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DETERMINANTS OF BIG DATA TECHNOLOGY ADOPTION IN SMART CITIES OF EUROPEAN UNION

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ABSTRACT

A smart city seeks to resolve public problems by employing information and communication technologies with the collaborative support of city management and other different groups of stakeholders. Cities generate an increasing amount of data that transforms into a valuable asset when managed employing big data technologies. The main goal of the paper is to identify and assess the determinants of big data technology adoption (BDTA) in European Union cities. The proposed research model highlights potential determinants of BDTA, based on literature review. The model's conceptualisation has its foundation in the Technology – Organisation – Environment framework. The data was gathered employing a structured questionnaire. The research targets cities within European Union member states that have populations exceeding 40 000 inhabitants. The research model was assessed applying the Partial Least Squares Structural Equation Modelling approach aided by SmartPLS software. The model assessment found that cities' technological readiness, absorptive capacity, city management support, existence of smart city management and stakeholder support positively influence BDTA. Moreover, BDTA in cities positively influences data utilisation for city management decision-making. No moderating effect of city size on the relationships between individual factors and BDTA was identified.

KEY WORDS

big data technology, adoption, smart city, European Union, TOE

CLASSIFICATION

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INTRODUCTION

In recent decades, the adoption of diverse information and communication technologies (ICT) in cities has become more prevalent. The demand for technology in cities is propelled by urbanisation, climate change, economic downturns, crisis, and a free flow of people and goods [1-3]. City decision-makers must evaluate which segments of the city's infrastructure require technological enhancements and strategise the development of cities accordingly. The unrestricted movement of goods, people, and information has increased competition among cities. Cities compete for the attraction of human resources, businesses, investors, tourists, and international events. The adoption of technology in cities has been accelerated by decreasing technology costs and an increasing range of technological options.

Due to their role in job creation and economic innovation, smart cities and advanced ICTs attract the attention of researchers and policymakers who advocate for the advancement and implementation of smart technologies [4]. The primary emphasis of the European Union's strategies, programs, and incentives is on digital infrastructure and digital transformation [5, 6]. However, there is also consideration for individuals, social capital, and the environment as significant catalysts for development in cities. Recent studies reveal how big data is increasingly employed to enhance labor market analytics, reflecting its role in optimizing human capital management in smart cities [7]. The technological enhancement of cities represents an expanding marketplace for diverse enterprises, thereby fostering economic growth at the national level through development of cities and investment. The adoption of diverse ICTs facilitates the evolution of cities into smart cities. In an optimal scenario, cities adopt big data technology (BDT) that facilitate the functioning of diverse smart solutions through data processing and analysis. BDT enable the extraction of insights concerning the city's infrastructure and community, thereby assisting decision-makers [8]. The use of advanced technologies, such as big data, presents advantages as well as challenges; therefore, it is essential to identify the factors that influence the big data technologies adoption (BDTA) in cities.

Existing literature investigates big data in various contexts, such as the level of digital divide among European countries according to the big data on the country level [9], big data in industries such as manufacturing [10], labor markets [7], sports [11], insurance industry [12]; or big data connection with other technologies such as Internet of Things or Artificial Intelligence [13]. Moreover, there are studies that describe the role of other advanced technologies in cities, such as 5G and IoT, or cloud computing, that are also connected to BDT [14, 15]. However, to the best of our knowledge, there is currently no research that systematically examines the and explains the determinants of BDTA in (smart cities). The study will fullfill research gap by connecting research fields of smart cities, BDT and identifying and assessing determinants of BDTA in cities within the European Union. Therefore, the main research goal is to assess determinants of BDTA in cities of European Union member states. The research model is based on Technology-Organisation-Environment (TOE) framework, which means that determinants are grouped into technological, organisational, and environmental context.

The target population of this study includes cities within the European Union member states that have more than 40 000 inhabitants. The sampling frame for this study is a list of respondents linked to cities based on the one city – one respondent principle. The questionnaire items were developed or modified based on existing literature. The questionnaire evaluated the following constructs: Technological readiness, Absorptive capacity, Compatibility, City management support, Existence of a smart city strategy, Stakeholder support, Big date technology adoption in cities, and Utilisation of data in decision-making by city management. Multilingual structured questionnaire was used to collect the data, with respondents contacted through email invitations or online forms on the city's website. The questionnaire was translated into English, German, and French. After the data collection and data preparation, the proposed model was assessed using Partial Least Squares Structural Equation Modelling (PLS-SEM).

This article is organised as follows. Literature review section encompasses explanation on model conceptualisation and hypotheses development. Methodology section describes target population, research instrument and methods for the model assessment. Next, the Results section brings results of measurement model assesment, structural model assesment and moderator analysis. Discussion section connects results with hypotheses, describes implications and gives recommendations. Finally, Conclusion section describes key findings and ends with the research limitations and recommendations for future research.

LITERATURE REVIEW

SMART CITY AND BIG DATA TECHNOLOGY

European Parliament Committee on Industry, Research and Energy agrees that a smart city is one that: "seeks to solve public problems through solutions based on information and communication technologies with the joint support of multiple stakeholders and local authorities" [16]. The definition emphasizes the role of ICT in smart cities in achieving the goals of increasing competitiveness and well-being. Futhermore, the definition gives equal importance to the joint support of the ecosystem of stakeholders. ICT cannot transform cities without human and organizational capital, but is complementary to it. The definition starts from the needs of citizens, other stakeholders and public problems that need to be solved. This makes it clear that the selection and introduction of ICT into the city's infrastructure is not an end in itself, but the forms of application will depend on the different needs and environment of a city. Therefore, ICT will not be used in the same way in all cities. Recent technological advancements have facilitated the creation of diverse innovative solutions and products to address the needs for different city infrastructure parts, with the objective of boosting the development of smart cities. The market for ICT solutions in cities is dynamic and expanding rapidly [17]. A broad range of manufacturers, ICT providers, and consulting firms are allocating resources to the city solutions market. The areas of the city's infrastructure that are most impacted by technological advancement are transport systems and energy networks.

City management must strategise for continuous improvement and adjustment of public services in response to the challenges and recognised needs of the city. Consequently, there is an increasing interest among managers of cities in smart city initiatives and a demand for innovative ICT, as these can address urban challenges and fulfil the city's requirements. City management establishes a strategy and adopts measures for the development of innovative ICT on the demand side. The objective of smart city initiatives is to enhance service efficiency despite limited resources and competition through the use of ICT. Enhancing service efficiency supports economic development and improves the quality of life in the city. Besides the city's government, various stakeholders contribute to the demand for ICT in cities. Stakeholders on the demand side for innovative ICT in a city encompass users of smart city services, members of the environmental movement, and non-profit organisations.

A smart city strategy must prioritise the needs of stakeholders, particularly the citizens. The implementation of ICT into a city's infrastructure does not inherently guarantee its appropriate usage or its recognition of the city as a smart city. ICT and data should be used to enhance decision-making, optimise infrastructure efficiency, and improve the quality of city living. In order to realise the full effects of technology adoption in the context of cities, city management and stakeholders must collaboratively monitor participate in the development of a smart city. The actions of each stakeholder influence the realisation of greater benefits for society. Transportation companies may observe that in specific areas of the city, residents lack adequate access to adequate transportation services during their daily commutes. Transport companies may identify this issue as a business opportunity and implement a new service in that area of the city. By implementing a service tailored to their needs, citizens will gain access to an innovative mode of commuting to work. Citizens can utilise real-time data regarding traffic conditions to inform their travel decisions. For instance, they may postpone their trip to the city in the case of traffic congestion, thereby simultaneously reducing the amount of vehicles on the roads, or they may use micromobility vehicles such as electric bikes or e-scooters [18]. Consequently, the decisions and actions of all stakeholders influence the overall efficiency of the city's functioning.

Big data requires advanced data management technologies. Conventional database technology cannot effectively manage big data. Big data technology (BDT) include technology for parallel and distributed generation, aquisition, storage, and analysis of large amounts of data. Smart city solutions based on big data technology improve city management, city infrastructure and the quality of life in the city. For example, the use of real-time information on public transport improves mobility, reduces greenhouse gas emissions and saves time for road users. The effects of incorporating BDT into the city's infrastructure are related to the reduction of greenhouse gas emissions, the amount of waste, resource losses and energy savings due to more efficient use of energy and natural resources. Solutions in the field of transport and mobility bring time savings, especially when real-time information is used to make better decisions. Time savings are especially important in responding to emergency situations. Citizens can save time with efficient transport infrastructure that will shorten the time needed for their commute. BDT enable solutions for prevention of crimes and incidents, predicting road accidents [19] which can directly save lives, mitigate the consequences of incidents that can affect citizens or improve decision-making on various smart safety incentives. The social effects of applying BDT in cities are increasing social connectivity and inclusion of citizens and developing human capital. For businesses, using efficient electronic services based on BDT creates a positive business climate in a city. Furthermore, cultural and tourism-focused cities can utilise online marketing tools and digital promotion strategies, supported by big data technology to attract and manage visitor flows [20].

Applications of BDT in smart cities are numerous. Cities ideally introduce BDT to areas of the city's infrastructure that really need it. Considering the BDTA may result in multiple benefits and advantages for cities, while also representing a complex set of advanced technologies, it is necessary to investigate the factors that influence their successful adoption in cities.

TECHNOLOGY-ORGANISATION-ENVIROMENT FRAMEWORK – HOW TO EXPLAIN A TECHNOLOGY ADOPTION?

The TOE was developed by Tornatzky, Fleischer and Chakrabarti [21] explain the innovation adoption process within business organisations. The TOE framework argues that the adoption of information technologies is determined by factors from three contexts: technological, organisational, and environmental. The TOE framework does not define a specific set of factors influencing technology adoption; instead, it emphasises taxonomic factors relevant to each context of the technology adoption process. TOE framework has been used to explain of various ICTs, such as big data technology [22-25] and cloud computing [26, 27]. Each technology, within its specific context, is impacted by a unique set of factors that influence its adoption.

PROPOSED DETERMINANTS OF BIG DATA TECHNOLOGY ADOPTION IN CITIES AND DEVELOPMENT OF HYPOTHESES

Determinants of BDTA in cities were proposed in Pivar [28]. At that point, BDTA in organisations or cities had not been researched. For that reason, the approach that was used to choose potential determinants of BDTA encompassed a comprehensive literature review regarding usage of the TOE framework for explaining configuration of determinants that influence adoption of different ICTs that are important for smart cities or related to big data technologies. Meanwhile, BDTA has been researched in the context of enterprises in various countries and industries, but in the context of cities, it remains unresearched. This will be seen in this section.

Endogenous Variables – Big Data Technology Adoption in Cities and Data Utilisation in Decision-Making by City Management

BDTA in cities involves the acceptance, integration, and utilisation of such technology. Within the TOE framework, a collection of factors that influence BDTA can be referred to as the BDTA configuration. Several scientific papers evaluate the factors influencing BDTA. Though there has been research from an organisational standpoint (e.g., small and medium enterprises), a gap remains in the study of BDTA within city environments. TOE factors influencing the adoption of BD analytics were examined in small and medium enterprises [29]. The influence of compatibility, competitiveness, and organisational readiness on the adoption of BD analytics is mediated by the support of top management. The factors influencing BD adoption were examined within the higher education sector [30] utilising TOE and DOI frameworks. The BDA is significantly influenced by relative advantage, complexity, compatibility, support from top management, financial resources, human expertise and skills, competitive pressure, security and privacy concerns, and government policies. Moreover, it was demonstrated that factors affecting the BDA within a government agency in the Western Cape, South Africa, included management support, financial resources, skills and talent, and organisational strategy [23]. Waqar and Paracha [31] investigated the factors influencing private enterprises' intentions to adopt BD analytics in developing economies, utilising the TOE framework alongside DOI theory. Their findings indicate that perceived advantages and management support are critical factors that influence the intention of BDA in the private sector. Babalghaith and Aljarallah [24] identified complexity, compatibility, uncertainty, top management support, organisational readiness, and a data-driven culture as factors that encourage enterprises' BDA. The utilisation of data in decision-making encompasses the collection, examination, analysis, interpretation, and application of data to support instructional, administrative, policy, and other types of decisions and practices. Big data technology, especially big data analytics, is utilised for identifying trends and patterns within urban environments, thereby facilitating more efficient city management. The premise is that the adoption of big data technology in cities influences data utilisation in city management's decision-making.

Accordingly, following reserach hypothesis was proposed regarding influence of BDTA on data utilisation in decision making by city management:

> **H_4:** *Big data technology adoption in cities significantly positively influences utilization in decision making by city management.*

Exogenous Variables from Technology-Organization-Environment Framework Perspective

Technological context of BDTA in cities – Technological readiness, absorptive capacity and compatibility: Technological readiness encompasses the existing knowledge of people, the physical information and communication infrastructure of a city, and the financial resources for adopting new technologies, including big data technology. Based on previous research, aspects of technological readiness influence the adoption of technologies. Rajak et al. [32] identified technological readiness as the most significant factor of the Internet of Things in port logistics. Cloud computing solutions adoption is also influenced by technological readiness [33].

Haddar and Bouaziz [34] concluded that technological readiness influences cloud ERP adoption by small and medium enterprises. For the purpose of this research, it refers to "(1) existing knowledge city/town employees have, (2) physical information and communication infrastructure of a city/town and (3) financial resources needed to seamlessly adopt new technology – including big data-related technologies" [28; p.579]. Lutfi et al. [35] examined factors of BD analytics in Jordan. They revealed that organisational readiness, along with factors such as top management support and government support, influences the BD analytics adoption.

Absorptive capacity is incorporated into a few models of ICT adoption. For example, absorptive capacity of competition influences the adoption of business intelligence systems [36] and RFID technology adoption [37]. Persaud and Zare [38] examined the mediating role of big data analytics-specific absorptive capacity on the ability of Canadian small and medium enterprises to generate strategic business value from their BDA investments. Based on their research, BD analytics-specific absorptive capacity amplifies the impact of technological and human capabilities on strategic business value. For the purpose of this study, absorptive capacity is "the ability of an organisation/city to recognise the value of new, external information and knowledge, assimilate it, and apply it for different purposes" [28; p.579]. The assumption is that cities that have experience and knowledge relating to advanced ICTs have skills and capacities needed to adopt big data technology.

According to the Diffusion of Innovation theory, compatibility is "the degree to which an innovation is perceived as consistent with existing values, past experiences, and the needs of potential adopters" [39; p.223]. The compatibility of new technologies with existing values and work procedures favours their adoption within organisations. Compatibility has been used in to explain the adoption of different technologies in different industries. It is a significant factor in the BDA in the higher education sector [30]. Furthermore, Babalghaith and Aljarallah [24] conducted a survey with small and medium enterprises in Saudi Arabia, and the results revealed that compatibility influences BD analytics adoption. Lutfi et al. [35] also confirmed the positive influence of compatibility on BD analytics adoption. Compatibility also influences adoption of other ICTs, such as cloud computing and RFID technology [33, 40]. For the purpose of this research, big data compatibility with existing technologies describes "the degree to which big data technology is perceived as being consistent with the existing infrastructure, practices and needs of the city" [28; p.580].

Based on those findings, following research hypotheses were proposed regarding technological context of BDTA.

H_1: *Technological readiness, absorptive capacity and compatibility as factors of technological context significantly positively influence big data technology adoption in cities.*

H_{1a}: *Technological readiness significantly positively influences big data technology adoption in cities, with city size having a moderating effect.*

H_{1b}: *Absorptive capacity significantly positively influences big data technology adoption in cities, with city size having a moderating effect.*

H_{1c}: *Compatibility significantly positively influences big data technology adoption in cities, with city size having a moderating effect.*

Organisational context of big data technology adoption in cities – City managament support and existence of smart city strategy: City management should ensure resources and management of technology adoption. Furthermore, city management should have a long-term vision and take responsibility for creating a positive environment for ICT adoption. City management support is essential for overcoming obstacles and resistance to changes with the aim of reducing organisational conflicts when adopting technologies. Based on previous research, top management support influences adoption of various ICT. Alam et al. [41]

confirmed that top management support, organisational resources, and employee readiness influence the intention of big data analytics – artificial technology acceptance among hospitality and tourism companies. Big data and big data analytics are also proved to be influenced by top management support in a context of medium and large manufacturing companies in Malaysia [42], medium and large enterprises in the supply chain industry in Saudi Arabia [43] and the retail industry in Jordan [35]. For the purposes of this research, municipalities, city councils, and city administrations are responsible for city management, and therefore they are the main promoters of technological initiatives in each city. City management support refers to "the degree to which top management is involved in and supports BDTA in a city" [28; p.581].

Smart city strategy refers to "a strategy that promotes smart city initiatives and encourages efficient resource management and development of the city" [28; p.581]. City management has the role of developing and reevaluating a smart city strategy based on the problems and critical parts of the city's infrastructure that need to be improved by implementing ICT. Smart city strategy can be focused more on the improvement of "hard" or "soft" city's infrastructure or on the transformation of the specific geographical area more than on the specific economic sector, depending on the city's needs. City management should also be aware that their city's strategy and goals should align with national and EU city technological development strategies. Although previous research did not include the existence of a "smart" strategy as a factor in technology adoption, the author decided to include it in this research. Smart city is primarily a vision of how an ideal city should look in the future; it takes a large investment in smart initiatives, and it has a long-term impact on a city. Therefore, in order to achieve this vision, its development should be planned long-term, strategically, and in cooperation with all smart city stakeholders. Smart city strategy is a guideline for urban development policies. Therefore, this research assumes that the existence of a smart city strategy has a positive influence on the BDTA in cities.

Based on the author's arguments presented above, following research hypotheses were preposed regarding organisational context of BDTA.

H_2: *City management support and the existence of a smart city strategy as factors of organizational context significantly positively influence big data technology adoption in cities.*

H_{2a}: *City management support significantly positively influences big data technology adoption in cities, with city size having a moderating effect.*

H_{2b}: *The existence of a smart city strategy significantly positively influences big data technology adoption in cities, with city size having a moderating effect.*

Environmental context of big data technology adoption in cities – Stakeholders support: According to the original TOE framework, environmental context includes conditions in which an organisation conducts its business, including industry characteristics, market structure, technology support infrastructure, and government regulation. Stakeholders of smart cities are all entities, institutions or individuals who are interested in smart city initiatives. A stakeholder is a subject that influences the development of a smart city or a subject that is impacted by the quality of life in a city [44]. In previous research, stakeholders' support for the adoption of certain ICT has been presented in various terms. For example, [22] confirmed that regulatory support and external support influence BD analytics adoption in the context of Malaysian manufacturing and service industries. Similarly, external support influences BD analytics adoption in Iranian small and medium manufacturing enterprises [29] and in Nigerian manufacturing and service industries [25]. Youssef et al. [45] investigated factors in BD analytics adoption in the retail industry across the United Kingdom, the United Arab Emirates, and Egypt. They revealed that the external support influences BD analytics adoption, but that influence is greater in the United Kingdom compared to the United Arab Emirates and Egypt.

For Korean enterprises, it was shown that government support and policy influence BDA [46]. Lutfi et al. [35] assessed factors affecting BDA in Jordanian small and medium enterprises. It was shown that government support, along with top management and organisational readiness, influences BDA. However, compatibility is shown to be insignificant for BDA. For the purpose of this research, stakeholder support refers to "stakeholders that (1) provide technology and technological solutions, (2) incorporate technology into their processes or (3) facilitate technological and policy frameworks related to technology adoption" [28; p.582].

Regarding environmental context of BDTA it is decided to propose following research hypothesis.

H_3: *Stakeholder support significantly positively influences big data technology adoption in cities, with city size having a moderating effect.*

CITY SIZE AS MODERATOR

City size is a structural characteristic that influences the adoption of smart city initiatives [47]. ICT adoption in cities is present in both larger and smaller cities. While larger cities have bigger financial resources that can be allocated to technology adoption initiatives and can also take higher risks regarding adoption, smaller cities have advantages as well. Smaller cities can experiment, implement more pilot projects, and coordinate and communicate with stakeholders. In previous research, there are no studies that assessed organisation/firm/enterprise or city size as a factor of BDTA. However, firm size has been shown to be a significant factor in the adoption of mobile reservation systems [48], information system outsourcing [49], computer-assisted audit tools and techniques [50], blockchain technology adoption [51], and e-business [52]. Moderating effect of firm size was investigated and confirmed in a context of customer relationship management and its influence on the relationship between compatibility, top management support, customer pressure and IT infrastructure [53]. In this study, it is assumed that city size does not directly affect BDTA in a city but rather that it influences the relationships between i) technological readiness and BDTA in cities, ii) absorptive capacity and BDTA in cities, iii) city management support and BDTA in cities, and iv) stakeholder support and BDTA in cities. The influence of factors on the relationships in the model is called the moderating effect.

Proposed Research Model Of Big Data Technology Adoption In Cities

Based on a review of previous research and a description potential determinants of BDTA in cities, a research model were proposed, Figure 1.

In accordance with the explained research subject and research model, the following research goals were set.

RG_1: *To determine the relationship between technological readiness, absorptive capacity and compatibility as factors of the technological context and big data technology adoption in cities.*

RG_2: *To determine the relationship between city management support and the existence of smart city strategy as factors of the organizational context big data technology adoption in cities.*

RG_3: *To examine and determine the relationship between stakeholder support and big data technology adoption in cities and the moderating influence of city size.*

RG_4: *To examine and determine the relationship between big data technology adoption in cities and data utilization in decision making by city management.*

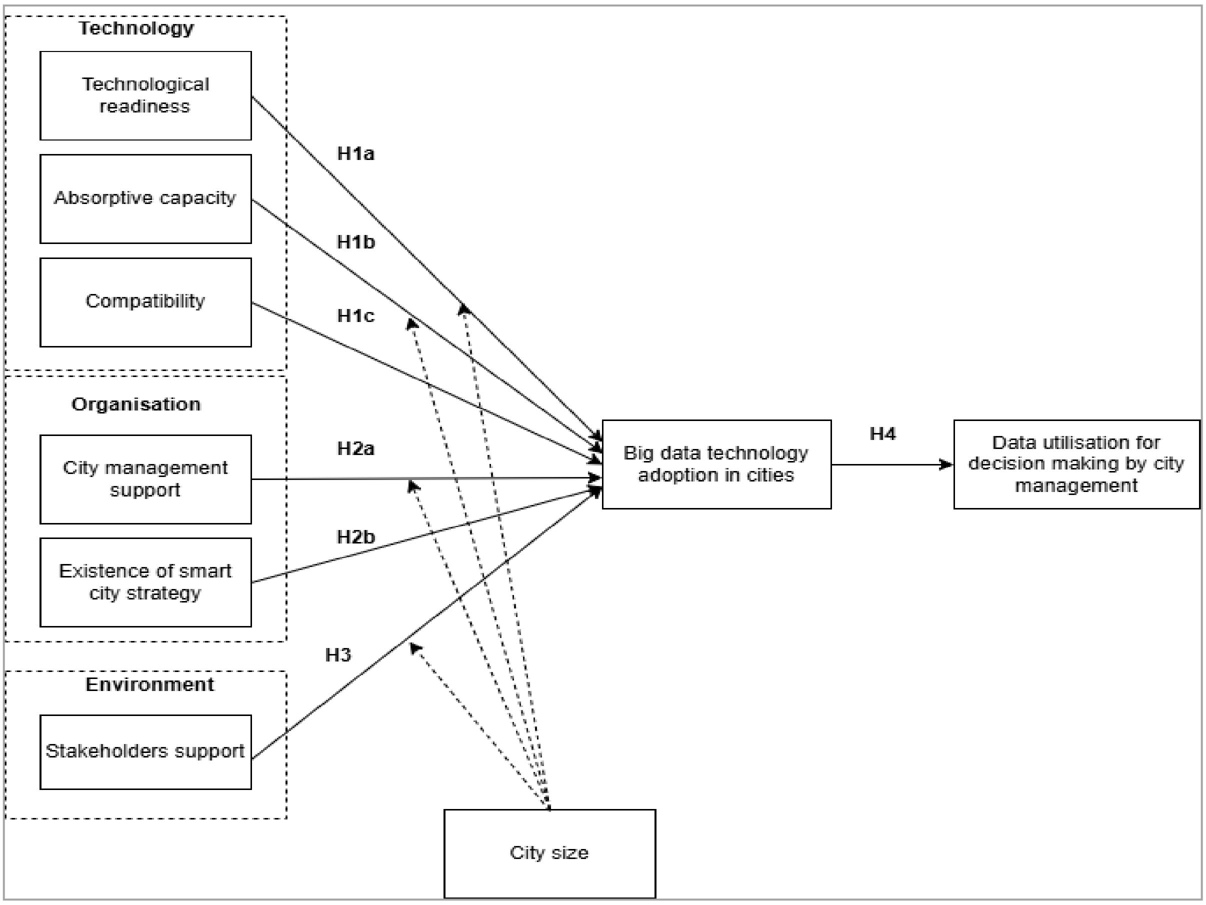

Figure 1. Research model of big data technology adoption in cities.

METHODOLOGY

POPULATION AND RESEARCH SAMPLE

In order to assess the theoretical constructs, a survey was conducted using a questionnaire. The target population of this study are cities in the European Union member states. The study encompassed cities with a population of over 40 000. At the moment of this research, there were 1481 cities across EU member states that met this size criteria. This ensured the inclusion of relatively smaller cities, which, in comparison to their larger cities, can more easily implement pilot projects and introduce technology initiatives. For the purpose of the study, a database of European Union cities was created according to data available on the websites of statistical offices. The target respondents to this research were members of city top management familiar with big data and smart city topics, including city mayors, managers of IT departments, chief information officers, or leaders of smart city initiatives. The plan was to conduct the survey in all of the cities with available contacts. Therefore, a questionnaire was sent to 946 cities that met city size criteria. For one city, only one response was possible.

DATA SOURCES

This study used primary and secondary data. Primary data were collected using a multilingual structured questionnaire. The items used in the questionnaire were created by the author or modifited to suit the big data technology context based on existing literature. The questionnaire was used to measure the determinants described in the previous chapter. According to the proposed research model, each determinant (construct) was measured using items on a Likert scale ranging from one to seven. Secondary data for the purpose of this study were gathered for City size as a moderator variable. City size was measured using secondary data sources on city population measured in number of inhabitants and the size of the urban area measured in square kilometres. The data were collected through official city websites, statistical offices, and the Eurostat urban database for the year in which the last census was held in each country.

RESEARCH INSTRUMENT

In order to assess the theoretical constructs and test the hypotheses, primary research was conducted using a structured questionnaire survey method. The questionnaire measured the following constructs: (1) Technological readiness, (2) Absorptive capacity, (3) Compatibility, (4) City management support, (5) Existence of smart city strategy, (6) Stakeholders support, (7) BDTA in cities, and (8) Data utilization in decision-making. The constructs were measured with the items shown in Table 1.

Table 1. Research instrument (continued on pp.742-743).

Section A – Technological Factors
Measure is *Likert scale: 1 – strongly disagree; 2 – mostly disagree; 3 – somewhat disagree; 4 – neutral (neither agree or disagree); 5 – somewhat agree; 6 – mostly agree; 7 – strongly agree; X – do not know or cannot estimate.*
Technological Readiness – TR
TR1 The city hires personnel with analytical skills that include data mining expertise and knowledge of methodologies for data processing, data integration, and data management. **TR2** The city hires personnel with the competencies in informatics and abilities to use programming languages, technologies, software tools such as Excel, SAS, SPSS, R , Java, visualization tools, SQL databases, NoSQL databases , Hadoop , and so on. **TR3** The city has physical ICT infrastructure which can be upgraded with current data technologies such as big data technologies, as well as related technologies such as the Internet of Things or cloud technologies. **TR4** The city management is aware of the costs and benefits of the investment in recent technologies. **TR5** The city management has financial resources to upgrade the city with recent technologies. **TR6** Overall, the city/town has knowledge, physical ICT infrastructure and financial resources needed to seamlessly adopt new technology.
Absorption Capacity - AC
AC1 City employees are motivated to use available information sources regarding current services city provides. **AC2** City departments are aware of the importance of the cross-departmental support for problem solving. **AC3** There is a cross-departmental communication of ideas and concepts, and quick information flow between city departments. **AC4** City employees absorb new knowledge, link existing knowledge with new insights, apply it in their practical work and make it available for future use. **AC5** In our city, there is an awareness of new technologies which are regularly reconsidered and adapted to make city services more effective. **AC6** Overall, the city recognizes the value of new, external information and knowledge, assimilates it, and applies it for different purposes. *Source: according to [54]*
Compatibility - COM
COM1 Big data technology is compatible with the existing technological infrastructure and can be seamlessly incorporated into the existing technological infrastructure of the city. **COM2** Changes introduced by the development of big data technologies are consistent with existing practices and experiences of the city with implementations of similar technologies. **COM3** Changes and benefits that the implementation of big data technologies brings are consistent with the needs of the city. **COM4** Big data technologies are compatible with the existing infrastructure, practices and needs of the city. *Source: according to [55, 56]*

Table 2. Research instrument (continuation from p.741, continued on p.743).

Section B – Organisational Factors
Measure *is Likert scale: 1 – strongly disagree; 2 – mostly disagree; 3 – somewhat disagree; 4 – neutral (neither agree or disagree); 5 – somewhat agree; 6 – mostly agree; 7 – strongly agree; X – do not know or cannot estimate.*
City Management Support - CMS
CMS1 Municipalities, city council and city administration provide strong leadership and are dedicated in the processes of technology adoption in the city. **CMS2** Municipalities, city council and city administration promote technology initiatives, determine implementation steps and select specific technological solutions to be implemented. **CMS3** Municipalities, city council and city administration are ready to accept the financial and organizational risks relating to the adoption of technology. **CMS4** Municipalities, city council and city administration engage citizens in technological innovation incentives and communicate benefits of technology. **CMS5** Overall, municipalities, city council, and city administration support technological initiatives that aim to enhance the city. *Izvor: according to[44, 57]*
Existence of Smart City Strategy - SCS
SCS1 Based on the challenges regarding city infrastructure and city needs, the city management actively develops strategies aimed at improvement of more efficient city resources management. **SCS2** The city strategy targets the efficiency and technological advancements of the city's hard infrastructure. **SCS3** The city strategy targets efficiency and technological advancements of the city's soft infrastructure. **SCS4** The city strategy is aligned with the country's/European Union's goals and the strategy related to city technology development. **SCS5** The city strategy is more focused on the transformation of a specific economic sector than on specific geographically determined districts, clusters, areas or even neighbors of the city. **SCS6** The city strategy is more focused on the local level than the entire country or national level. **SCS7** Overall, the city strategy promotes smart cities initiatives, and encourages efficient resources management and development of the city. *Source: according to description of characteristics of smart city strategy by [17]*
Section C – Environmental Factors
Measure *is Likert scale: 1 – strongly disagree; 2 – mostly disagree; 3 – somewhat disagree; 4 – neutral (neither agree or disagree); 5 – somewhat agree; 6 – mostly agree; 7 – strongly agree; X – do not know or cannot estimate*
Stakeholders Support – SS
<u>Tehnology enablers – TE</u> **SSTE1** ICT companies research, innovate and provide the standard, compatible, scalable ICT infrastructure and technical solutions that support and integrate city services. **SSTE2** City services companies, in some cases, create a new service that covers a new or an uncovered city need. **SSTE3** Utility providers are responsible for the deployment of some smart city features. **SSTE4** There are stakeholders which enable technology and technical solutions related to technology adoption in the city. <u>Technology drivers - TD</u> **SSTD1** National and regional governments promote and manage technology adoption initiatives as well as define policies and legal frameworks for such initiatives. **SSTD2** National and regional governments facilitate ICT development and competition. **SSTD3** Citizens and citizen organizations support technology adoption initiatives. **SSTD4** There are stakeholders which are interested in technology adoption initiatives in the city. <u>Framework enablers - FE</u> **SSFE1** Academia, research organizations and specialized bodies drive and support the research and innovation in fields related to technology adoption initiatives. **SSFE2** International, regional, multilateral organizations and industry associations provide funds and make promotion programs to drive technology adoption initiatives.

Table 3. Research instrument (continuation from pp.741-742).

SSFE3 Standardization bodies lay the framework and define standards for technology adoption and smart cities. **SSFE4** There are institutionalized stakeholders which support technology adoption to enhance the city. **SS0** Overall, different stakeholders support technology adoption to enhance the city. *Source: according to [44]*
Big Data Technology Adoption in Cities – BDTA
BDTA1 The city collects a large amount of structured, semi-structured and unstructured data from various sources. **BDTA3** The city has adopted big data infrastructure or platforms needed for knowledge discovery in big data. **BDTA5** The city has adopted big data technologies to enhance city's hard infrastructure. **BDTA7** The city has adopted big data technologies to enhance city's soft infrastructure. **BDTA9** Overall, the city has adopted big data technologies to enhance city's services. *Source: Author's definition*
Data Utilization in Decision Making - DU
DU1 We search for relevant data concerning city services in order to improve city services. **DU2** We use data to identify problems and possible solutions regarding city services. **DU3** We use data to continuously monitor execution of city services. **DU4** We use data to do research to examine the impact of city management/council decisions on the city. **DU5** Overall, we utilize data to support decision making practices in decision making bodies. *Source: Author's definition*
City Size & Respondents Characteristics
City Size - CS
Secondary data (according to reports published at web sites of statistical offices of EU28 countries) **CS1**: City population – number of inhabitants **CS2**: City area – km^2 *Source: according to [47]*
Demographic characteristics of respondents
DCR1 What is the highest level of education you have completed? *high school graduate, bachelor's degree, master's degree, doctoral degree* **DCR2** What is your position in your current job? **DCR3** How long have you worked in your current position? **DCR4** What department do you work in?

Table 2 shows important notes regarding constructs' items in the research model. Some modifications have been made regarding items in the questionnaire. In order to improve the clarity of the questions to the respondents, some items were divided into two or more statements. While preparing data for the analysis, average values for these statements were calculated to get the value of the items that were divided. Such values were then used to assess the proposed research model. Furthermore, global items were added to the questionnaire. In the preparation phase, the global item serves as an aid in detecting inconsistent response patterns. If the difference between the score of the global item and the average score of all other items of a particular construct is significant, we can speak of response inconsistency. The score of the global item also serves as a guideline in resolving the problem of missing values. When assessing the measurement model, global items are used to assess the convergent validity of formative constructs.The questionnaire also included additional questions related to the city's strategy and the intention to adopt big data technologies in the city. The aim of adding additional questions is to collect data for additional analyses and future research. Also, the questionnaire added questions about the demographic characteristics of the respondents.In order to better understand the questionnaire by the respondents, the Croatian version of the questionnaire was translated into English, German and French.

Table 4. Adjustements regarding research instrument and research model.

Construct	Item	Changes
TR	TR4	divided into questions TR4 and TR5; TR4_5 calculated as its average value
	TR6	added global item
AC	AC2	divided into questions AC2 and AC3; AC2_3 calculated as its average value
	AC6	added global item
CMS	PMG5	added global item
SCS	SCS7	added global item
SS	SS1	divided into questions SSTE1, SSTE2 & SSTE3; SS1 calculated as its average value
	SS2	divided into questions SSTD1 & SSTD2; SS2 calculated as its average value
	SS4	divided into questions SSFE1, SSFE2 & SSFE3; SS3 calculated as its average value
	SSTE4, SSTD4, SSFE4,SS-0	added global items
BDTA	BDTA9	added global item
DU	DU5	added global item

ASSESSMENT OF THE PROPOSED RESEARCH MODEL

The Partial Least Squares Structural Equation Modelling (PLS-SEM) method was used with SmartPLS software to test the proposed research model. SEM-PLS was used in various studies that assessed technology adoption models based on the TOE framework. Some of the reasons for using it are related to research risk, considering that PLS-SEM analysis can be done with data that is not normally distributed, such as variables measured with different measurement scales, data collected from smaller samples, and moderator and mediator analysis.

The advantage of the PLS-SEM method is that it allows the simultaneous assessment of both reflective and formative measurement models. The assessment of reflective and formative measurement models is carried out using different criteria. If there are problems in the model related to the measurement model, it is necessary to choose a procedure for solving these problems. Solving the measurement model problems is particularly important because the assessment of the structural model is allowed only when there are no problems in the measurement model. The structural model consists of the relationships between the constructs in the model. The relationships between the constructs are also the research hypotheses.

The assessment of the proposed PLS-SEM model was carried out with the support of specialised SmartPLS software carried. The assessment had three phases as follows.

Phase 1: Assessment of Measurement Model

The evaluation of a reflective measurement model includes an assessment of the internal consistency, convergent validity, and discriminant validity of the constructs. As part of evaluating the formative measurement model, the convergent validity of the construct, the collinearity between items, and the significance and relevance of outer weights are all looked at.

Phase 2: Assesment of Structural Model

Once the measurement model is reliable and valid, the structural model results was assessed. In the assessment of the structural model it is necessary to assess the model [58]: i) for the collinearity problem; ii) the significance and relevance of relationships between constructs; iii) coefficients of determination; iv) the size of the f2 effect; v) the predictive relevance of the q2 effect; and vi) the model fit.

Phase 3: Moderator Analysis

Moderator analysis was used to test the influence of City size – CS on direct relationships between Absorption capacity – AK, Technological readiness – TS, City management support – PMG and Stakeholders support – PG, and Big data technology adoption in cities – TA. City size was measured by the indicators Number of inhabitants and City area measured in km².This part describes the results of reflective measurement model assessment, formative measurement model assessment, structural model assessment and moderator analysis after solving the measurement model problem.

RESULTS

The assessment of the proposed PLS-SEM model was carried out using the specialised SmartPLS software. In the final analysis, 67 cities were included in the analysis although data being collected for a total of 94 cities. This decision is based on the requirements of data consistency and quality. Cities with incomplete or unreliable data, as well as those whose data failed to meet the methodological requirements of the research, were omitted from the analysis. This methodology ensures the validity and reliability of the findings while reducing the likelihood of bias and incorrect conclusions.

STEP 1. RESULTS OF MEASUREMENT MODEL ASSESEMENT

Based on the indicators in Table 3, it can be concluded that the reliability and validity of all mentioned constructs are satisfactory. For all reflectively measured constructs, the values of Cronbach's alpha and composite reliability indicators are within the acceptable ranges. Also, the AVE indicator value for all of them is greater than 0,500. Futhermore, the table shows the outer loading values for all items used in the proposed model. All items have an external loading value greater than 0,700. Item TR3 was removed from the construct TS since it has an external loading less than 0,700. Item TS3 indicates the respondents' agreement with the statement "the city has a physical ICT infrastructure that can be upgraded with big data technologies". However, this aspect of technological readiness is already included, in some extent, in the compatibility of the city's technological infrastructure, so it was excluded from the model. Furthermore, according to the Fornell-Larcker criterion (Table 4), it can be concluded that the model does not have the problem with discriminant validity. Discriminant validity was checked using the HTMT indicator values and the confidence intervals of those values, Table 5. This shows that the model does not have a problem with discriminant validity.

Figure 2 shows the results of the convergent validity analysis for the formative constructs Absorptive capacity – AC and Big data technology adoption in cities – TA. The values of the path coefficients and the coefficients of determination show that there is no convergent validity problem in the model.

Table 6 shows the values of the VIF criteria for the indicators of all constructs. In the initial assessment of the model, there was a problem of collinearity for the DU2 indicator and a high correlation between the DU2 and DU3 indicators. DU2 describes the extent to which the city uses data to identify problems and possible solutions related to city services, and DU3 describes the extent to which the city uses data to continuously monitor the performance of city services. For this reason, the DU2 and DU3 indicators were combined in order to solve the problem of collinearity and enable valid conclusions about whether the adoption of big data technology in cities affects management's use of data in decision-making. The problem of collinearity is still present for the DU2_3 indicator; however, its level has been reduced, and, due to its substantive and conceptual importance, it remains in the model.

Table 5. Reliability, validity and outer loadings of the reflective constructs after solving the measurement model problem. Source: author's work, supported by SmartPLS software.

Construct	Cronbach's Alpha	Composite Reliablity	Average Variance Extracted (AVE)	Items	Outer loadings
COM	0,887	0,922	0,747	COM1	0,825
				COM2	0,910
				COM3	0,776
				COM4	0,937
SS	0,801	0,869	0,625	SS1	0,763
				SS2	0,747
				SS3	0,848
				SS4	0,800
DU	0,924	0,952	0,868	DU1	0,911
				DU2_3	0,960
				DU4	0,924
SMS	0,913	0,939	0,794	CMS1	0,882
				CMS2	0,938
				CMS3	0,880
				CMS4	0,863
SCS	0,908	0,935	0,784	SCS1	0,879
				SCS2	0,887
				SCS3	0,890
				SCS4	0,885
TR	0,810	0,888	0,726	TR1	0,884
				TR2	0,879
				TR4_5	0,790

Table 6. Fornell-Larcker criterium for the reflective constructs after solving the measurement model problem.

Fornell-Larcker	COM	SS	DU	CMS	SCS	TR
COM	0,864					
SS	0,188	0,790				
DU	0,356	0,600	0,932			
CMS	0,427	0,675	0,736	0,891		
SCS	0,389	0,620	0,741	0,774	0,885	
TR	0,565	0,378	0,489	0,597	0,596	0,852
BDTA	0,314	0,723	0,761	0,784	0,786	0,631

Table 7. Confidence intervals of HTMT indicator after solving the measurement model problem.

HTMT	HTMT value	Arithm. Average HTMT - sample	Confidence Intervals, %		Confidence Interval of HTMT does not include 1
			5,00	95,00	
SS → COM	0,245	0,313	0,137	0,590	yes
DU → COM	0,374	0,391	0,177	0,620	yes
DU → SS	0,685	0,682	0,500	0,835	yes
CMS → COM	0,463	0,472	0,254	0,686	yes
CMS → SS	0,778	0,781	0,666	0,884	yes
CMS → DU	0,814	0,812	0,708	0,898	yes
SCS → COM	0,417	0,431	0,192	0,669	yes
SCS → SS	0,722	0,720	0,564	0,853	yes
SCS → DU	0,810	0,807	0,708	0,888	yes
SCS → CMS	0,849	0,851	0,771	0,921	yes
TR → COM	0,662	0,662	0,487	0,823	yes
TR → SS	0,459	0,470	0,256	0,680	yes
TR → DU	0,564	0,564	0,371	0,733	yes
TR → CMS	0,692	0,690	0,528	0,829	yes
TR → SCS	0,691	0,691	0,530	0,834	yes

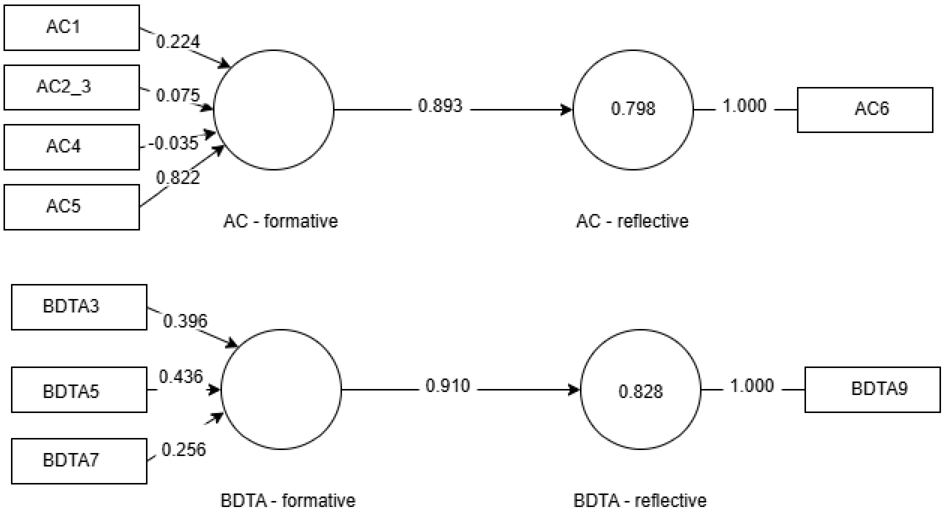

Figure 2. Analysis of the convergent validity of the constructs Absorptive capacity and Big data technology adoption after solving the measurement model problem.

Table 8. VIF values for items of all constructs after solving the measurement model problem.

Item	VIF value	Item	VIF value
AC1	2,706	**CMS1**	2,986
AC2_3	3,050	**CMS2**	4,646
AC4	3,168	**CMS3**	2,709
AC5	2,256	**CMS4**	2,403
COM1	2,203	**SCS1**	2,698
COM2	3,126	**SCS2**	2,873
COM3	2,015	**SCS3**	2,782
COM4	3,749	**SCS4**	2,653
SS1	1,415	**TR1**	2,186
SS2	1,660	**TR2**	2,221
SS3	1,939	**TR4_5**	1,459
SS4	1,993	**TA3**	2,518
DU1	3,251	**TA5**	3,431
DU2_3	5,341	**TA7**	3,357
DU4	3,549		

The external weight of the BDTA1 indicator is not significant, and the external loading of the item is less than the minimum required value of 0,500. This means that the item does not contribute to the construct of BDTA. The BDTA1 item describes the degree to which a city collects large amounts of structured, semistructured, and unstructured data from various sources. However, it was shown that it is not significant either absolutely or relatively for the assessment of the extent to which a city adopts big data technologies in cities. It can be concluded that collecting large amounts of data does not necessarily mean that a city adopts big data technologies. For this reason, a decision was previously made to remove it from the BDTA construct.

Table 7 shows the results of the bootstrapping procedure related to the significance of the external weights of the constructs Absorptive Capacity – AC and Big data technology adoption in cities – BDTA after removing the BDTA1 item. The other items of the construct BDTA are absolutely and relatively important for the construct. The external weights items – AC1 and AC2_3 of the Absorption Capacity construct are not significant. However, they are absolutely important, so they remain in the model.

Table 9. Significance and importance of formative items after solving the measurement model problem.

Item → Construct	Outer weight	p-value	Outer weight significance	Outer loading	Importance of an item	Decision to keep it
AC1 → AC	0,005	0,979	no	0,754	absolute	yes
AC2_3 → AC	-0,026	0,928	no	0,797	absolute	yes
AC4 → AC	0,644	0,015	yes	0,931	absolute/relative	yes
AC5 → AC	0,482	0,007	yes	0,869	absolute/relative	yes
TA3 → BDTA	0,517	0,000	yes	0,939	absolute/relative	yes
TA5 → BDTA	0,269	0,034	yes	0,899	absolute/relative	yes
TA7 → BDTA	0,302	0,016	yes	0,902	absolute/relative	yes

STEP 2. RESULTS OF STRUCTURAL MODEL ASSESMENT

The collinearity assessment is carried out based on the internal VIF values (Table 8). The results show that the structural model does not identify a critical level of collinearity among the proposed factors for the adoption of big data technologies in urban areas. Therefore, it is possible to draw valid conclusions below about the significance of the impact of Absorptive capacity, Compatibility, Stakeholders support, City management support, Existence of smart cty strategy and Technological readiness on BDTA in cities.

Table 10. VIF values between constructs.

Conctruct	DU	TA
AC		2,204
COM		1,556
SS		2,004
CMS		3,470
SCS		2,869
TR		2,202
BDTA	1,000	

Results of testing the significance of the path coefficients of the structural model are presented in Table 9. The significance the path coefficents tells about the significance of proposed relationship in the research model. According to the results, Absorptive capacity positively influences big data technology adoption in cities (AC → BDTA, path coefficient 0,216, p-value 0,069), Stakeholder support positively influences BDTA (SS → BDTA, path coefficient 0,271, p-value 0,000), City management support positively influences BDTA (CMS → TA, path coefficient 0,184, p-value 0,085), Existence of smart city strategy positively influences BDTA (SCS → BDTA, path coefficient 0,279, p-value 0,012) and Technological readiness positively influencesBDTA (TR → BDTA, path coefficient 0,191, p-value 0,052) at 10% confidence level. Finally, it has been comfirmed that BDTA influences data-utilisation in decision-making by city management (BDTA → DU, path coefficient 0,761, p-value 0,000).

Table 11. Significance of path coefficients in the structural model.

Connection	Path coeff.	Sample Mean	Stand. dev.	t-value	Error	Confidence intervals, %		p-value	Significance 10% confidence
						5,00	95,00		
AC → BDTA	0,216	0,233	0,119	1,820	0,017	0,012	0,390	0,069	yes
COM → BDTA	-0,131	-0,116	0,087	1,507	0,015	-0,299	-0,016	0,132	no
SS → BDTA	0,271	0,280	0,076	3,543	0,009	0,132	0,383	0,000	yes
CMS → BDTA	0,184	0,172	0,107	1,722	-0,012	0,007	0,349	0,085	yes
SCS → BDTA	0,279	0,267	0,111	2,516	-0,011	0,098	0,461	0,012	yes
TR → BDTA	0,191	0,193	0,098	1,947	0,002	0,015	0,339	0,052	yes
TA → DU	0,761	0,767	0,051	14,789	0,006	0,652	0,830	0,000	yes

Based on the values of the coefficient of determination and the adjusted coefficient of determination (Table 10) of the structural model, the predictive power of the model is at a satisfactory level. That means that proposed factors explain a satisfactory amount of the variance of BDTA. It was also shown that BDTA explains a medium amount of the variance of Data utilisation in decision-making by city management.

Table 12. Coefficient of determination and Adjusted coefficient of determination of the structural model.

Construct	Coeff. of Determination	Adjusted Coeff. of Determination
DU	0,579	0,573
TA	0,791	0,770

Given the significance of the path coefficients, the level of the effect of individual constructs on endogenous constructs (Table 11) is expected. BDTA has a large effect on Data utilisation in decision-making by city management – DU. Stakeholder support – SS, Existence of smart city strategy – SCS and Absorptive capacity – AC have a medium to small effect on BDTA.

Table 13. Effect size – f^2.

Construct	DU	BDBTA	Interpretation
AC		0,101	medium effect
COM		0,052	medium to small effect
SS		0,175	medium effect
CMS		0,047	small effect
SCS		0,130	medium effect
TR		0,079	medium to small effect
BDTA	1,377		big effect

Based on the results of the blindfolding procedure shown in Table 12, the constructs Existence of smart city strategy – SCS (q^2 = 0,074), Stakeholder support – SS (q^2 = 0,055), Absorption capacity – AC (q^2 = 0,034) and City management support (q^2 = 0,012) influence the predictive power of the model, i.e., they are important for predicting the BDTA.

Table 14. Predictive power of the model and predictive relevance of exogenous constructs.

	DU	BDTA	Effect size - q^2	Interpretation
SSO	268,000	201,000	-	-
SSE	108,356	83,838	-	-
q^2 (= 1 –SSE/SSO)	0,461	0,583	-	-
q^2 excluding TS	0,461	0,580	0,007	No effect
q^2 excluding KM	0,461	0,582	0,002	No effect
q^2 excluding AK	0,461	0,569	0,034	Small effect
q^2 excluding SPG	0,461	0,552	0,074	Small effect
q^2 excluding PMG	0,461	0,578	0,012	Small effect
q^2 excluding PD	0,459	0,560	0,055	Small effect

MODEL FIT

The residual value of the standardised root mean square (SRMR) criterion for the estimated model (Table 13) is less than 0,10, which indicates a satisfactory and good model fit. Table 14 contains the original values of the discrepancy measures (d_ULS, d_G1, and d_G2) and their confidence intervals. The original value of the d_ULS indicator for the estimated model is greater than the upper limits of the confidence interval, which indicates a satisfactory model fit. Original values of d_G1 and d_G2 are lower than the upper limit of the confidence interval, which means a satisfactory fit to the data. Therefore, the results indicate that the difference between the correlation matrix implied by the model and the empirical correlation matrix is so small that it can be attributed to sampling error.

Table 15. SRMR value.

SRMR	Original value	Sample mean	Stand.dev.	t-value	p-value
estimated model	0,081	0,066	0,010	7,536	0,000

Table 16. Values and confidence intervals of discrepancy measures for the model.

Dicrepany measures	Original value	Sample mean	Confidence interval, %	
			5	95
d_ULS	2,878	1,935	1,170	3,008
d_G1	2,864	3,661	2,329	5,340

STEP 3. RESULTS OF MODERATOR ANALYSIS

The moderator analysis tested the influence of the third variable – City Size – CS on the direct relationship between the constructs Absorptive capacity – AC, Technological readiness – TR, City management support – CMS and Stakeholder support – SS on the construct Big data technology adoption in cities – BDTA. Table xx shows the results of the moderator analysis. For example, the relationship CS → AC-BDTA → BDTA is read as follows: City size has a significant impact on the relationship between Absorptive capacity and BDTA.

P-values indicate that City size does not have a significant impact on the relationships between the exogenous constructs – AC, TR, CMS and SS – on the endogenous construct TA. Thus, parts of the research hypotheses related to the moderator influence are rejected. More precisely, these are research hypotheses: $\mathbf{H_{1a}}$, $\mathbf{H_{1b}}$, $\mathbf{H_{2a}}$, and $\mathbf{H_3}$. Rejecting parts of Hypotheses $\mathbf{H_{1a}}$, $\mathbf{H_{1b}}$, $\mathbf{H_{2a}}$, and $\mathbf{H_3}$ does not reject the direct or main influences of the exogenous constructs AC, TR, CMS, and SS on the endogenous construct BDTA.

Table 17. Results of a moderator analysis of the proposed relationships.

Moderator connection	Original value of moderator influence	Sample mean	Stand. dev.	t-value	p-value
CS → AC-BDTA → BDTA	0,058	0,073	0,112	0,522	0,602
CS → TR-BDTA → BDTA	0,099	0,083	0,117	0,847	0,397
CS → CMS-BDTA → BDTA	0,048	0,043	0,105	0,455	0,649
CS → SS-BDTA → BDTA	0,028	0,020	0,073	0,382	0,702

DISCUSSION

Based on the results of the model assessment, conclusions can be drawn about the acceptance or rejection of the hypotheses of this research. A summary of the assessment of the structural relationships of the model is presented in Table 16.

Table 18. Summary of structural model assesment – hypotheses.

Context	Hypothesis	Supported main/direct influence (10% confidence)	Moderator influence supported (10% confidence)	Hypothese supported (10% confidence)
T	$\mathbf{H_1}$	**partially**	**-**	**partially**
	H_{1a}	yes	no	**partially**
	H_{1b}	yes	no	**partially**
	H_{1c}	no	-	**no**
O	$\mathbf{H_2}$	**yes**	**-**	**yes**
	H_{2a}	yes	no	**partially**
	H_{2b}	yes	-	**yes**
E	$\mathbf{H_3}$	**yes**	**no**	**partially**
-	$\mathbf{H_4}$	**yes**	**-**	**yes**

In this research, technological readiness, absorptive capacity, city management support, the existence of smart city strategy, and stakeholder support were identified as factors that directly influence big data technology adoption in cities (BDTA). It was also shown that BDTA in cities directly influences data utilisation in city management decision-making. The moderating effect of city size on the relationship between technological readiness, absorptive capacity, and city management support with BDTA in cities was not supported. However, further research is needed to explore the potential moderating effects of other variables on the relationship between these factors and BDTA in cities. Additionally, investigating the influence of cultural factors on the adoption of big data technology in cities could provide valuable insights for policymakers and city managers.

The research findings indicate that a city's technological readiness positively affects the adoption of big data technology (hypothesis $\mathbf{H_{1a}}$). This is in line with previous research [32-34, 59]. The competencies of human resources within a city are crucial for the adoption of big data technology, particularly analytical abilities, IT competence, and expertise in programming languages, all of which are essential to the usage of big data technology. A city's physical information and communication infrastructure will facilitate the adoption of big data technologies if it can be enhanced with such technologies. Moreover, cities are more likely to adopt big data technology if municipal management recognises the associated costs and advantages, and if the city owns substantial financial resources. The demonstrated correlation between technological readiness and the adoption of big data technologies in cities remains unaffected by city size. This suggests that the city's size has no impact on the influence of technological readiness on the adoption of big data technologies in cities. Hypothesis $\mathbf{H_{1a}}$ is partially accepted, as the direct impact of technological readiness on the adoption of big data technology in urban areas has been proved.

The absorptive capacity of a city as an organisation positively BDTA in cities (hypothesis $\mathbf{H_{1b}}$). In the domain of big data technology, the higher the motivation of city employees to utilise diverse big data sources relevant to city services, the more relevant the influence of absorptive capacity on the adoption of big data technologies. Additionally, greater comprehension among city departments regarding the importance of collaboration and quick interaction concerning various ideas and concepts, such as the application of big data for city needs, will result in a more positive influence on the adoption of big data technologies. A supportive atmosphere among city employees that promotes learning and the integration of new knowledge with existing practices significantly increases the probability of BDTA to enhance departmental operations. City size does not affect the proven influence of the city's absorptive capacity on having a positive influence on BDTA in cities. The characteristics associated with city size have no effect on the influence of the city's absorptive capacity on BDTA. Hypothesis $\mathbf{H_{1b}}$ is partially accepted as the direct effect of absorptive capacity on the adoption of big data technology in cities has been confirmed.

The influence of compatibility on BDTA in urban areas remains unproven. This rejects the hypothesis $\mathbf{H_{1c}}$. Likewise, [35] demonstrated that compatibility was not significant for BDTA. Research indicates that technological readiness and absorptive capacity directly influence cities' BDTA. Nonetheless, it has not been confirmed that compatibility makes an influence.

The findings of the research assessment indicate that city management support positively impacts the adoption of big data technology in cities (hypothesis $\mathbf{H_{2a}}$). City management has been recognised as an important driver of technological initiatives in the context of cities. City management support was also confirmed as important drives of technology adoption in [41-43]. City management must be dedicated to the processes of technological integration within the city. This requires providing dynamic leadership, engaging with citizens, motivating participation, and accepting the risks associated with the adoption of technologies in cities.

Research indicates that city size does not affect the established relationship between city management support and the adoption of big data technology; that is, the characteristics associated with city size do not enhance or diminish the effect of technological readiness on BDTA in cities. Hypothesis $\mathbf{H_{2a}}$ is partially accepted, as the direct effect of absorptive capacity on BDTA in cities has been confirmed.

The existence of a smart city strategy positively impacts BDTA in cities (hypothesis $\mathbf{H_{2b}}$). The smart city strategy that advocates for initiatives aimed at improving the efficiency of city resource management and development is going to directly influence big data and other information and communication technologies that facilitate the delivery of the smart strategy. The proactive approach of urban management in recognising city challenges and needs, the development of active strategies, and the clear definition of which aspects of city infrastructure require technological advancement enable the adoption of big data technology in cities. Considering that the main objective of the European Union is the technological advancement of urban areas, cities that align their strategies with the European Union's framework are more likely to adopt big data technology. Consequently, hypothesis $\mathbf{H_{2a}}$ is accepted. Hypothesis $\mathbf{H_2}$ is accepted as the direct effect of city management support and the existence of a smart city strategy on BDTA in cities has been confirmed.

The research findings indicate that stakeholder support positively influences BDTA in cities (hypothesis $\mathbf{H_3}$). The greater support that comes from individual groups of stakeholders for technological projects in a city, the more successful BDTA will be. Support from stakeholders for technology adoption was also confirmed to be significant in other context such as in [22, 25, 45]. City management and supporters of technological initiatives should actively encourage citizen involvement and support for these initiatives. The success of BDTA will increase with the willingness of important national, regional, and multilateral organisations, in addition to industry associations, to allocate financial resources and push for such initiatives. Cities have a tendency to adopt standardised technologies; thus, increased standardisation initiatives by standardisation organisations in the area of smart cities and big data technology will positively impact the adoption of big data technology. The size of a city has no effect on the relationship between stakeholder support and the adoption of big data technology; more particularly, city size does not enhance or diminish the impact of technological readiness on BDTA in cities. Hypothesis $\mathbf{H_3}$ is partially accepted, as the direct impact of stakeholder support on the adoption of big data technology in urban areas has been confirmed.

BDTA in urban areas positively impacts data utilisation in decision-making of city management (hypothesis $\mathbf{H_4}$). Increased BDTA to enhance a city's hard or soft infrastructure and services corresponds with a higher probability of utilising collected data in decision-making. The analysis of big data and the insights gained will serve as the foundation for informed decision-making and the identification of issues and potential challenges concerning city services. Hypothesis $\mathbf{H_4}$ is accepted.

The lower responsiveness of cities represents a limitation of this research, as it may skew the results of the model estimation and the formulation of general conclusions.

RESEARCH IMPLICATION AND CONTRIBUTION

There is a scarcity of research examining the factors that influence BDTA in cities. The literature contains case studies and discussions on individual factors, such as city management or city size, as well as discussions on technology adoption in general or on the adoption of specific technologies in cities. As of the time of this study, no organizational-level theories, including the TOE framework, have been utilised for analysing technology adoption in smart cities or urban settings in general. No research has been conducted examining the adoption of big data technology in cities and organisations within European Union countries. The demand for research on big data is significant due to its critical role in enhancing the competitiveness of cities and organisations within member states and the valuable insights it can reveal. The research has greater relevance because of the European Union's encouragement for information and communication technology in cities.

The results of this research hold importance and serve the research community, managers, and other stakeholders, including companies engaged in ICT activities. This research developed a model of BDTA based on the TOE framework, serving as a theory for organizational-level technology adoption. The resulting model serves as an instrument for stakeholders, highlighting the factors influencing big data technology in cities. The model explains the rationale behind the adoption of big data technologies by certain cities, while comparable competing cities refrain from adopting it. This research expands the domain of technology adoption in cities.

Moreover, for decision-makers involved in urban big data initiatives, the model may act as a valuable source for insights and assist in making informed choices regarding the adoption of technology. The study emphasises the necessity of evaluating the technological, organisational, and environmental contexts prior to launching the implementation of big data solutions. The evaluation of the TOE context is anticipated to facilitate the development of big data adoption strategies, and the findings from this research are expected to enhance the efficacy of BDTA in urban areas. Ultimately, the research is anticipated to provide a framework or basis for further research. Significant factors can be employed to evaluate the adoption of interconnected technologies in cities. Future research could concentrate on establishing a maturity model for the adoption of big data technologies in smart cities. As the adoption of big data technology in urban areas becomes more widespread, it will be intriguing to observe the progress of these initiatives and the implications of adopting big data technologies in cities.

RECOMMENDATIONS FOR PRACTICE AND POLICY

The existence of a smart city strategy proves essential for a city aiming to evolve into a smart city. City management ought to establish a smart city strategy that aligns with the technological development objectives of the entire country and/or the European Union.

The city ought to investigate approaches to enhance its absorption capacity. Hiring professionals with data management expertise would enhance the city's capacity to adopt advanced ICTs including big data technology. A crucial aspect of a city's technological readiness is the management being familiar with the costs and benefits related to technological investments and the available financial resources. City management should continuously expand its knowledge, monitor advancements in information and communication technologies, while assessing how these technologies can benefit the city. Enhanced awareness among city management regarding the costs and benefits of technological investments will increase the city's technological readiness. Management will subsequently participate in the implementation phases and the selection of technological solutions for incorporation into the city's infrastructure.

A crucial step in the adoption of big data technology in urban areas is to secure broader stakeholder support and especially by engaging citizens and citizen initiatives in promoting and participating in technology adoption initiatives. Citizen support is the stakeholder support aspect with the greatest potential for improvements. In the typical city within the European Union, is a minimal degree of citizen engagement in technological initiatives and an inadequate level of communication from city government regarding the positive aspects of technology. As a result, citizen support for smart initiatives in the city is poor. As citizens are vital stakeholders in the advancement of a smart city, the local government must enhance its engagement with citizens to ensure their commitment to the city. In this context, city management and other major stakeholders of smart initiatives in a city must play an important role in citizen engagement.

Moreover, stakeholders who can significantly facilitate the adoption of big data technology in city settings include the academic and research community, which can bolster research and innovation related to technological advancement in cities. Furthermore, diverse national, regional, and multilateral organisations, along with industry associations, can enhance the adoption of big data technologies in urban areas by offering financial resources and establishing promotional programs to initiate technology adoption initiatives. The responsibility of city management in this context is to keep track of funding and collaboration opportunities offered by multiple organisations and to engage in dialogue with them. Standardisation organisations greatly influence the adoption of big data technologies in urban areas by establishing frameworks and defining standards relevant to integration of technology and smart cities. It is necessary for city management and other key stakeholders to be informed of the standards and frameworks that can support the development of a smart city.

The implementation of a smart city development strategy is related to technological readiness, absorptive capacity, city management support, and stakeholders support. A city can enhance its technological readiness and absorptive capacity prior to and during the development of a smart city, considering its current situation and opportunities for improvement to achieve the objectives outlined in a strategy. Nonetheless, the support of stakeholders and the support of city management are crucial at the early stages of smart city development. City management and stakeholders must collaboratively decide the development trajectory and accept responsibility for their respective roles in smart city development.

Cities are advised to focus on specific phases of smart city development, depending upon their current stage of progress. Cities starting their transition to smart city status should prioritise the following: i) vision formulation, ensuring political commitment, and strategic planning. This is crucial to achieve a higher maturity level of a smart city. This also establishes conditions for the adoption of advanced ICTs, including big data technology. Consequently, cities that have not adopted smart city initiatives or are in the early stages of development must establish conducive conditions: the existence of a smart city strategy, support city management, support from all relevant stakeholders, an adequate level of technological readiness and absorptive capacity.

Smart cities that have yet to implement big data technology can concentrate on strategising further initiatives for its adoption in specific sectors of urban infrastructure by monitoring and evaluating the current circumstances and challenges within the city. For these cities, enhancing absorptive capacity and technological readiness for the adoption of big data technology is key.

Cities adopting big data technologies have to assess the effects and adjust action plans accordingly. Experienced smart cities that have effectively implemented diverse smart city initiatives, including the adoption of big data technology, can share their expertise and serve as example models for other cities. Consequently, it is advisable for cities to enhance every aspect of a smart city strategy, increase city management support, and engage stakeholders, particularly during the initial phases of their transition to a smart city. Technological readiness and absorption capacity must be evaluated during these phases and continuously enhanced to achieve the optimal maturity of the smart city. Thus, a city will fulfil the requirements for the adoption of big data technology.

CONCLUSION

The primary objective of this research, to examine the factors that influence BDTA in European Union cities, was achieved through the assessment of the proposed research model. Structural model assessment demonstrated that absorptive capacity, technological readiness, the existence of a smart city strategy, city management support, and stakeholder support positively influence the adoption of big data technology in cities. Moreover, it was demonstrated that city size does not influence the relationships between absorptive capacity, technological readiness, city management support, stakeholder support, and the adoption of big data technology in cities.

The main limitation of this research pertains to its lower responsiveness. The quantity of responses gathered is not proportional with the number of cities over 40 000 inhabitants per country. The responsiveness of German cities was substantially higher compared to that of other countries. A limitation of the research is an absence of translations of the questionnaire into other languages such as Spanish and Italian, which resulted in lower participation from cities in Spain, especially Italy. This can be attributed to the language barrier and the restriction of available email addresses for potential respondents, which only accept correspondence from certified citizen addresses, thereby rejecting all foreign addresses. The lower responsiveness of French cities is due to the isolated nature of city management and the lack of accessible public contact information. Additionally, a constraint of this study is the measurement of City size. A more suitable metric may be the total amount of a city budget. Nonetheless, this data was unattainable for multiple cities. Additional metrics of regulatory and cultural context have been reviewed, including the perception of corruption in cities. Yet, the majority of the secondary data, including perceptions of corruption, were not available at the city level.

Future research should focus on expanding the model adoption to include the construct of intention to adopt big data technology in cities. Moreover, the current model can be enhanced by developing a higher-order construct, Stakeholder Support, which comprises lower-order constructs representing stakeholder groups:NTechnology Providers, Technology Drivers, and Framework Providers. Furthermore, the unutilised data gathered on smart city strategies can be employed to investigate the characteristics and distinctions among European Union cities in relation to their smart city initiatives.

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