complexity of economic relationships. Emphasizing the multifaceted nature of these connections, the conclusion provides guidance to policymakers and researchers, urging a focus on theoretical implications, diagnostic test results, and a holistic perspective on the transformative potential of technological infrastructure, particularly smart cities, in fostering economic development.

Keywords:- *Smart Cities , Economic Growth, Technology, GDP, Innovation, Efficiency.*

I. INTRODUCTION

In today's ever-changing world, our cities are grappling with the rapid pace of change, limited resources, and the urgent need for environmental sustainability. Enter the thesis titled "Smart Cities: Boosting Economic Growth through Innovation and Efficiency," a bold exploration into the potential of smart urbanization. Think of it as a journey into the future of our cities.

Imagine cities not as mere dots on a map but as living, breathing ecosystems powered by cutting-edge technology, sustainable practices, and efficient governance. This isn't just about urban development; it's a paradigm shift. We're moving beyond traditional notions, where cities were confined to their geographical boundaries, and embracing a new vision where they transform into interconnected hubs of innovation.

At its essence, this research is an attempt to decipher the complex dynamics shaping our modern urban experience. Picture cities as dynamic entities, capable of leveraging innovation to tackle the pressing challenges we face today. It's like standing at the crossroads of technological progress and the expansion of our urban spaces, with this thesis serving as a gateway into a realm where Information and Communication Technologies (ICT), the Internet of Things (IoT), and data-driven decision-making converge to redefine urban living itself.

Take a trip back in time to the historical roots of urbanization, and juxtapose that with the urgent needs of today. This sets the stage for a nuanced exploration of smart cities—a narrative unfolding through theoretical frameworks and insights drawn from diverse fields like urban planning, technology, economics, and governance. It's like navigating a rich intellectual landscape, probing the symbiotic relationship between technological innovation and economic growth. Smart city initiatives aren't just projects; they're catalysts sparking a positive loop, propelling cities towards sustainable development.

Now, delve into the details—from smart infrastructure to digital connectivity and data-driven governance models. The thesis isn't just a compilation of theories; it's an intellectual tapestry weaving together practices and case studies. Imagine it as an invitation for you, the reader, to traverse this landscape, shedding light on how smart cities become not just innovation hubs but also engines for economic dynamism and models for a better quality of life.

This exploration extends an invitation to the heart of smart urbanization—a space where cities aren't static but living laboratories of progress. It's where the fusion of technology, sustainability, and governance takes center stage as powerful drivers for economic growth. Ultimately, this thesis aspires to contribute to a deeper understanding of how smart cities aren't just shaping the way we live in urban environments but also influencing the course of global economic development in the 21st century.

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II. STUDY AIM AND OBJECTIVES

A. Objective of the Research:

A study of the impact of the smart cities and their impact on the economic growth.

B. The Problem of our Research:

The problem of our research is to know the effect of the development in smart cities on economic growth .to answer this problem, we will put forward some hypotheses.

C. Research Questions:

- How did the idea of smart cities come about, and how does it change the way we think about building our urban spaces?
- What makes our modern urban experience so complex, and how do we see cities as living, breathing entities that use innovation to tackle our daily challenges?
- Can you describe specific examples of how cities, envisioned as dynamic entities, are using innovation to address societal challenges?
- How exactly does the use of technologies like Information and Communication Technologies (ICT), the Internet of Things (IoT), and data-driven decision-making change the way we live in cities?
- How have the needs and challenges of building our cities evolved over the years?
- Why is it important to bring together knowledge from different fields like urban planning, technology, economics, and governance to understand smart cities better?
- How do technology and economic growth work together in smart city initiatives, and can you explain how this helps cities develop sustainably?
- In everyday terms, how do smart cities become hubs for innovation and engines for economic dynamism?

D. Hypotheses of the Study:

To answer the problem of study, we will put forward some hypotheses:

- H_0: There is no significant relationship between the independent variables (Exports of ICT goods, Fixed broadband subscriptions, Research and Development expenditure, and Foreign direct investment) and GDP growth.
- H_1:There is a significant relationship between the independent variables (Exports of ICT goods, Fixed broadband subscriptions, Research and Development expenditure, and Foreign direct investment) and GDP growth.

➢ *Individual Hypotheses for Independent Variables*

- H_{01}: The percentage of ICT goods in total exports has no significant impact on GDP growth.
- H_{11}: A higher percentage of ICT goods in total exports is associated with a significant increase in GDP growth.
- H_{02}: The number of fixed broadband subscriptions per 100 people has no significant impact on GDP growth.
- H_{12}: A higher number of fixed broadband subscriptions per 100 people is associated with a significant increase in GDP growth.
- H_{03}: Research and Development expenditure has no significant impact on GDP growth.
- H_{13}: Increased Research and Development expenditure is associated with a significant increase in GDP growth.
- H_{04}: Foreign direct investment has no significant impact on GDP growth.
- $H_{14:}$ Higher levels of Foreign direct investment are associated with a significant increase in GDP growth.

E. The Importance of this Research:

Study of the impact of the smart cities and their impact on the economic growth.

F. Significance of the Study:

This study on "Smart Cities: Boosting Economic Growth through Innovation and Efficiency" is significant for many different kinds of reasons. Firstly, it includes some beneficial data for those who are developing cities and making decisions. It serves as an invaluable tool for city planners and decision-makers, offering ideas on how to develop societies that are both forward-thinking and ecologically conscious.

Beyond that, it's more than theory; it's practical knowledge. The study investigates a particular situation, such as China, to find out how all of this smart city stuff might work there. That's very interesting because it's more than concepts; it's honest advice for people to consider in similar circumstances.

On the academic side, it provides something new to our knowledge of cities, technological devices, finances, and the way we manage things. It's similar to contributing to a lot of information that will assist everyone comprehend and arrive at better choices.

The study also addresses how all of these cutting-edge technologies affects our cities. Consider it an inside look into the future, illustrating how innovation is enhancing cities while simultaneously emphasizing the importance of problems such as pollution and everyday life. And speaking of humans, the research didn't ignore us! It all comes down to developing cities that are not only high-tech but also locations where people may live better lives. So it's more than buildings and technology but also about guaranteeing our lives are safe.

III. THEORETICAL BACKGROUND AND LITERATURE REVIEW

This section offers a comprehensive exploration, spanning the historical evolution of Smart Cities, economic theories underpinning their growth, and the intricate relationship between technology adoption, urban transformation, and economic impacts. Addressing concerns

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24APR504

and critiques, it conceptualizes key variables and identifies gaps in the existing literature. This review not only informs the research but positions it within the broader scholarly discourse on Smart Cities, emphasizing their potential to drive economic prosperity through innovation and efficiency. In essence, it serves as a navigational guide through the intellectual landscape of urban innovation, charting a course towards unexplored territories.

Abu Bakar and Aina (2016) conducted a study titled "Achieving Sustainable Cities in the Kingdom of Saudi Arabia: Addressing the Challenges of Competitive Urbanization." The primary objective of the study was to elucidate the effectiveness of environmental sustainability and smart city strategies in confronting the challenges of urbanization in the Kingdom of Saudi Arabia from 1995 to 2016. The study employed an analytical approach using a critical method.

The results of the study highlighted the significant contributions of these sustainability strategies in mitigating pollution and environmental degradation. Emissions of nitrogen dioxide decreased, and fossil fuel consumption declined due to the implementation of initiatives promoting the use of renewable energy. Additionally, these strategies played a pivotal role in the enhancement of public transportation, infrastructure development, and the promotion of tourism. The latter, in turn, provided numerous employment opportunities and preserved historical sites.

Furthermore, the study revealed the role of knowledge-based strategies in addressing the challenges of manufacturing and employing the Saudi youth. The majority of jobs in the manufacturing sector were occupied by foreign workers, leading to various shortcomings in the gains of the manufacturing industry. Embracing the industry not only reduces dependence on oil revenues but also creates diversified employment opportunities, fosters technological advancements, and stimulates economic growth. In essence, the study emphasized the multifaceted positive impacts of sustainable and knowledge-driven urbanization strategies on the Kingdom's development, ranging from environmental preservation to economic diversification and youth empowerment.

The current study conducted **by Khalifa (2018)** in the United Arab Emirates during the period from 1997 to 2018, sharing a common goal. Khalifa's study aimed to scrutinize the motives behind the proliferation of smart cities and the resultant benefits of this expansion. Employing an analytical methodology using an inductive approach, the findings elucidated that the exacerbation of population growth, the desire to attract exceptionally skilled individuals and innovative minds, and the aspiration to enhance the quality of human life by reducing harmful carbon emissions, controlling traffic congestion, curtailing energy wastage, and fostering higher rates of economic development were all driving factors that propelled the global shift towards smart cities.

This study draws parallels with Khalifa's work, emphasizing the universal reasons compelling various countries worldwide to transition towards smart cities. The collective pursuit of addressing challenges such as population growth, environmental concerns, and the quest for economic advancement underscores the global impetus for the adoption and expansion of smart city initiatives.

From a different perspective, **Solaf (2019)** presented a study published in Algeria titled "Smart Cities and their Relationship to Sustainable Development." The study aimed to identify the correlation between smart cities and sustainable development, utilizing an analytical and descriptive methodology to analyze the impacts and repercussions of establishing smart and sustainable cities. The conceptualization of smart cities and sustainable development was explored by reviewing relevant literature and references spanning the period from 1995 to 2019.

The results unveiled a comprehensive relationship between smart cities and sustainable development, focusing on three dimensions: the economic dimension, the environmental dimension, and the social dimension. Smart cities align with the dimensions of sustainable development, with a distinctive feature of incorporating the technological and technical dimension. This addition enhances the capacity to achieve sustainable development. The study recommended the adoption of policies that promote innovation, clean technology, and reliance on renewable energy to preserve the environment. Furthermore, it emphasized investing in individuals' education in advanced technology as a key strategy for fostering sustainable development.

Ghaneem (2019) offered a complementary study to that of Solaf (2019), focusing on the results. The objective of Ghaneem's study was to delineate the relationship between the concept of smart cities and sustainable development, specifically examining the extent to which smart cities contribute to achieving sustainable urban development in Egypt. This investigation employed an exploratory approach using content analysis, covering the period from 2006 to 2019.

The results illuminated that innovation and technology, the cornerstones of smart cities, play a pivotal role in addressing the challenges that cities face on the path to achieving sustainable development. The findings emphasized that the concept of smart cities serves as the bedrock for sustainable urban transformation in Egypt. Furthermore, the study recommended a nuanced approach, underscoring the imperative of taking into consideration poverty rates and technological literacy when formulating initiatives for sustainable smart cities.

In practical terms, the study suggested that leveraging innovation and technology within the framework of smart cities not only aids in confronting the myriad challenges confronting cities but is also integral to realizing sustainable development goals. The results underscored the notion that the concept of smart cities is fundamental to Egypt's

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24APR504

sustainable urban evolution. Additionally, the study advocated for a thoughtful consideration of poverty rates and technological literacy in the implementation of sustainable smart city initiatives.

The study by Wanhel and Hoier (2015) aligns with a previous investigation, but it diverges in terms of temporal and spatial boundaries as well as outcomes. Wanhel and Hoier (2015) conducted a comprehensive literature review covering the period from 1987 to 2014 in Switzerland. The study employed a synthesis of both evaluative and conclusive methods, aiming to elucidate the relationship between smart cities and sustainable cities.

The study's results shed light on the potential to distinguish between the concepts of a smart city and a sustainable city. It suggested the possibility of considering a city sustainable when the use of smart technology is excluded in achieving sustainable development goals. Conversely, the study indicated that the incorporation of smart technologies in cities does not necessarily contribute significantly to sustainable development. The findings emphasized that a city can only be deemed both smart and sustainable when technology is utilized with the explicit purpose of enhancing overall sustainability.

Furthermore, the study recommended the development of assessment tools for cities to ensure a clear differentiation between smart sustainable cities and those that are sustainable without a significant reliance on smart technologies. The emphasis on discerning between smart and sustainable cities underscores the importance of intentional and purposefuluse of technology in urban development for achieving sustainability objectives.

In 2007, Al and Giffinger conducted a study that stood out from previous research efforts. Their work, titled "Smart Cities - Ranking of European Medium-Sized Cities," spanned the years 2001 to 2007. What made this study unique was its approach—it went beyond just analyzing data and instead opted for a comparative study of European medium-sized cities. The researchers identified six key indicators, including aspects like a smart economy, smart environment, smart mobility, smart people, smart living, and smart governance.

The main goal of the study was to classify 70 medium-sized European cities based on their levels of smartness. The findings were insightful, showcasing the distinct features, developmental opportunities, as well as the strengths and weaknesses of each European city. The researchers stressed the importance of these classifications being not just informative but also providing a comprehensive and accurate understanding of the intelligence levels and unique characteristics of European cities.Moreover, the study emphasized the need for these rankings to be presented in a way that is easy to comprehend. They recommended that any results should be shared with a clear explanation of the indicators and features taken into account when determining the intelligence level of each city. This approach aimed to ensure transparency and accuracy in the evaluation process, fostering a more human-centered understanding of the smart city landscape in Europe.

Al et Chu (2021) conducted a study in China from 2005 to 2017, exploring the impact of smart city innovations on the environment, economy, and public health. Employing the Differences in Difference methodology, the study found that efficient resource allocation positively influences environmental quality and economic growth. Foreign direct investment in smart cities was also noted for attracting clean industries and contributing to economic growth. Additionally, smart cities were found to reduce healthcare expenditures due to lower pollution levels. The study recommended that decision-makers and governments in developing nations adopt smart city initiatives and promote policies supporting innovation to create a sustainable urban environment.

In 2019, Zhang and Yu conducted a comprehensive study titled "Does Smart City Policy Improve Energy Efficiency? Evidence from a Quasi-Natural Experiment in China." This study shared similarities with a previous one conducted by Al et Chu (2021) in terms of spatial boundaries and the use of standard research methodologies. However, it differed in terms of the temporal scope and the specific objective.

Zhang and Yu aimed to measure the impact of smart city policies on energy efficiency and the economy across 251 Chinese cities during the period from 2003 to 2016. The study findings indicated that technological advancement and a high level of economic development had a significantly positive impact on energy efficiency. On the contrary, foreign direct investment and the added value of the secondary industry had a negative effect on energy efficiency due to their focus on heavy industries.The results also highlighted that smart city policies contribute to promoting a green, low-carbon economy. The study recommended that governments should increase investment in information technology and transition from traditional industrial structures to intelligent industrial frameworks. Overall, the research underscored the potential of smart city policies to enhance energy efficiency and stimulate a more environmentally friendly and economically sustainable urban development.

The study by Bo Del and Garagliu (2019) explores the impact of smart city policies on urban economies and innovation, diverging from a similar study. Conducted in European Union cities from 2008 to 2013, the research, using Propensity Matching Score, reveals a strong positive influence of smart city policies on urban innovation, measured through patent numbers. The study also highlights the positive impact of these policies on knowledge stock, a crucial driver of economic growth. Recommendations include the need for more research on smart cities to aid governments in designing beneficial urban policies, as well as promoting greater involvement of citizens, private companies, and stakeholders in decision-making processes for smart cities. This collaborative approach aims to ensure effective and inclusive urban policies.

➢ *Conclusion*

Researchers explored the impact of smart city policies on urban development. Bo Del and Garagliu (2019) found positive effects on innovation and knowledge stock in European Union cities from 2008 to 2013. Zhang and Yu (2019) studied China from 2003 to 2016, revealing that technological progress and high economic development enhance energy efficiency.

Al et Chu (2021) focused on smart cities in China from 2005 to 2017, uncovering relationships between resource allocation efficiency, foreign direct investment, and environmental/economic facets. Overall, the studies highlight the synergy between smart cities and sustainable development, advocating for more sustainable, innovative, and inclusive urban landscapes.

The researchers call for collaboration, envisioning a future where citizens, companies, and stakeholders actively shape smart city trajectories. Together, they form a community dedicated to unraveling urban development complexities, with each study contributing to understanding how smart city policies can create positive transformations.

IV. EMPIRICAL RESEARCH METHODOLOGY

This chapter delves into the empirical research methodology employed to investigate the relationship between smart city initiatives andeconomic growth.Given the limited availability of comprehensive data related to smart city initiatives and its impact on economic growth, the study focuses on a selected group of countries, including Singapore, Korea, Chine, Australia, Germany, Saudi Arabia, covering the period from 2000 to 2021.

The research methodology adopted in this study encompasses the selection of appropriate data sources, the identification of key variables, and the application of relevant statistical techniques. The primary data sources for this study include reliable economic databases, such as the World Bank, which provide access to a wide range of economic indicators. The key variables selected for analysis include GDP growth rate,Exports of ICT goods (% of total exports of goods),Fixed broadband subscriptions, and Research and Development (R&D) expenditure,Foreign direct investment.

To effectively examine the relationship betweensmart city initiatives and economic growth, the study employs a panel data analysis approach. Panel data analysis allows for the consideration of both cross-sectional and time-series variations in the data, providing a more comprehensive understanding of the underlying dynamics between the variables.

The chapter outlines the specific statistical techniques employed in the analysis, including regression models and econometric tests. These techniques help to identify and quantify the impactsmart city initiatives and economic growth, while controlling for other relevant factors that may influence economic performance.

Through the application of rigorous statistical methods and careful consideration of data limitations, this chapter provides an empirical framework for investigating the relationship betweensmart city initiativesand economic growth**.**

V. PRESENTATION OF THE MODEL

A. Data of the variables used

The objective of this study is to investigate how the smart city initiatives impacts economic growth**.** To achieve this objective, we will employ a quantitative research approach. It's important to note that data related to smart city initiativesand innovation are often limited and scarce. Therefore, we have selected a subset of countries, includingSingapore, Korea, Chine, Australia, Germany, Saudi Arabia, covering the period from 2000 to 2021.

Our primary source of data will be reliable economic databases, which provide access to a wide range of economic indicators. We will focus on key variables, including GDP growth rate (GDP),Exports of ICT goods (% of total exports of goods) (ICT),Fixed broadband subscriptions (FBS), Research and Development (R&D) expenditure,and Foreign direct investment (FDI).

Following data collection, we will conduct a comprehensive analysis using appropriate statistical techniques and methods. This analysis will provide valuable insights into the relationship betweenthe smart city initiatives and economic growth., given the limited data availability.

➢ *Dependent Variable*

- *GDP Growth*

In this thesis, the dependent variable we have chosen to investigate is GDP growth, specifically focusing on the 6-country selected. The primary data source for GDP growth in this study is the World Bank.

GDP growth is a critical variable in this thesis for several reasons. Firstly, A high GDP growth rate signifies economic expansion, which can lead to increased employment opportunities, higher incomes, and an improved standard of living for the population.

Secondly, GDP growth is an essential metric to assess the impact of smart city initiatives and economic growth**.**

By analyzing the relationship between GDP Growth, Exports of ICT goods (% of total exports of goods) (ICT),Fixed broadband subscriptions (FBS), Research and Development (R&D) expenditure, and Foreign direct investment (FDI), we can gain insights into whether Smart cities initiatives have a significant positive effect on economic growth.

Furthermore, GDP growth is used as the dependent variable in this thesis because it allows for meaningful comparisons between different countries and regions. We

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24APR504

can assess how smart cities initiatives impacts economic growth in countries with varying levels of technological advancement and economic development.

In summary, GDP growth is selected as the dependent variable in this thesis because it is a comprehensive and widely recognized measure of economic performance. It provides a clear picture of how smart cities initiatives may influence the economies of countries, helping us draw valuable insights for policymakers, businesses, and researchers interested in the impact of smart cities initiatives on economic development.

➢ *Independent Variables*

- *Exports of ICT goods (% of total exports of goods)*

Exports of ICT goods (% of total exports of goods) is a key independent variable that measures the proportion of a country's total exports represented by Information and Communication Technology (ICT) goods. This indicator provides insights into the importance of the ICT sector in a nation's international trade. A high percentage suggests that a significant portion of a country's exports is comprised of ICT products, indicating a strong presence and competitiveness in the global ICT market.The primary data source for ICT in this study is the World Bank.

The inclusion of this variable in the regression equation is relevant for assessing the impact of ICT exports on GDP growth in the context of smart cities. A positive coefficient for this variable in the regression equation would imply that an increase in the share of ICT goods in total exports is associated with higher GDP growth. This aligns with the thesis's focus on understanding how smart city initiatives, particularly those related to ICT, contribute to economic growth.

- *Fixed Broadband Subscriptions (FBS)*

Fixed broadband subscriptions (FBS as the second independent variable, represent the number of high-speed, fixed-line internet subscriptions per 100 people in a given population. This variable is crucial for understanding the level of broadband internet access, which is a fundamental component of smart city infrastructure.The primary data source for FBS in this study is the World Bank.

- *Research and Development (R&D) Expenditure*

Research and Development (R&D) expenditure as the third independent variable in the regression equation is crucial for assessing a country's innovation capacity and its impact on smart city initiatives. R&D spending reflects a commitment to technological progress, contributes to human capital development, and enhances global competitiveness. A positive coefficient for R&D expenditure in the regression equation would indicate that increased innovation investment is associated with higher GDP growth, highlighting the integral role of research and development in fostering economic growth within the realm of smart cities. The primary data source for R&D in this study is the World Bank.

- *Foreign Direct Investment (FDI)*

Incorporating Foreign Direct Investment (FDI) as the fourth independent variable in the regression equation is vital for understanding the external economic influence on smart city initiatives. FDI reflects international confidence and capital inflows, impacting a country's economic growth. A positive coefficient for FDI would suggest that higher foreign investment is associated with increased GDP growth, emphasizing the role of global participation in shaping the economic outcomes of smart city projects.The primary data source for FDI in this study is the World Bank.

➢ *Data Collection and Analysis*

The data for this study was obtained from the World Bank. In this study, the dependent variable is GDP Growth, and the main independent variable is Exports of ICT goods (% of total exports of goods) (ICT),Fixed broadband subscriptions (FBS), Research and Development (R&D) expenditure, and Foreign direct investment (FDI) collected from 2000 to 2021. Statistical software, E-views, is utilized to analyze the data.

B. Econometric Framework

➢ *Panel Data*

Panel data analysis is the evaluation of sections of countries, companies and individuals in a certain time period (Gujarati and Porter, 1999). Panel data analysis is one of the most innovative and effective methods of economics. Because the panel provides an environment for developing data predictions and theoretical results (Greene, 2003). Panel data analysis has some important advantages over time series or cross-section methods for economic research because it employs both time series variation and cross-sectional variation. Panel data analysis provides an opportunity to improve the efficiency of econometric measurements by estimating model parameters accurately and reliably. It offers a greater opportunity for constructing more realistic behavioral hypotheses. Panel data analysis enables the analysis of the important questions of the economy that cannot be answered by time series or cross-section methods, by mixing intercountry differences with intercountry dynamics (Hsiao, 2014). The main advantages of panel data analysis, which reduce the disadvantages of time series analysis by combining them with the horizontal-section analysis method, can be listed as follows:

- The estimations obtained as a result of the analysis made with panel data provide more information and the effects that cannot be achieved with only cross-section or time series analysis.
- By combining cross-sectional and time-series observations of panel data analysis, it allows econometric analysis to be performed even in cases where the number of observations is higher and the time series size is short and/or the cross-section observation is insufficient.
- The degree of freedom increases due to the increase in the number of observations. 4.Reducing the multicollinearity problem, which is frequently encountered in applications with time series data.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24APR504

- Allows heterogeneity to be controlled.
- Allows the reduction of problems and estimation deviations caused by neglected variables.

➢ *Implementation of Models using Panel Data*

This section shows the implementation of pooled ordinary least square, fixed effects and random effects estimations according to the procedures established by (Baltagi, 2005)and(Cameron & Trivedi, 2009). And the implementation of GMM estimator for dynamic panel models which is used to make adjustments, which were developed by (Arellano & Bond, 1991). This study uses panel data which allows the inclusion of variables at different levels of analysis suitable for multilevel or hierarchical modeling. In the first stage of the methodology, a pooled OLS regression for the model is conducted to use for comparison purposes. In the second stage of the methodology, this study uses two estimation methods for the model: the fixed effects method (within) and random effects method (FGLS).Both of these methods take into account the heterogeneity of the data, but will differ regarding the nature of specific effects (Adair & Berguiga, 2014).

After both of the estimations have been performed, this study will use will use the Breusch-Pagan Lagrange multiplier (LM), which helps to decide between random effects or a simple OLS regression. The null hypothesis for the LM test is that there is no significant individual variance (zero) (i.e. no panel effect)(Torres-Reyna, 2007). In the case where random effects are chosen the Hausman specification test (1978) is used to capture the nature of these individual effects and help decide which of these two estimation methods “fixed or random” is appropriate for the data used in this study. If the probability test of the Hausman is over 5%, we will accept the null hypothesis, which is that the estimators of the two methods are convergent, but only the random estimators are asymptotically efficient (Adair & Berguiga, 2014).

It is important to note that endogeneity may arise in the dynamic panel model due to the inclusion of a lagged dependent variable as a control variable. This can create issues such as biased and inconsistent estimates. However, in models without a lagged dependent variable, there should not be any endogeneity problem. Cross-sectional dependence can also be an issue where the individual units in the panel are not independent of each other. To address these issues, a dynamic panel with GMM estimator can be employed, which includes instruments that are correlated with the endogenous variable but not with the error term (instruments are lagged values of the explanatory variables, including the second lag of the dependent variable).

The data used for the models is unbalanced, meaning that each panel doesn’t contain the same time periods. Furthermore, countries represent the entities or panels (i) and years represent the time variable (t).

➢ *Implementation of the Pooled OLS Regressions*

For the pooled OLS regression, we assume that the explanatory variables are no stochastic and uncorrelated with the error term, therefore strictly exogenous (Gujarati & Porter , 1999). The explanatory variables are assumed to be exogenous in nature and the error term is described as ν_{it} rather than the term being decomposed into $\eta_i + \varepsilon_{it}$. Simple OLS does not take into account the country-time nature of the data and treats each observation as separate. Therefore, it comes with the problem of not accounting for unobserved heterogeneity of the panels.

➢ *Implementation of Fixed Effects Estimations*

The fixed parameters in this model are represented by η_i, which will be estimated in the subsequent equations. It is important to note that X_{it} in this case are not independently and identically distributed (IID) as they are explanatory variables. Instead, the remaining component of the error terms (represented by ν_{it}) should be assumed to be IID. According to Baltagi (2005), in a fixed effect model, η_i should be treated as fixed parameters that need to be estimated, while X_{it} is assumed to be independent of the error term νit for all countries (i) and years (t). The general framework for the fixed effects model is presented below:

$$Y_{it} = \beta 0 + \beta 1\ X_{it} + \mu_{it}$$

- *The Error Term can be Decomposed as:*

$$\mu it = \eta i + \nu it$$

(η_i) represents the time invariant dimension of the model and accounts for any individual specific effect that is not taken into account within the panel regression model, while (ν_{it}) indicates the remaining error term that varies over time, in addition to cross-sectionally (Baltagi, 2005). After estimating the fixed effects η_i the remaining residuals, ν_{it} are expected to be independently and identically distributed in a properly specified model.

With a fixed effects estimation we can account for both ‘within effects’ and ‘between effects’ estimations (Singh & Padhi, 2019). The within model is essentially found by subtracting the time-averaged model away from the original model (Cameron & Trivedi, 2009).

Thus the unobserved effect is removed, along with the time invariant regressors, due to the fact that: the within effects estimator is considered a consistent estimator of the fixed effect model (Cameron & Trivedi, 2009). We use this within effects estimation to take into account the country-specific fixed effect, focusing on the time-series dimension of the dataset (Singh & Padhi, 2019). The between effects estimation essentially shows us the means of countries over time, in order to analyze the cross-sectional nature of data (Singh & Padhi, 2019).

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24APR504

- *Implementation of Random Effects Estimations*

By using random effects estimations, we are essentially combining features of both the within-effects estimation with the between-effects estimation. When using random effects estimations we assume that the individual effect is a random error term η_i is independent and identically distributed (IID) and is assumed to be independent of ν_{it} for all i and t (Baltagi, 2005).

- *Below we Present the General Framework for the Random Effects Model:*

$$Yit = \beta 0 + \beta Xit + \mu it \quad \text{where: } \mu it = \eta i + \nu it$$

μ_{it} is essentially the between error and ν_{it} is within error. The random effects estimations do not use dummy variables to capture the individual effect, rather it assumes that the individual effect is a random variable (Singh & Padhi, 2019). Despite the fact that both fixed and random adjust for unobservable heterogeneity, in the fixed effects estimation, η_i is assumed to be fixed and requires estimating, while in the random effects model, we assume η_i to be random and is allowed to vary. We also assume η_i to be independent and identically distributed.

Therefore, the major difference between fixed and random effects estimations is that with random effects, variation across countries is assumed to be random with the explanatory variables included in the models.

- *Implementation of GMM Estimator for the Dynamic Panel Model*

The GMM estimator for dynamic panel model is used when there is endogeneity introduced by controlling for a lagged dependent variable in a dynamic panel model. This occurs when the lagged dependent variable is correlated with the error term, making it no longer appropriate to use standard fixed effects or random effects models. In such cases, the GMM estimator can be used with lagged values of the dependent variable and instrumental variables as instruments for the endogenous lagged dependent variable to estimate the model parameters.

The general equation for the dynamic panel data model using the GMM estimator is as follows:

$$Yit = \alpha i + \varphi 1Yit\text{-}1 + \beta Xit + \varepsilon it$$

Where Yit is the dependent variable, αi is the individual-specific effect, φ1 is the coefficient on the lagged dependent variable, Xit is the vector of independent variables, βis the vector of coefficients for the independent variables, and εit is the error term.

To use the GMM estimator for dynamic panel model, the moment conditions are specified and estimated using the instrumental variables. The Sargan test can be used to test the validity of the instruments, and the Arellano-Bond test can be used to test the first order and second order autocorrelations of the error term.

In this study, a dynamic panel model using GMM estimator is employed to address potential endogeneity problems in the relationship between GDP growth and AI. The lagged value of the dependent variable, GDP growth, is used as an instrument for GDP_{it-1}. Thus, it provides efficient and consistent estimates of the parameters of the model and is particularly useful in cases where there is a potential for endogeneity in the data.

C. *Presentation of the Model*

This study developed its econometric model for capturing the impact of artificial intelligence on unemployment based on the literature review.The model includes various variables to reflect the effects of artificial intelligence on unemployment.

$$GDP_{it} = c + \beta_1 ICT_{it} + \beta_2 FBS_{it} + \beta_3 R\&D_{it} + \beta_4 FDI + \varepsilon_{it}$$

- C: Constant
- GDP: GDP Growth
- ICT:Exports of ICT goods (% of total exports of goods)
- FBS: Fixed broadband subscriptions
- R&D : Research and Development
- FDI : Foreign Direct Investment
- $\beta 1. \dots . \beta s$ = Coefficient.
- ε : error term

For the dynamic panel model using GMM estimator:

$$GDP_{it} = GDP_{it-1} + \beta_1 ICT_{it} + \beta_2 FBS_{it} + \beta_3 R\&D_{it} + \beta_4 FDI + \varepsilon_{it}$$

D. *Model Validation*

Model validation is a crucial step in econometric analysis to ensure that the chosen model is reliable to estimate the relationships between the variables of interest. In this study, we use several statistical tests to validate the model specification and select the appropriate model to use.

We validated the models by conducting multiple tests, such as checking for multicollinearity and addressing unit root problems.

The main tests that are used in selecting the appropriate model are the Breusch Pagan LM test that is used to choose between Pooled OLS and Random effects and the Hausman test, which is used to compare the Fixed effects and Random effects models. Moreover, the Sargan test and the Arellano-Bond test are used in GMM estimator for dynamic panel model to assess the validity of the over identifying restrictions in the model. The Sargan test examines the validity of moment conditions in the first differenced equation, while the Arellano-Bond test assesses the validity of moment conditions in the level equation and in higher-order differences of the first-differenced equation and the second differenced equation.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24APR504

E. Conclusion

In summary, this chapter presents the sample selection process, variables specification, research design, data collection and analysis, econometric framework, model specification, and model validation methodology used in this study. The selection of a 22-year period, including 6 countries, based on the availability of data and policy relevance, demonstrates the importance of accurately capturing the impact of smart cities initiative on economic growth. The use of appropriate regression models, such as Pooled OLS, fixed effects models, random effects models, and GMM estimator for dynamic panel model.

Thus, a proper methodology is essential for conducting reliable and trustworthy research. This chapter highlights the research design and methodology employed in this study of the impact of smart cities initiatives on economic growth, and it serves as a guide to understanding the empirical methods and technical tools used in this study. The following chapter discusses the findings and results of the analysis.

VI. RESULT AND DISCUSSIONS

In this chapter, we present the results and analysis of the empirical investigation of the impact of smart cities initiatives on economic growth in the 6 countries over the period of 2000-2021. That is based on panel data analysis, utilizing pooled OLS, fixed effects, random effects and GMM estimator for dynamic panel model.

A. Descriptive Statistics

Descriptive statistics is a branch of statistics that deals with summarizing and describing the main characteristics or features of a set of data, without making any inferences or conclusions beyond the data that has been collected. It involves the use of different statistical measures, such as measures of central tendency (mean, median, mode), variability (standard deviation, variance), and correlations, to provide a framework for understanding, organizing, and presenting data in a meaningful way. Thus, descriptive statistics plays a critical role in data analysis, data visualization, and data interpretation, helping to make sense of large amounts of complex data.

The descriptive statistics reveal key characteristics of the variables in the dataset. The mean GDP growth rate of 4.135 indicates a moderate overall economic performance, with a slight positive skewness (0.314) and kurtosis (3.353), suggesting a relatively normal distribution with some variability. Exports of ICT goods exhibit a substantial mean of 15.75, indicating the importance of the ICT sector in international trade. Fixed Broadband Subscriptions (FBS) have a mean of 20.685, signifying widespread broadband access, and the negative skewness (-0.095) implies a slight leftward tail in the distribution. Research and Development (R&D) expenditure, with a mean of 2.058, suggests varying levels of innovation investment, while the skewness of 0.162 indicates a generally symmetric distribution. Foreign Direct Investment (FDI) shows a mean of 5.374, highlighting the presence of foreign capital. These statistics offer insights into the central tendency, variability, and distributional characteristics of the key variables in the dataset.

Table 1: Descriptive Statistics

	Mean	Median	St. dv.	Minimum	Maximum	Skewness	Kurtosis	Num.of Obs
GDP Growth	4.135	3.571	3.685	-5.693	14.519	0.314	3.353	132
ICT	15.75	11.428	14.589	0.0015	54.974	0.467	2.125	132
FBS	20.685	23.808	13.554	0.001	44.268	-0.095	1.768	132
R&D	2.058	2.0804	1.004	0.0266	4.928	0.162	3.406	132
FDI	5.374	2.607	7.435	-3.608	32.691	1.963	5.803	132

B. Panel Uni-Root Test

The first step in selecting an appropriate estimation strategy is always an examination of the data's characteristics and integration order. We implement the straightforward test proposed by Im., Pesaran, and Shin W-stat to test the variables' stationarity, the results show that the panel series is stationary under the alternative hypothesis and are non-stationary under the null.

➢ *We can Formulate the Hypothesis for Testing the Unit Root as Follows:*

- Null hypothesis H0: The data has a unit root (non-stationary)
- Alternative hypothesis H1: The data does not have a unit root (stationary)

The table below provides the Panel unit root test for the variables at level using Im, Pesaran & Shin W-stat.

Table 2: Unit Root Test using Im, Pesaran & Shin W-stat

Variables	Statistics	Prob.
Growth	-3.415	0.0003
ICT	-2.1306	0.0166
FBS	1.346	0.9110
R&D	1.5133	0.934
FDI	-2.902	0.0019

Source: Eviews

- GDP Growth: The W-stat of -3.415 yields a p-value of 0.0003, rejecting the null hypothesis. This suggests that GDP growth is likely stationary.
- Exports of ICT (ICT): The W-stat of -2.1306 results in a p-value of 0.0166, indicating rejection of the null

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24APR504

hypothesis. This suggests that ICT exports are likely stationary.

- Fixed Broadband Subscriptions (FBS): The W-stat of 1.346 produces a high p-value of 0.9110, failing to reject the null hypothesis. This implies that FBS may be non-stationary.
- Research and Development (R&D): The W-stat of 1.5133 with a p-value of 0.934 does not provide enough evidence to reject the null hypothesis. R&D may be non-stationary.
- Foreign Direct Investment (FDI): The W-stat of -2.902 results in a p-value of 0.0019, rejecting the null hypothesis. This indicates that FDI is likely stationary.

In summary, GDP Growth, Exports of ICT, and Foreign Direct Investment appear to be stationary, while Fixed Broadband Subscriptions and Research and Development may exhibit non-stationary behavior.

To address this problem, we take the first difference of the series by subtracting each observation from the previous one.

The table below provides the Panel unit root test after first differencing for the variables that has a unit at level using Im, Pesaran & Shin W-sta.

Table 3: Unit Root Test after First Difference

Variables	Statistics	Prob.
FBS	-2.459	0.007
R&D	-3.988	0.0000

Based on the above table, after first differencing, all variables have a probability that is less than the critical value at the significance level of 5%, indicating that they are stationary. Therefore, first differencing removed the unit root and made these variables suitable for regression analysis.

C. Multi-Collinearity Test

Multi-collinearity is a phenomenon in which two or more predictor variables in a multiple regression model are highly correlated. This can cause problems when interpreting regression coefficients, and can lead to unreliable or unstable estimates of the regression coefficients.

This indicates that there is a high linear correlation between the predictor variables in the data, which might result in unreliable regression model results. So, a correlation coefficient greater than 0.5 or less than - 0.5 indicates the presence of multi-collinearity; and as a result, highly correlated variables should not be included in the same model.

To determine if there is multi-collinearity among the variables we need to examine the correlation coefficients for each pair of variables. The correlation matrix table displays the pairwise correlations between all the variables in the dataset. Each cell in the matrix represents the correlation coefficient between two variables. The values range between -1 and 1, where -1 represents a perfect negative correlation, 0 represents no correlation, and 1 represents a perfect positive correlation.

Table 4: Correlation Matrix of the Variables

	Growth	ICT	FBS	R&D	FDI
Growth	1	0.403	-0.336	-0.196	0.156
ICT	0.403	1	0.027	0.29	0.466
FBS	-0.336	0.027	1	0.733	-0.047
R&D	-0.196	0.29	0.733	1	-0.071
FDI	0.156	0.466	-0.047	-0.071	1

The correlation matrix sheds light on the relationships between key variables in the study, offering valuable insights into potential patterns and connections.

Firstly, there exists a moderate positive correlation (0.403) between GDP Growth and Exports of ICT goods, indicating that as a country's GDP grows, there tends to be a moderate increase in the export of ICT goods.

Conversely, a moderate negative correlation (-0.336) is observed between GDP Growth and Fixed BroadBand Subscriptions (FBS). This suggests that an increase in GDP growth may be associated with a moderate decrease in fixed broadband subscriptions.

Furthermore, the weak negative correlation (-0.196) between GDP Growth and Research and Development (R&D) Expenditure implies a subtle negative relationship. As GDP grows, there is a weak tendency for a decrease in R&D expenditure.

In terms of Foreign Direct Investment (FDI), a weak positive correlation (0.156) with GDP Growth is noted, indicating a mild positive association between these variables.

Moving to the relationships among other variables, a strong positive correlation (0.733) is identified between Fixed Broadband Subscriptions (FBS) and Research and Development (R&D) Expenditure. This suggests that an increase in fixed broadband subscriptions is strongly linked to higher R&D expenditure.

However, the relationship between Fixed Broadband Subscriptions (FBS) and Foreign Direct Investment (FDI) appears to be very weak (correlation of -0.047), indicating limited association between these two variables.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24APR504

Regarding Exports of ICT goods and Foreign Direct Investment (FDI), a strong positive correlation (0.466) suggests a robust association between higher ICT exports and increased FDI.

In summary, the correlation matrix provides a comprehensive overview of the relationships between variables.

Table 5: Collinearity Statistics

Coefficients[a]			
Model		Collinearity Statistics	
		Tolerance	VIF
1	Exports of ICT goods	0.601	1.664
	Fixed Broadb and Subscriptions	0.410	2.44
	Research and Development	0.355	2.819
	Foreign Direct Investment	.0.771	1.406
a. Dependent Variable: Gdp growth			

The collinearity statistics, Tolerance and Variance Inflation Factor (VIF), shed light on the potential multicollinearity among the independent variables in the regression model predicting GDP growth. Examining these indicators allows us to gauge the degree to which the chosen variables may be correlated.

The VIF (Variance Inflation Factor) is a measure of how much the variance of an estimated regression coefficient is increased due to collinearity among the predictor variables. A VIF of 1 indicates no collinearity, while a VIF greater than 5 indicates a high degree of collinearity. In this case, the VIF for all four predictor variables is less than 5, indicating that there is no significant collinearity among the predictor variables. This means that the regression coefficients are not inflated due to collinearity, and we can be confident in our interpretation of the coefficients.

Starting with "Exports of ICT goods," the Tolerance of 0.601 implies that roughly 60.1% of the variability in ICT exports is not explained by the other variables in the model. Despite a VIF of 1.664, indicating relatively low collinearity, this variable demonstrates a moderate degree of independence from the rest of the predictors.

Moving to "Fixed Broadband Subscriptions (FBS)," its Tolerance of 0.410 suggests that around 41% of the variability in broadband subscriptions is not accounted for by the other variables. Although the VIF is still within acceptable limits at 2.44, indicating moderate collinearity, caution should be exercised in interpreting this variable's coefficient.

The variable "Research and Development (R&D)" exhibits a Tolerance of 0.355, indicating that approximately 35.5% of the variability in R&D is not explained by the remaining variables. With a VIF of 2.819, there is a moderate level of collinearity, necessitating careful consideration of this variable's contribution to the model.

Finally, "Foreign Direct Investment (FDI)" shows a Tolerance of 0.771, suggesting that about 77.1% of the variability in FDI is not elucidated by the other variables. With a relatively low VIF of 1.406, this variable appears to have minimal collinearity.

D. Regression Analysis

- *Pooled OLS Model:*

$$Y= 5.00071 +0.1308ICT_{it}-0.056FBS_{it}-0.7105R\&D_{it}-0.053FDI_{it}+ \varepsilon_{it}$$

The Pooled OLS (Ordinary Least Squares) model results reveal important insights into the relationship between the dependent variable (GDP growth) and the independent variables (ICT, FBS, R&D, FDI).

The constant term (C), the coefficient of 5.00071 with a p-value of 0.000 indicates that the intercept is statistically significant, suggesting a substantial impact on GDP growth. The positive sign implies a baseline level of economic growth even in the absence of the predictor variables.

- *ICT (Information and Communication Technology):*
- Coefficient: 0.1308 (p-value: 0.000)

The positive coefficient signifies that an increase in ICT is associated with a positive impact on GDP growth. The low p-value indicates statistical significance.

- *FBS (Fixed Broadband Subscriptions):*
- Coefficient: -0.056 (p-value: 0.0743)

The negative coefficient suggests a potential negative impact on GDP growth, but the result is marginally significant with a p-value close to the conventional threshold of 0.05.

- *R&D (Research and Development):*
- Coefficient: -0.7105 (p-value: 0.1084)

The negative coefficient implies a negative association with GDP growth, but the result is not statistically significant, as the p-value exceeds 0.05.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24APR504

- *FDI (Foreign Direct Investment):*

- Coefficient: -0.053 (p-value: 0.2181)

The negative coefficient and non-significant p-value suggest that FDI may not be a significant predictor of GDP growth in this model.

The R-squared value indicates that approximately 76.5% of the variability in GDP growth is explained by the model.

- *F-Statistics: 13.701 (p-value: 0.000)*

The F-Statistics test indicates that the overall model is statistically significant.

Heteroscedasticity Test (Breusch Pagan):Chi-Square Value: 60.275 (p-value: 0.000)

The significant p-value suggests the presence of heteroscedasticity, indicating that the variance of the errors is not constant across observations.

The Pooled OLS model highlights significant relationships between GDP growth and certain variables, emphasizing the importance of ICT, while caution should be exercised in interpreting the results for FBS, R&D, and FDI. The model, overall, demonstrates a good fit with a substantial portion of the variance explained. The heteroscedasticity test indicates a need for further investigation into the variability of errors.

➢ *Fixed Effect Model:*

$$Y= 5.379 -0.033ICT_{it}-0.0632FBS_{it}-0.344R\&D_{it}+0.154FDI_{it}+ \varepsilon_{it}$$

The constant term (C), the coefficient of 5.379 with a p-value of 0.0017 indicates that the intercept is statistically significant, suggesting a substantial impact on GDP growth. The positive sign implies a baseline level of economic growth even in the absence of the predictor variables.

- *ICT (Information and Communication Technology):*

- Coefficient: -0.033 (p-value: 0.9495)

The coefficient is not statistically significant (p-value > 0.05), suggesting that there is no significant relationship between ICT and the dependent variable in the Fixed Effect Model.

- *FBS (Fixed Broadband Subscriptions):*

- Coefficient: -0.0632 (p-value: 0.0357)

The coefficient is statistically significant (p-value < 0.05), indicating that there is a significant negative relationship between FBS and the dependent variable in the Fixed Effect Model.

- *R&D (Research and Development):*

- Coefficient: -0.344 (p-value: 0.6105)

The coefficient is not statistically significant (p-value > 0.05), suggesting that there is no significant relationship between R&D and the dependent variable in the Fixed Effect Model.

- *FDI (Foreign Direct Investment):*

- *Coefficient: 0.154 (p-value: 0.0576)*

The coefficient is marginally significant (p-value>0.05), suggesting that there is no significant relationship between FDI and the dependent variable in the Fixed Effect Model.

The R-squared value indicates that approximately 86.5% of the variability in GDP growth is explained by the model.

- *F-Statistics: 12.07 (p-value: 0.000).*

The F-Statistics test indicates that the overall model is statistically significant.

➢ *Fixed Effect or POLS*

- This model allows of heteronomy or individually for all countries by allowing to have it is own intercept value
- To choose the better model POLS and fixed effect model , I have to state the hypothesis as:
- H_0:POLS is the best model ,if we can't reject H_0 or if we accept H_1
- H_1:Fixed effect model is the best model if we accept H_1 or reject H_0

Redundant Fixed Effects Tests
Equation: Untitled
Test cross-section fixed effects

Effects Test	Statistic	d.f.	Prob.
Cross-section F	22.591071	(4,43)	0.0000
Cross-section Chi-square	59.989864	4	0.0000

Fig 1: Rebundant Fixed Effects Tests

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24APR504

P=0.000 <5% , Reject H_0 and Accept fixed effect model.

➢ *Random Effect Model:*

$Y=4.7097+0.08029ICT_{it}-0.057FBS_{it}-0.4229R\&D_{it}+0.042FDI_{it}+\varepsilon_{it}$

- *ICT :Coefficient: 0.08029, p-value: 0.007*

The coefficient is statistically significant (p-value < 0.05), indicating that there is a significant positive relationship between ICT and the dependent variable in the Random Effect Model.

- *FBS (Foreign Direct Investment):Coefficient: -0.057, p-value: 0.0454*

The coefficient is statistically significant (p-value < 0.05), indicating that there is a significant negative relationship between FBS and the dependent variable in the Random Effect Model.

- *R&D (Research and Development):Coefficient: -0.4229, p-value: 0.3902*

The coefficient is not statistically significant (p-value > 0.05), suggesting that there is no significant relationship between R&D and the dependent variable in the Random Effect Model.

- *FDI (Foreign Direct Investment):Coefficient: 0.042, p-value: 0.4148*

The coefficient is not statistically significant (p-value > 0.05), suggesting that there is no significant relationship between FDI and the dependent variable in the Random Effect Model.

R-squared measures the proportion of the variance in the dependent variable that is explained by the independent variables. An R-squared of 0.845 indicates that the Random Effect Model explains 84.5% of the variance in the dependent variable.

The F-Statistics tests the overall significance of the model. A low p-value (0.000) indicates that the overall model is statistically significant.

➢ *Hausman Test:*

- H0: The random effect model is appropriate
- H1:The fixed effect model is appropriate

Correlated Random Effects - Hausman Test
Equation: Untitled
Test cross-section random effects

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	338.471936	4	0.0000

Fig 2: Hausman Test

The Hausman Test compares the efficiency of the Random Effect Model with the Fixed Effect Model. A low p-value (0.0010) suggests that the Fixed Effect Model is more appropriate, indicating that there might be a systematic difference between the fixed and random effects.

In summary, the Random Effect Model suggests significant relationships between the dependent variable and ICT, as well as FBS. However, the Breusch Pagan Test indicates the presence of heteroscedasticity, and the Hausman Test suggests that the Fixed Effect Model might be more appropriate.

➢ *Dynamic Panel:*

$Y=0.789GDP_{-1}+0.478ICT_{it}-0.902FBS_{it}-0.067R\&D_{it}+0.568FDI_{it}+\varepsilon_{it}$

GDP-1 (lagged GDP):Coefficient: 0.789, p-value: 0.000

The coefficient is statistically significant (p-value < 0.05), suggesting a significant positive relationship between lagged GDP and the current dependent variable in the Dynamic Panel Model.

- *ICT (Information and Communication Technology):Coefficient: 0.478, p-value: 0.003*

✓ Interpretation: The coefficient is statistically significant (p-value < 0.05), indicating that there is significant relationship between ICT and the dependent variable in the Dynamic Panel Model.

- *FBS (Foreign Direct Investment):Coefficient: -0.902, p-value: 0.04*

✓ Interpretation: The coefficient is statistically significant (p-value < 0.05), suggesting a significant negative relationship between FBS and the dependent variable in the Dynamic Panel Model.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24APR504

- *R&D (Research and Development):Coefficient: -0.067, p-value: 0.847*

✓ Interpretation: The coefficient is not statistically significant (p-value > 0.05), suggesting that there is no significant relationship between R&D and the dependent variable in the Dynamic Panel Model.

- *FDI (Foreign Direct Investment):Coefficient: 0.568, p-value: 0.0029*

✓ Interpretation: The coefficient is marginally significant (p-value<0.05), indicating a potential relationship between FDI and the dependent variable in the Dynamic Panel Model.

R-squared measures the proportion of the variance in the dependent variable that is explained by the independent variables. An R-squared of 0.82 indicates that the Dynamic Panel Model explains 82% of the variance in the dependent variable.

- *F-Statistics: Value: 6.098366, p-value: 0.000001*

The F-Statistics tests the overall significance of the model. A low p-value (0.000001) indicates that the overall model is statistically significant.

The Arellano-Bond test for serial correlation in panel data is used to assess the presence of autocorrelation in the residuals of a dynamic panel model. The test specifically checks for the existence of first-order (AR1) and second-order (AR2) serial correlation. Here's the interpretation of the results:

Prob.(AR1) = 0.046:

The p-value associated with the first-order autocorrelation (AR1) is 0.046.

A low p-value (typically below the significance level of 0.05) suggests evidence against the null hypothesis of no serial correlation.In this case, the p-value of 0.046 is less than 0.05, indicating that there is statistically significant evidence of first-order serial correlation in the residuals.

Prob.(AR2) = 0.837:

The p-value associated with the second-order autocorrelation (AR2) is 0.837.

A higher p-value for AR2 suggests that there is no significant evidence against the null hypothesis of no second-order serial correlation. In this case, the p-value of 0.837 is relatively high, indicating that there is no statistically significant evidence of second-order serial correlation in the residuals. The Arellano-Bond test results suggest the presence of first-order serial correlation in the residuals of the dynamic panel model. This indicates that there might be a systematic pattern in the unexplained variation of the dependent variable that persists over time. It's important to consider the implications of serial correlation, as it can affect the efficiency and reliability of the model estimates.

Table 6: Panel Estimation Results

Variables	**Pooled OLS Model**	**Random Effect Model**	**Fixed Effect Model**	**Dynamic Panel**
C	5.00071(0.000)	4.7097(0.000)	5.379(0.0017)	
GDP_{-1}				0.789(0.000)
ICT	0.1308(0.000)	0.08029(0.007)	-0.033(0.9495)	0.478(0.003)
FBS	-0.056(0.0743)	-0.057(0.0454)	-0.0632(0.0357)	-0.902(0.04)
R&D	-0.7105(0.1084)	-0.4229(0.3902)	-0.344(0.6105)	-0.067(0.847)
FDI	-0.053(0.2181)	0.042(0.4148)	0.154(0.0576)	0.568(0.0029)
R^2	0.765	0.845	0.865	0.82
F-Statistics	13.701(0.000)	6.609(0.000)	12.07(0.000)	6.098366(0.000001)
Breusch Pagan Test60.275(0.000)				
Hausman Test		18.572(0.0010)		
Sargan Test				6.92 (0.792)
Arellano-Bond for Serial Correlation test				
Prob.(AR1)				0.046
Prob.(AR2)				0.837

E. Conclusion

In conclusion, this chapter delves into the empirical investigation of the impact of Smart cities initiatives on economic growth in the six countries from 2000 to 2021. Utilizing panel data analysis and various estimation strategies, including pooled OLS, fixed effects, random effects, and GMM estimator for the dynamic panel model, the results are presented and thoroughly analyzed.

The analysis conducted in this chapter provides valuable insights into the relationships between various economic indicators and GDP growth. The descriptive statistics offer a comprehensive overview of the central tendency, variability, and distributional characteristics of key variables in the dataset. The panel unit root tests indicate the presence of stationarity in GDP growth, exports of ICT goods, and foreign direct investment (FDI), while fixed broadband subscriptions (FBS) and research and development (R&D) may exhibit non-stationary behavior.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24APR504

To address non-stationarity, first differencing is employed, making the variables suitable for regression analysis. The correlation matrix reveals relationships among variables, with notable connections between GDP growth, ICT exports, and FDI. The multicollinearity test suggests that the selected variables are not highly correlated, ensuring the reliability of regression coefficients.

Three regression models—Pooled OLS, Fixed Effect, and Random Effect—are employed to explore the relationships further. The Pooled OLS model identifies significant relationships between GDP growth and ICT, emphasizing the importance of information and communication technology. However, caution is advised in interpreting results for FBS, R&D, and FDI.

The Fixed Effect model incorporates individual country intercepts, revealing a significant negative relationship between FBS and GDP growth. The Random Effect model highlights the significance of ICT and FBS but suggests potential systematic differences between fixed and random effects, as indicated by the Hausman Test.

The Dynamic Panel model introduces lagged GDP, indicating a significant positive relationship. Moreover, ICT and FBS are found to be significant predictors of GDP growth. However, the model should be interpreted cautiously, considering the potential presence of heteroscedasticity.

In conclusion, while the Fixed Effect model is favored based on the Hausman Test, the choice of the most appropriate model necessitates a comprehensive consideration of statistical significance, theoretical implications, and addressing diagnostic test results.

VII. CONCLUSION

As we reach the conclusion of our expedition by the world of "Smart Cities: Boosting Economic Growth through Innovation and Efficiency," explore the rich tapestry of concepts constructed over six different countries from 2000 to 2021. This study offered a lot more than an analysis; it was an exciting journey into the core of Smart Cities and their impact on economic growth. Consider us researchers, with analytical tools and an acute awareness of interest, going into the complex landscapes of data to find the tale that these numbers had to tell.

It wasn't just about statistics when we delved into the descriptive statistics; it was about demonstrating the pulse of each country's economy. The narrative's central tendencies, fluctuations, and unique distributional characteristics constituted the narrative's threads, providing a vivid representation of economic environments as distinct as the countries themselves.

The journey gave us through an intricate network of panel unit root tests, analyzing which economic parameters moved to the beat of stationarity. We utilized the alchemy of initial differentiation to make sense of non-stationary variables like fixed-speed internet subscriptions (FBS) and research and development (R&D), transforming them into characters suitable for our regression analysis—a transformation similar to introducing individuals in a story to life.

Exploring the correlation matrix was like uncovering our variables' social network, where GDP growth, ICT exports, and foreign direct investment (FDI) were not isolated entities but interconnected players influencing each other in unexpected ways. We did the multi collinearity test to confirm the robustness of our results, which is a curtain check to make sure our variables aren't too friendly with each other. Our story was then told utilizing the three musketeers of regression modeling: Pooled OLS, Fixed Effect, and Random Effect. Like an annexing hero, the Pooled OLS model announced the fundamental connections between GDP growth and the star of the show, information and communication technology (ICT). However, among the excitement, a note of caution came out related to FBS, R&D, and FDI, reminding us of the complexities in the relationships with economic growth.

The Fixed Effect model requires the spotlight, offering a country-by-country perspective and finding a significant inverse relationship between FBS and GDP growth. Its accomplishment in the Hausman Test instilled trust in its role as the main character in understanding the complex movement of economic changes. At the same time, while emphasizing the importance of ICT and FBS, the Random Effect model hinted at behind-the-scenes variations, providing measurements to our story. The Dynamic Panel model made an outstanding access in the grand finale, combining lagged GDP and finding an important positive relationship. It was as if we were predicting what was to come based on past reflections. Once more, ICT and FBS emerged as the main characters in this economic history nevertheless with a word of caution about the potential role of heteroscedasticity—a touch of uncertainty in our tale.

As we conclude up on our research trip, it's more than just a collection of findings; it's an invitation to deeper comprehension of economic relationships. It tells us that these relationships are complex and multifaceted, and that, like life, they demand an exhaustive strategy. The Fixed Effect model, based on the Hausman Test, nudges us to choose the correct way forward, not just based on statistical significance, but also with an eye on theoretical implications and an in-depth review of diagnostic test results. In more general terms, this research highlights the revolutionary possibilities of technological infrastructure, such as Smart Cities, in fostering economic development. In addition to the statistical significance and testing, it enables politicians, developers of cities, and other researchers to employ a broader perspective.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24APR504

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ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24APR504

APPENDIX

Table 7: Data of the Variables Used

Year	Country	GDP Growth (annual %)	Exports of ICT goods (% of total exports of goods)	Fixed broadband subscriptions (per 100 people)	Research and development expenditure (% of GDP)	Foreign direct investment, net inflows (% of GDP)
2000	Singapore	9.03831633	54.9744823	1.70218981	1.81699002	16.1488936
2001	Singapore	-1.07086275	52.2165545	3.66385957	2.00929999	18.9398554
2002	Singapore	3.92336077	51.4033039	6.46428816	2.03281999	6.65366712
2003	Singapore	4.54825543	47.7507964	9.86888648	1.99679005	17.4624187
2004	Singapore	9.93998268	47.8902195	12.7669479	2.07858992	21.2027279
2005	Singapore	7.36632239	15.8823203	15.1036749	2.14806008	15.1133634
2006	Singapore	9.00676608	14.4564285	17.5612487	2.11655998	26.3271578
2007	Singapore	9.02151951	34.1397826	19.85737	2.31985998	26.1619831
2008	Singapore	1.86348345	34.2413086	22.1395411	2.59674001	7.02328525
2009	Singapore	0.12795338	33.6207922	24.6172993	2.12789989	12.071092
2010	Singapore	14.5197497	34.0829217	25.919951	1.92918003	23.0694773
2011	Singapore	6.21493417	28.327776	26.6636674	2.06955004	17.5960297
2012	Singapore	4.43549759	27.9069128	26.6270012	1.91832995	18.7435275
2013	Singapore	4.81763099	29.245721	27.2615056	1.92104006	20.934481
2014	Singapore	3.93554028	29.5432732	26.4608109	2.08227992	21.8184881
2015	Singapore	2.97679932	32.4009416	26.304341	2.17444992	22.6541827
2016	Singapore	3.60165604	32.8021938	27.8697247	2.07427001	20.4880402
2017	Singapore	4.54472822	32.0210769	25.5998496	1.89952004	29.7605172
2018	Singapore	3.57543271	29.5657006	25.6873463	1.80902004	21.5355392
2019	Singapore	1.33126133	29.2984734	25.6375071	1.88516998	27.9412566
2020	Singapore	-3.9010534	33.6976578	25.5454012	1.89365363	22.5170338
2021	Singapore	8.882354	34.7141562	25.6907017	1.93763738	32.6911667
2000	Korea	9.06083333	34.4962605	8.27124715	2.12519002	1.99754203
2001	Korea	4.85239957	29.8284089	16.6111864	2.27865005	1.19094348
2002	Korea	7.72514268	32.9303075	21.989305	2.20774007	0.87287911
2003	Korea	3.14729119	33.7034001	23.5140105	2.27722001	0.99755616
2004	Korea	5.19739136	33.3098273	24.9782467	2.4421401	1.6760992
2005	Korea	4.30854271	29.9961394	25.4558774	2.5229001	1.45932013
2006	Korea	5.26432659	26.4756543	29.2255751	2.71934009	0.8698968
2007	Korea	5.79954842	25.4912182	30.5056297	2.87258005	0.75275402
2008	Korea	3.01298487	21.4067337	31.9739056	2.98886991	1.06818323
2009	Korea	0.79269899	21.8709903	33.6473298	3.14668989	0.95576859
2010	Korea	6.80482492	21.4015149	35.22475	3.31577992	0.83014371
2011	Korea	3.68566778	17.9854902	36.3220791	3.59198999	0.77982926
2012	Korea	2.40253099	17.1644712	36.7743744	3.85039997	0.74277963
2013	Korea	3.16470864	19.1428638	37.4015497	3.95124006	0.93132804
2014	Korea	3.20245379	19.7898095	37.974045	4.07785988	0.62477169
2015	Korea	2.80910327	21.7198552	39.2678777	3.97819996	0.27999556
2016	Korea	2.94688172	22.270229	40.0617607	3.98704004	0.8068933
2017	Korea	3.15963574	24.7417296	41.1478237	4.2920599	1.10307799
2018	Korea	2.90740377	27.8426797	41.1902765	4.51632977	0.70630089
2019	Korea	2.24397786	25.7717846	42.0081508	4.6270299	0.58339386
2020	Korea	-0.70941536	28.8883369	43.0655136	4.79571009	0.53304335
2021	Korea	4.14532395	29.1783064	44.2681969	4.9287222	1.21816331
2000	China	8.49009341	17.7103647	0.00179258	0.89315999	3.47512597
2001	China	8.33573348	20.000517	0.02642174	0.94033003	3.51298868
2002	China	9.13363079	24.0308314	0.25750822	1.05786002	3.60908135
2003	China	10.0380305	27.6944946	0.87045091	1.12037003	3.48741876
2004	China	10.1136214	29.9569877	1.92314224	1.21498001	3.48364146
2005	China	11.3945918	30.7218558	2.86231558	1.30791998	4.5542633
2006	China	12.7209557	30.7195938	3.87278351	1.36854005	4.50860069

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24APR504

2007	China	14.2308609	29.3407281	5.02560238	1.37369001	4.40098363
2008	China	9.65067892	27.7085255	6.23072071	1.44591999	3.73361071
2009	China	9.39872563	29.6510538	7.76461897	1.66480005	2.56889433
2010	China	10.6358711	29.124908	9.37085068	1.71371996	4.00354459
2011	China	9.55083218	26.7601821	11.5310236	1.78033996	3.7088067
2012	China	7.86373645	27.0555775	12.8192612	1.91214001	2.82710526
2013	China	7.7661501	27.4221132	13.727851	1.99785995	3.03985503
2014	China	7.42576366	25.9389723	14.4733248	2.02242994	2.55924765
2015	China	7.04132888	26.5630712	19.8782327	2.05700994	2.19217762
2016	China	6.84876221	26.4976248	23.0115825	2.10033011	1.55563696
2017	China	6.94720079	27.0686127	27.9512671	2.11602998	1.34912371
2018	China	6.74977383	27.3695907	28.7482025	2.14057994	1.69389433
2019	China	5.95050075	26.4784294	31.5978877	2.2446301	1.31071593
2020	China	2.23863836	27.0997277	33.9349704	2.40666008	1.72317562
2021	China	8.44747829	25.5035055	37.5755001	2.65378282	1.93078624
2000	Australia	3.90117137	2.85218876	0.549272	1.57319999	3.58137747
2001	Australia	2.04141734	2.68693371	0.63798362	1.67282922	2.8250724
2002	Australia	3.99358986	2.24110688	1.3252314	1.74749005	3.70508626
2003	Australia	3.11139821	2.23667998	2.62348356	1.8227282	1.92198614
2004	Australia	4.21663327	1.97984546	5.07903215	1.84902	6.98450782
2005	Australia	3.15375271	1.67984951	9.99418444	2.1172882	-3.60894017
2006	Australia	2.7406357	1.44908727	19.0550363	2.18010998	4.08487726
2007	Australia	3.77791678	1.37585324	20.6383982	2.2678282	5.20115546
2008	Australia	3.56827003	1.11078998	25.0142685	2.39995003	4.277789
2009	Australia	1.87048696	1.07066296	24.1033472	2.3278899	3.08877306
2010	Australia	2.20656631	0.96181153	25.0236521	2.37074995	3.06561619
2011	Australia	2.39138513	0.84592646	24.8333478	2.23483992	4.68766147
2012	Australia	3.90200781	0.87595663	25.2317837	2.20837363	3.72024479
2013	Australia	2.57875429	0.91618936	25.8785757	2.17843008	3.45520867
2014	Australia	2.57901711	1.08033523	27.8488166	2.0282772	4.30656603
2015	Australia	2.15273591	1.40372383	28.6647034	1.92070997	3.47204882
2016	Australia	2.73054799	1.30732722	30.4764884	1.91627282	3.56131494
2017	Australia	2.28218364	1.10386255	32.2159105	1.87977004	3.63360691
2018	Australia	2.88304512	1.00285808	33.7372929	1.86252526	4.24892049
2019	Australia	2.17139622	1.10186909	34.7144417	1.82892001	2.79837517
2020	Australia	-0.05088534	1.03879409	35.4483869	1.918262	1.15357968
2021	Australia	2.23621244	0.86560002	35.0474396	1.9272652	1.5994543
2000	Germany	2.91250296	8.40042954	0.32494733	2.40982008	12.7315036
2001	Germany	1.68146848	8.15943801	2.57622662	2.40437007	2.9267554
2002	Germany	-0.19797383	7.90016447	3.93524703	2.43621993	2.46661519
2003	Germany	-0.70011669	7.38827133	5.49499114	2.47461009	2.61434522
2004	Germany	1.17508813	7.93948215	8.61361705	2.43518996	-0.72515471
2005	Germany	0.73170716	7.89736926	13.2822461	2.44193006	2.10179308
2006	Germany	3.81644191	7.38070367	18.4498681	2.47232008	2.91996036
2007	Germany	2.97645513	5.8937931	24.3292291	2.46047997	1.48433865
2008	Germany	0.95987913	5.42120518	27.9621277	2.61512995	0.82650341
2009	Germany	-5.69383634	5.16496339	30.7216479	2.74266005	1.66219803
2010	Germany	4.1798825	5.28316752	32.1695924	2.73024011	2.53076202
2011	Germany	3.9251927	4.63975368	33.4757617	2.8055501	2.6014193
2012	Germany	0.41849759	4.50682252	34.2835322	2.88165998	1.85541341
2013	Germany	0.4375913	4.33312861	35.0658102	2.83598995	1.7997646
2014	Germany	2.20954343	4.52006222	36.1266094	2.87784004	0.50222719
2015	Germany	1.49193153	4.65161955	37.4146728	2.93378997	1.86072918
2016	Germany	2.22999987	4.70854806	38.6995624	2.94039011	1.86590692
2017	Germany	2.68023111	4.95506026	40.2209389	3.04710007	2.96641686
2018	Germany	0.98123261	4.96300022	41.1983042	3.11011004	4.1997218
2019	Germany	1.0566039	4.90075517	42.3237568	3.16778994	1.90252471
2020	Germany	-3.69678871	5.16693123	43.4606298	3.1092999	4.13404481

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24APR504

2021	Germany	2.62698727	5.03508094	44.2167646	3.1028227	2.25130176
2000	Saudi Arabia	5.62541615	0.02878358	0.0572829	0.05617171	-0.99256922
2001	Saudi Arabia	-1.21074387	0.03709827	0.06338878	0.045672	0.01066594
2002	Saudi Arabia	-2.8191744	0.03782785	0.15374337	0.0266262	-0.32389987
2003	Saudi Arabia	11.2420614	0.02850917	0.19861908	0.06233	-0.27177287
2004	Saudi Arabia	7.95844167	0.03941347	0.2903413	0.05315	-0.12920966
2005	Saudi Arabia	5.57385012	0.06763913	0.27788749	0.0423	3.6830495
2006	Saudi Arabia	2.78840222	0.07495793	0.85954031	0.04245	4.8535863
2007	Saudi Arabia	1.84713025	0.07787789	2.3602818	0.04521	5.84630543
2008	Saudi Arabia	6.24977275	0.08119047	3.81996762	0.04902	7.59063322
2009	Saudi Arabia	-2.05924919	0.18449582	5.0474942	0.07338	8.4963517
2010	Saudi Arabia	5.03949289	0.11212269	5.81940069	0.884	5.53432464
2011	Saudi Arabia	10.9937616	0.11001888	6.47229133	0.89784002	2.41020494
2012	Saudi Arabia	5.42739427	0.12342872	8.24147902	0.87684	1.6421613
2013	Saudi Arabia	2.85034299	0.21851579	9.36728292	0.81515998	1.17590002
2014	Saudi Arabia	4.02765122	0.11574285	13.8373636	0.81263738	1.04509842
2015	Saudi Arabia	4.69014507	0.16036678	19.345302	0.80276374	1.21601443
2016	Saudi Arabia	2.36307458	0.22462871	19.1449884	0.7622922	1.1189992
2017	Saudi Arabia	-0.06969802	0.14720168	19.4579805	0.7192833	0.19844114
2018	Saudi Arabia	2.76224374	0.09221888	19.4809729	0.6252282	0.50167597
2019	Saudi Arabia	0.83228033	0.00159261	18.985347	0.5637382	0.54409322
2020	Saudi Arabia	-4.34138768	0.27510999	21.9191537	0.51990998	0.73530831
2021	Saudi Arabia	3.92172412	0.40451167	29.4521485	0.46423	2.22034968