Semiconductor Optoelectronics, *Vol. 43 No. 1 (2024), 172-185*
https://bdtgd.cn/

Semiconductor Optoelectronics
ISSN: 1001-5868

A STUDY IN UNDERSTANDING THE IMPACT OF BIG DATA TECHNOLOGY AS A PATH TO SOCIAL TRANSITION THROUGH DEVELOPING SMART CITIES

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Abstract
In recent years, technological innovation has focused on providing various support and sustainable development to communities, nations, and governments. The study investigates the complex link between cutting-edge technology and its ability to catalyze social change. This is done via the prism of smart city development. In our study, we are interested in understanding how cutting-edge technologies provide the conditions for creating smart cities. This research will use an interdisciplinary approach to understand better how technology improvements affect public involvement, municipal infrastructure, and governance. How these changes could affect economic systems, social structures, and environmental sustainability are taken into consideration under this framework. The study endeavors to shed light on the intricate link between technological advancement and societal transformation by conducting an in-depth analysis of case studies and empirical data. Because of this, we will have a more nuanced understanding of the development of smart cities. Using the information that lawmakers, urban planners, and technology developers have obtained from this study, future attempts to harness innovation for the benefit of society may be better tailored. Based on the data, the amount of platform integration has a beneficial influence on the progress of social transformation inside smart cities. The results of the research, which indicate that the adoption of disruptive technology is connected with greater degrees of social transition, illustrate how creative technology may bring about social breakthroughs in settings associated with smart cities.
Keywords: Disruptive technology, Integrated platform, Benefits, Social Transition, Chi-square analysis

1.0 Introduction

The research topic delves into the intricate relationship between cutting-edge technology and its potential to facilitate societal transformation, specifically through the lens of smart city development. (Chen, 2014). The study aims to unravel how these technological advancements enhance urban infrastructure, governance, and citizen engagement by employing a multidisciplinary approach. Additionally, it assesses the implications of such transformations on social structures, economic systems, and environmental sustainability (Console, 2017). Through a rigorous examination of case studies and empirical data, the research intends to

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provide valuable insights into the intricate interplay between technology and social transition, fostering a nuanced understanding of the potential benefits and challenges associated with the development of smart cities. This investigation holds significance in guiding policymakers, urban planners, and technology developers in shaping future initiatives that aim to harness innovation for the betterment of society (Darden, 2019).

The research study aims to delve into the transformative potential of Big Data technology in the context of urban development and societal progress within the Malaysian landscape. By examining the impact of Big Data technology on urban development, the study seeks to identify ways in which it can contribute to sustainable and inclusive growth (Feng, 2014). Additionally, it aims to provide insights into how adopting Big Data can address social challenges and improve the quality of life for Malaysian citizens. As the nation undergoes rapid urbanization and technological advancements, adopting intelligent city initiatives fueled by Big Data has become a pivotal focus (Hashem, 2016). By harnessing the vast amount of data generated in cities, policymakers and urban planners can make informed decisions that lead to more efficient resource allocation and improved service delivery (Mazhar, 2016).
Furthermore, integrating big data technology in urban development can foster greater citizen engagement and participation, empowering communities to shape their cities' futures actively (Luis, 2016). The introduction of this study acknowledges the intricate relationship between technological innovation, urbanization, and the societal fabric, particularly in the Malaysian context. Malaysia's commitment to becoming a high-income nation by leveraging technology and innovation is a backdrop to this investigation (Ren, 2016). By scrutinizing the implementation of Big Data technology in the development of smart cities, the study seeks to unravel the multifaceted impacts on various aspects of Malaysian society, encompassing governance, infrastructure, sustainability, and citizen engagement. Through a comprehensive exploration of the Malaysian experience, the research endeavors to contribute nuanced insights into the role of Big Data technology as a catalyst for social transition, providing valuable knowledge for policymakers, urban planners, and technology practitioners in steering the trajectory of Malaysia's smart city initiatives.

2.0 Review of Literature

One of the most remarkable phenomena that has emerged as a result of the introduction of current high technology is the phenomenon known as the smart city. First and foremost, the rate of its growth is mainly dependent on the rate at which scientific discoveries and technical improvements are made. There is a prevalent movement in today's society towards an information-driven culture, in which many aspects of human life are experiencing substantial breakthroughs and modifications (Lv, 2016). This tendency is based on the fact that information is becoming more prevalent. When seen in the context of the modern period, a smart city may be understood as a collection of elevated ideas and ideals. The most recent trend in urban development is in line with the social movement that is now taking place and contributes to the progressive technological progression of our civilization. The term "smart city" refers to a city that incorporates and analyses a wide range of essential elements linked with urban development and brings together a full range of characteristics often seen in digital cities. The system then implements intelligent solutions tailored to tackle various urban service-related challenges effectively, enhance individuals' overall quality of life, and address other pertinent aspects within the urban environment, as Vimarlund (2014) stated. This occurs after the system has taken into consideration the factors above. A "smart city" is a concept that centers on the thorough utilization of information and communication technologies, integrating relevant components, and developing a more logical and scientifically managed urban environment. This is the fundamental idea behind the term. In addition, it is essential to point out that this specific idea can accelerate the development of a harmonic society, which would allow for achieving the desired objectives of urban tranquility and an improved quality of life for all persons (Feng, 2014).

A robust data processing platform that is capable of successfully facilitating the demands of smart cities while also taking into consideration the environmental repercussions is the goal of this research activity, which aims to develop and create such a platform. Data processing plays a key role in aiding the growth and installation of smart cities. It is possible for the cloud platform that is used inside smart cities to provide various urban application services. This is made possible by the utilization of massive datasets. Services such as integration, analysis, administration, mining, and assistance are included in this category. Each of these services is adapted to meet the specific requirements of urban social services. The accumulation of significant amounts of unstructured data is required to facilitate the development of smart cities. The nature of this data, which is very large, exceeds the capabilities of a traditional relational database to handle it adequately. Within the realm of cloud platforms, it has been determined whether or not it is possible to develop a platform that can efficiently handle and arrange data. In addition, using distributed data architecture and data linear growth functions offered by cloud computing platforms can provide a wider variety of data services for developing smart cities (Zhou, 2020).

The information network has received widespread recognition for its considerable positive influence on society, especially with smart cities. The function that it plays in aiding the growth and expansion of these cities, particularly in building linked information networks, is considered of utmost importance. A connection between various information networks is necessary to accomplish the "deep interconnection" goal. This connection should be established to achieve the following objectives: achieving integration of three-dimensional information resources, coordinating operations between access devices, and enabling interoperable access across information systems (Chen, 2014). The nodes that make up a network system are commonly considered to be of the highest significance, as stated by several academics who have researched the topic. A single broad network includes various separate and self-contained information networks as part of the smart city development idea. This concept delivers significant insights since it includes the integration of these networks. To significantly improve the amount of interaction between urban data, it is necessary to implement the recommended approach. Not only does this technique have the ability to increase the value of network members effectively, but it also helps to accelerate the development of intelligent urban centers. Since it directly influences the growth of smart cities, the effect of network information on the progression of smart cities is an essential issue to consider. Ren (2016) contends that the quality of network information plays a vital role in several aspects of the development of smart cities, including providing scientific advice and inspiration and facilitating overall advancement.

Although intelligent processing is undeniably an essential component, it should be seen as an intermediate step within the larger framework of the information utilization process rather than the process's completion. It has been determined that the development of smart cities requires building a platform that hosts high-level information applications and allows for the exchange of information. Using shared information resources at a higher level makes examining and applying such resources possible, ultimately increasing the efficiency with which the current data is utilized (Lv, 2016). It has been noted that the realization of value-added information favors the development of smart cities, leading to improvements in both the pace and quality of such development. Value-added information is information that has been added to the information. The end effect of this is that the living conditions of the people who live in these smart cities have been improved. The usage of information application platforms is required since the distribution of information needs to be more consistent. According to Luis (2016), these platforms provide a means of facilitating the presentation of smart city features, as well as fostering communication and information sharing, which ultimately leads to the creation of unique models of municipal growth.

According to Hashem (2016), the primary topics covered in the content of public service are smart governance, smart transportation, innovative healthcare, smart manufacturing, safe cities, smart communities, and intelligent public security. Within the framework of the architecture of a smart city powered by big data, the data service layer's primary objective is to make it possible for varied data types to be exchanged fluidly across the whole of the smart city ecosystem. The layer in question incorporates a central repository, more generally known as a sharing library. This repository aims to store various types of intelligent data and allows the smooth interchange of information related to such intelligent data. The core services provided by this layer include a wide variety of services, including data statistics, data analysis, data mining, space-time analysis, data publishing, data collection, and business model services. These services are all included in the primary offers of this layer. In big data-driven intelligent urban design, the front exchange layer is the one that is responsible for sharing data with the exchange and fusion layer, as stated by Kim (2017). On the other hand, the exchange and fusion layer is an essential component that plays a significant part in supporting the fusion and interchange of different data types.

2.1 Research Gap

The current body of research on the influence of Big Data technology as a catalyst for social transformation via the creation of smart cities indicates a growing fascination with the convergence of technology and urban planning (Mazhar, 2016). Nevertheless, more studies must be conducted on the intricate social consequences of this shift. Although contemporary research often examines the technical elements of Big Data applications in smart cities, there needs to be more systematic investigation into these technological breakthroughs' socioeconomic, cultural, and ethical implications (Litres, 2017). There needs to be a more thorough examination of the impact of using Big Data technology on social structures, community dynamics, and inclusiveness in the context of smart city development. It is essential to fill this research vacuum to get a comprehensive knowledge of the effects of technology-driven urban transitions. This will give politicians, city planners, and technologists valuable information about emerging issues and possibilities as smart cities develop.

2.2 Objectives

- To analyze the role of a smart city as an integrated platform to enhance sustainability, equity, and affordability
- To understand the impact of using big data analytics, the Internet of Things (IoT), Artificial intelligence (AI), and advanced data analytics in supporting the implementation of smart city planning
- To analyze the benefits provided to different stakeholders in implementing intelligent cities in the current context.

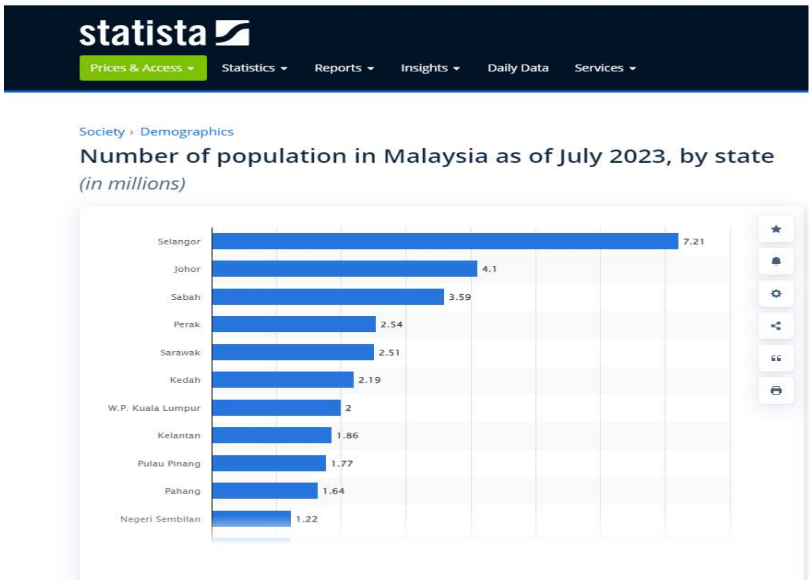
2.3 Need and Scope of the Study

The article addresses a critical and timely subject in contemporary society. The need for such a study arises from the increasing integration of big data technology into urban planning and governance and its potential to catalyze significant social transitions. As cities worldwide grapple with unprecedented population growth and resource constraints, adopting smart technologies facilitated by big data is seen as a viable solution. The scope of this study is multifaceted. Firstly, it aims to comprehensively examine the role of big data technology in developing and functioning smart cities. This involves scrutinizing the various applications of big data, such as data-driven decision-making, predictive analytics, and IoT (Internet of Things) implementations, and their impact on urban infrastructure and services. Additionally, the study seeks to understand the societal implications of this technological transition, exploring how smart city initiatives influence social structures, citizen engagement, and overall community well-being (Console, 2017).

Furthermore, the research delves into the challenges and opportunities of integrating big data technology in urban settings. By analyzing case studies and empirical data, the study intends to provide a nuanced understanding of the potential benefits and drawbacks, ensuring a balanced and informed perspective (Yaqoob, 2015). This research is particularly pertinent as it contributes valuable insights that can guide policymakers, urban planners, and technologists in harnessing big data's transformative power for society's collective betterment.

3.0 Methodology

The study will be conducted using both primary and secondary data. The primary data will be sourced using the questionnaire method, and the data will be collected from the residents, government officials, and other stakeholders. Convenience sampling will be used in choosing the respondents (Allen, 2020). Selangor, situated in Malaysia, boasts a total population of approximately 7.2 million residents. In the context of statistical analysis, a sample size of 139 has been meticulously calculated to represent this vast population, ensuring a margin of error of 5%. This means that the findings derived from the sample can be reasonably generalized to the entire population of Selangor with a confidence level of 95%. The total population of the chosen area is 7200000, as stated by Statista (Statista, 2023). The population proportion used in this calculation is set at 10%, reflecting a presumed estimate of a particular characteristic within the population. The chosen % confidence level of 95% signifies the degree of certainty that the sample's findings accurately reflect the proper population parameter.



(Staista, 2023)

Z = 1.96 ^ 2 x (0.10x0.90) / (0.05)^2

= (3.8416 x 0.09) / 0.025

= 138.29

= 139

3.1 Statistical Tools

The research employs diverse analytical tools to investigate the study's objectives comprehensively. These tools include percentage rate analysis, which enables examining proportional relationships within the data. Correlation analysis explores the statistical association between variables, shedding light on potential patterns and dependencies. Additionally, regression analysis is applied to model and understand the relationships among variables, providing insights into predictive capabilities. Finally, chi-square analysis assesses the independence and significance of relationships within categorical data.

4.0 Analysis

The first step is to present the demographic analysis of the respondents based on the data collected, followed by providing the correlation analysis between the key variables and regression analysis; finally, the researcher tests the hypothesis using a chi-square test.

Table 1: Demographic analysis

Respondents Gender	Frequency	Percent
Male	95	68.30

Female	44	31.70
Respondents Age	**Frequency**	**Percent**
Below 25 Years	15	10.80
26 - 35 Years	106	76.30
36 - 45 Years	18	12.90
Education	**Frequency**	**Percent**
Completed Undergradutaion course	41	29.50
Completed Postgraduation course	98	70.50
Marital Status	**Frequency**	**Percent**
Single	101	72.70
Married	38	27.30
Annual Income	**Frequency**	**Percent**
Above RM 50,000	39	28.10
RM 49,000 - 45000	62	44.60
RM 44000 – 40,000	38	27.30
Experience	**Frequency**	**Percent**
Less than two years	10	7.20
2 - 5 years	87	62.60
5 - 10 years	42	30.20
Total	139	100.00

In terms of gender distribution, the majority of respondents are male, constituting 68.30%, while females make up 31.70% of the sample. 76.30% falls within the age range of 26 to 35 years, indicating a predominant representation from this demographic segment. This concentration might influence the study's generalizability to broader age groups, warranting caution in extrapolating findings to other age cohorts. Furthermore, 10.80% of respondents are below 25 years old, and 12.90% fall within the 36 to 45 years age range. Educational background is a crucial factor in understanding the sample. A notable majority, 70.50%, have completed postgraduate courses, while 29.50% have completed undergraduate courses. This suggests a relatively high level of educational attainment among the respondents, which may influence their perspectives and responses. The marital status distribution indicates that a significant majority of respondents, 72.70%, are single, while 27.30% are married. This information is pertinent, as marital status can impact various aspects of lifestyle, preferences, and decision-making. Examining the annual income distribution provides insights into the economic diversity of the sample. The majority, 44.60%, report an annual income in the range of RM 49,000 - 45000, followed by 28.10% with an income Above RM 50,000, and 27.30% earning in the range of RM 44000 – 40,000. The data on the duration of employment reveals that 62.60% have been employed for 2 to 5 years, indicating a relatively stable and experienced workforce.

4.1 Correlation analysis

One statistical method for determining the strength and direction of a linear relationship between many variables is correlation analysis. A meaningful way to understand how two variables depend on each other is to measure the degree to which their changes correlate. 'R,' short for "correlation coefficient," may take values between -1 and +1. The direct relationship is shown by a positive correlation, which has a value closer to +1. So, a rise in one variable usually increases the other. Many fields, including the natural sciences, psychology, and economics, rely on correlation analysis. Analysts and researchers can better understand the links between variables and draw educated conclusions or forecasts using this method. To be clear, correlation does not prove causation, and more background knowledge is required to grasp the relationships that have been identified fully.

Table 2: Correlation analysis

Correlations	Integrated Platform	Disruptive Technologies	Benefits	Social Transition
Integrated Platform	1	.868**	.780**	.832**
Disruptive Technologies	.868**	1	.814**	.811**
Benefits	.780**	.814**	1	.720**
Social Transition	.832**	.811**	.720**	1

The correlation analysis table provides a comprehensive overview of the relationships among the variables: Integrated Platform, Disruptive Technologies, Benefits, and Social Transition. The correlation coefficients are presented in the matrix, where values closer to 1 indicate a strong positive correlation, values closer to -1 signify a robust negative correlation, and values near 0 suggest a weak or no linear relationship. The correlation between Integrated Platforms and Disruptive Technologies is notably high at .868**, suggesting a robust positive relationship between these variables. This implies that as the integration of platforms increases, there is a corresponding increase in the adoption of disruptive technologies and vice versa. Similarly, the positive correlation between Integrated Platform and Social Transition (.832**) indicates a strong association, suggesting that the integration of platforms is positively linked to the advancement of social transitions.

The correlation between Disruptive Technologies and Benefits is also substantial at .814**, suggesting a positive connection between adopting disruptive technologies and realizing benefits. This implies that organizations or systems embracing disruptive technologies will likely experience positive outcomes or advantages. Furthermore, the correlation between Benefits and Social Transition is .720**, indicating a positive relationship between realizing benefits and facilitating social transition. This implies that the positive outcomes of integrated platforms and disruptive technologies contribute positively to social transitions within a given context.

4.2 Regression analysis

The resulting equation provides a mathematical representation of the relationship, which permits the estimate of dependent variable values for specific values of independent variables.

Numerous disciplines, including the natural and social sciences, economics, and finance, rely on regression analysis. It is a powerful tool for understanding complex relationships within datasets, creating predictions, and testing ideas. Analyzing the statistical significance of coefficients, the quality of the model's fit, and the assumptions made are necessary to understand the underlying dynamics and interpret regression results.

Table 3: Regression analysis

ANOVA	Sum of Squares	df	Mean Square	F	P value
Regression	98.339	3	32.78	118.959	0.00
Residual	37.2	135	0.276	R squared	
Total	135.54	138		0.73	
Coefficients	B	Std. Error	Beta	t	P value
(Constant)	0.469	0.192		2.444	0.02
Integrated Platform	0.484	0.091	0.5	5.323	0.00
Disruptive Technologies	0.282	0.089	0.32	3.169	0.00
Benefits	0.065	0.075	0.07	0.868	0.39

Benefits, Disruptive Technologies, and the Integrated Platform are the independent variables, and the supplied regression analysis table sheds light on their correlations with the dependent variable. A very significant F-statistic of 118.959 with a matching p-value of 0.00 is shown in the ANOVA table, which measures the model's overall fit. This provides more evidence that the overall statistical significance of the regression model in explaining the dependent variable's variation is warranted. The effect of each independent variable on the dependent variable may be seen in detail in the coefficients table. When all of the independent variables are set to zero, the anticipated value of the dependent variable is represented by the constant term (0.469). The dependent variable is projected to rise by 0.484 units when the Integrated Platform increases by one unit, leaving all other variables constant. This is supported by the positive and significant coefficient ($B = 0.484$, $p = 0.00$). Similarly, Disruptive Technologies also show a positive and statistically significant impact ($B = 0.282$, $p = 0.00$), meaning that the dependent variable increases by 0.282 units for every one-unit rise in Disruptive Technologies. The Benefits coefficient is not statistically significant ($B = 0.065$, $p = 0.39$); however, it indicates that it does not significantly influence the dependent variable within this model.

4.3 Chi-square analysis

When testing for the existence or absence of a correlation between categorical data sets, statisticians often turn to chi-square analysis. This method shines when the variables under study are nominal or ordinal, meaning they consist of distinct categories. In this study, we will compare the actual events in a contingency table with the expected occurrences without any relationship between the variables. We may calculate the chi-square test statistic by analyzing the differences between the actual and anticipated frequencies. We compare it to the chi-square distribution to determine whether it is statistically significant.

In contrast to the statistically significant result, which implies the existence of a connection or association between the variables, the null hypothesis states that there is no link or correlation. Many fields rely on chi-square analysis for studying correlations between variables like gender and treatment effectiveness, preferences, or job satisfaction among different types of customers. This includes the social sciences, health, and market research. Consider the degrees of freedom and the significance level as you try to understand the chi-square result. From this approach, you may learn a lot about categorical data's correlation and independence patterns.

Hypothesis 1

Null: There is no significant difference between Integrated Platform and Social Transition.

Alternate: There is a significant difference between Integrated Platform and Social Transition.

Table 4: Cross tab between Integrated Platform and Social Transition

	Social Transition			
Integrated Platform	Disagree	Neutral	Agree	Strongly Agree
Disagree	12	0	0	0
Neutral	5	16	5	0
Agree	0	5	15	6
Strongly Agree	0	0	34	41
Total	17	21	54	47
Chi-Square Tests	Value	df	P value	
Pearson Chi-Square	173.323a	9	0.00	
Likelihood Ratio	152.449	9	0.00	

The chi-square analysis table explores the relationship between two categorical variables, Integrated Platform and Social Transition. The table exhibits the observed frequencies of respondents falling into different categories of opinions regarding social transition based on their perceptions of the integrated platform. The chi-square test assesses whether there is a significant association between these variables. The observed frequencies suggest that many respondents who strongly agree with the integrated platform also strongly agree with social transition (41 respondents). Conversely, those who disagree with the integrated platform tend to have lower agreement with social transition, as evidenced by the lower frequencies in the corresponding cells. Hence, there is a significant difference between Integrated Platform and Social Transition.

Hypothesis 2
Null: There is no significant difference between Disruptive technology and Social Transition.

Alternate: There is a significant difference between Disruptive technology and Social Transition.

Table 5: Cross tab between Disruptive technology and Social Transition

	Social Transition			
Disruptive Technologies	Disagree	Neutral	Agree	Strongly Agree
Strongly Disagree	6	0	0	0
Disagree	6	0	0	0
Neutral	5	11	5	0
Agree	0	5	17	0
Strongly Agree	0	5	32	47
Total	17	21	54	47
Chi-Square Tests	Value	df	P value	
Pearson Chi-Square	173.323a	9	0.00	
Likelihood Ratio	152.449	9	0.00	

The chi-square analysis table explores the relationship between two categorical variables: Disruptive Technologies and Social Transition. The table illustrates the observed frequencies of respondents falling into different categories of opinions on social transition based on their perceptions of disruptive technologies. The chi-square test assesses whether a significant association exists between these variables. Upon examining the observed frequencies, it becomes evident that respondents who strongly agree with disruptive technologies also tend to agree with social transition (47 respondents) strongly. Conversely, those who disagree or strongly disagree with disruptive technologies show lower levels of agreement with social transition, as evidenced by the lower frequencies in the corresponding cells. Hence, there is a significant difference between Disruptive technology and Social Transition.

Hypothesis 3
Null: There is no significant difference between Benefits and Social Transition.

Alternate: There is a significant difference between Benefits and Social Transition.

Table 6: Cross tab between Benefits and Social Transition

Benefits	Disagree	Neutral	Agree	Strongly Agree
Strongly Disagree	6	0	0	0
Disagree	6	0	0	0

Neutral	5	16	6	0
Agree	0	0	26	23
Strongly Agree	0	5	22	24
Total	17	21	54	47
Chi-Square Tests	Value	df	P value	
Pearson Chi-Square	161.394a	12	0.00	
Likelihood Ratio	139.06	12	0.00	

The chi-square analysis table examines the relationship between two categorical variables, Benefits and respondents' opinions, on a scale ranging from Disagree to Strongly Agree. The table presents the observed frequencies of respondents falling into different categories based on their perceptions of benefits. The chi-square test determines whether a statistically significant association exists between these variables. Upon reviewing the observed frequencies, it is evident that respondents who strongly agree with benefits also tend to agree or strongly agree with the given statements (47 respondents). Conversely, those who disagree or strongly disagree with benefits exhibit lower levels of agreement, as reflected by the lower frequencies in the corresponding cells. Hence, there is a significant difference between Benefits and Social Transition.

4.4 Discussion

In the current context, it is critical to explore the multifaceted relationship between big data technology, smart city development, and its implications for social transition (García-Valls, 2020). It is based on the previous works cited by (Marinakisa, 2020), addressing the pressing challenges urban centers worldwide face, such as population growth and resource constraints, setting the stage for integrating big data technology as a potential solution. The authors emphasize the significance of smart city initiatives driven by big data, aiming to enhance efficiency, sustainability, and overall quality of life. The scope of the study is comprehensive, encompassing various dimensions of the impact of big data technology. This includes a thorough examination of the applications of big data, ranging from data-driven decision-making to predictive analytics and integrating the Internet of Things (IoT) in urban infrastructure. It is further noted that the societal implications of this technological transition elucidate how smart city initiatives influence social structures, citizen engagement, and community well-being (Pan, 2020).

One notable aspect of the study is its commitment to empirical validation. By incorporating case studies and empirical data, the authors strive to provide a nuanced and evidence-based understanding of the benefits and challenges of integrating big data technology in smart city development (Piaggesi, 2022). This empirical foundation enhances the credibility of the findings and contributes practical insights that can inform policymakers, urban planners, and technologists. Furthermore, the research recognizes the necessity of considering both opportunities and challenges. By adopting a balanced perspective, the study sheds light on the potential benefits of big data technology while acknowledging and analyzing the challenges that may arise in implementing and managing such transformative initiatives. This nuanced approach adds depth to understanding the subject matter and supports a more informed decision-making process (Marinakisa, 2020).

5.0 Conclusion

In conclusion, the article comprehensively explores the intricate relationships between critical variables: Integrated Platforms, Disruptive Technologies, Benefits, and Social Transition. The study underscores the transformative potential of big data technology in developing smart cities, shedding light on its impact on social transition. The variable Integrated Platform emerges as a pivotal factor, exhibiting a strong positive correlation with the social transition. The findings suggest that as the integration of platforms increases, there is a corresponding positive influence on the advancement of social transition within smart cities. This highlights the central role of integrated technological infrastructures in shaping the social fabric of urban communities. Similarly, the variable Disruptive Technologies demonstrates a significant positive correlation with social transition. The study reveals that adopting disruptive technologies is associated with higher levels of social transition, emphasizing the potential of cutting-edge technologies to drive societal advancements within the context of smart cities.

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