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APPLYING ARTIFICIAL INTELLIGENCE SENSIBLY IN SMART CITIES TO IMPROVE SUSTAINABLE DEVELOPMENT OUTCOMES: INSIGHTS FROM A COMPARATIVE RESEARCH ACROSS CITIES IN DIFFERENT REGIONS

Cheng Boon YAP
EUCLID University, Gambia; 0009-0007-3340-553X,

Klemens KATTERBAUER
EUCLID University, Gambia; 0000-0001-5513-4418,
&
Laurent CLEENEWERCK DE KIEV
EUCLID University, Gambia; 0000-0002-9267-0428

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ABSTRACT

More than 50% of the world's population currently live in cities and the proportion is likely to grow to 70% by 2050 (World Bank Group, 2023). Thus, cities arguably play a pivotal role in efforts to achieve the Sustainable Development Goals (SDGs). Specifically, smart cities, which integrate information and communications technology (ICT), energy, and transport to improve cities' resilience and efficiency, could possibly drive much progress for the SDGs. The advent of artificial intelligence (AI) could also augment smart cities' potential to contribute to the SDGs. However, AI could be a double-edged sword that brings both pros and cons on the economic, environmental, and social fronts. Moreover, people's attitude and practices in using AI might differ due to various factors. This paper hypothesizes that sociocultural differences across regions could influence how their smart cities adopt AI to support sustainable development. To validate this hypothesis, this research employed a survey which yielded 401 responses. Four major population subgroups emerged from the responses, reflecting views from Africa, China, Singapore, and the Europe and North America (ENA) region. This paper presents the significant findings from the survey that could help in advancing the sustainable development agenda. For instance, people in the ENA region seem comparatively less comfortable in using AI, so relevant local authorities in the region might need to step up efforts to alleviate concerns. Through sharing such insights, this paper brings significant value to urban planners and policymakers in making decisions about sensible AI applications in smart cities for sustainable development.

KEYWORDS: Artificial Intelligence, Smart Cities, Sustainable Development Goals, Culture, Sustainable Development Policy

1. INTRODUCTION

a. Background

The United Nations (UN) established the SDGs in 2015 to help balance social, economic, and environmental sustainability priorities to protect the planet and ensure all people enjoy peace and prosperity by 2030. However, the world's progress in achieving the SDGs is falling behind, with only 17% of targets on track (UN, 2024). Therefore, it is paramount to explore approaches for the world to catch up and make up for this shortfall.

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Against this backdrop, there might be merits to ramp up efforts to drive sustainable development in cities. More than 50% of the world's population currently live in cities and the proportion is likely to grow to 70% by 2050 (World Bank Group, 2023). Furthermore, cities account for 60% to 80% of global energy consumption, 75% of carbon emissions, and up to half of the worldwide waste generation (Siemens, 2024). Therefore, addressing sustainability issues in cities should significantly support efforts to achieve the SDGs. Moreover, smart cities could be useful platforms to amplify efforts to pursue the SDGs.

It is also noteworthy that researchers, such as Kolesnichenko et al. (2021), highlighted that as nations work toward the SDGs, it is inevitable that new technologies, such as AI will be used in cities. Therefore, it is timely to explore the interplay between smart cities, AI, and sustainable development.

b. Hypothesis and Research Question

The number of publications on smart cities only picked up since 2010, in tandem with the growing number of smart city projects globally since that time (Jucevicius et al., 2014). Furthermore, according to a systematic literature review by Nikitas et al. (2020), more than 90% of the publications that investigate the interplay between smart cities, AI, and sustainable development only appeared from 2010 onwards. Inducing from these facts, the research volume in this field is probably low compared to other topics. Correspondingly, there is a need for more research to address the question of how to support sustainable development using AI sensibly in smart cities. To do so, the research objective of this paper is to understand potential factors that could shape considerations in applying AI in smart cities to support the SDGs.

Specifically, this paper hypothesizes that sociocultural differences may influence how smart cities in different regions adopt AI for sustainable development. Thus, the research objective of this paper is to investigate this hypothesis, which could help to address the question of how to sensibly apply AI in smart cities for the SDGs.

c. Brief Review of the Literature

Despite the ubiquitous use of the term, practitioners and academia still do not have a clear and consistent definition of smart cities (Chourabi et al., 2012). However, since the emergence of the term in the early 1990s, there has been a common perception that smart cities employ diverse technologies representing the intersections between ICT, energy, and transport to remotely connect and command municipal systems to improve the cities' resilience, efficiency, connectivity, sustainability, and communication with stakeholders (Almihat et al., 2022).

The advent of AI could lead to further transformations of smart cities. Ecological economics researchers, Inclezan and Pradamos (2017), suggested that AI could "help design a truly smart city, namely, a city that satisfies needs for most citizens through satisfactors that either minimize social or ecological externalities, or, even better, are socio-ecologically regenerative." Syed et al. (2021) also highlighted that a diverse range of AI applications could serve the needs of people living and working in smart cities, ranging from smart health to intelligent energy management.

However, AI is not a panacea that can solve all the challenges in our society, including sustainable development. Specifically, Vinuesa et al. (2020) researched the role of AI in achieving the SDGs and found that AI can bring both positive and negative impacts to the targets of the SDGs. Heilinger et al. (2023) corroborated this view as they found that AI could be a positive enabler to a considerable extent on the environmental front (SDGs 13, 14, and 15), but it could also negatively impact as many as 38% of the targets for societal outcomes (SDGs 1, 2, 3, 4, 5, 6, 7, 11, 16). Thus, AI is a double-edged sword. Consequently, governments need to be prudent when making decisions regarding applying AI in smart cities to support sustainable development.

Yet, there is a noticeable lack of research on the nexus between AI and sustainable development. Chavarro et al. (2021) highlighted from their data analysis based on publications from the IEEE Xplore database that current engineering sciences research on AI only addresses "sustainable development to a small extent." Yigitcanlar et al. (2020) also highlighted that the current volume of scholarly research investigating the risks of AI utilization and disruptions of AI in cities and societies is low.

Notably, Yeh et al. (2021) pointed out that "although the people's attitudes or perceptions of AI-related digital technology are of interest to many researchers, few official studies in academic forms can be found in the literature." Hence, this research focuses on the possible sociocultural considerations in applying AI to develop sustainable smart cities, which creates the potential to contribute immense value by plugging this current gap in the literature. Specifically, by examining the potential influence of sociocultural differences on attitudes and behavior in adopting AI in smart cities for sustainable development, this paper seeks to glean insights that could be helpful for urban planners and policymakers to make sensible decisions on this front.

2. METHODOLOGY

The main instrument of this research is a survey. As this research hypothesizes that there would be regional differences in how smart cities leverage AI to support the SDGs, the survey deliberately kept the sample population broad to capture data and opinions from diverse geographies and cultures. This research initially planned to use the Statistical Package for the Social Sciences software to determine the sample size methodically. Doing so would typically require researchers to provide values for power and standard deviation to ensure a high power when conducting hypothesis analysis. For the standard deviation, researchers could refer to previous pilot studies to assume a standard deviation (Serdar et al., 2021). However, this approach proved challenging as there is limited research on this topic of interest thus far. Hence, it was challenging to identify a relevant standard deviation from existing literature. Thus, it was necessary to consider potential rules of thumb instead to determine the sample size.

A rule of thumb statisticians suggest is that thirty is the minimum sample size to produce meaningful results (Bullen, 2022). This rule of thumb purports that a sample size or sub-group size of thirty or more is sufficient for the Central Limit Theorem to hold for most sample distributions and for them to approach normal distribution (Felderer et al., 2022). Another rule of thumb is that a sample size that is viable to represent a large population is minimally 384 to achieve a tolerable limit of error of five percent (Oribhador & Anyanwu, 2019). The rationale behind this number lies in the following well-established statistics formula and assumptions:

$n = z^2 \times p\,(1 - p) / e^2$
Where:
n = sample size
z = z score (1.96 for the common assumption of a 95% confidence interval)
p = population proportion (typically 0.5 for an unlimited population)
e = the margin of error, which is typically five percent
So, $n = z^2 \times p\,(1 - p) / e^2 = 1.96^2 \times 0.5\,(1 - 0.5) / 0.05^2 = 384.16$

Hence, this research will strive for a total sample size of minimally 384, within which it would identify major population subgroups with at least thirty respondents that could help with comparative analysis to evaluate the hypothesis that sociocultural factors could influence how smart cities from different regions deploy AI to support the SDGs. This approach in defining the sample size is also consistent with Roscoe's set of guidelines, a common choice in the last few decades, that suggests that a sample size greater than thirty and less than five hundred is suitable for most behavioral studies (Memon et al. 2020).

"Form.SG," a survey platform that the Singapore government created, hosted the survey and the link was sent through various digital channels. Other than being a secure site to store data, Form.SG comes with data processing and analysis capabilities using Microsoft Excel, which makes it an ideal platform to run the survey. The survey asked respondents to state their views relating to the interplay between smart cities, AI, and the SDGs to elicit attitudes and behavior for sentiments analyses and comparison across subgroups of different sociocultural backgrounds.

3. RESULTS

The survey ran from 22 June 2024 to 29 September 2024 and yielded 401 responses. Table 1 provides a summary of the profile of the respondents.

Table 1: Overview of the Backgrounds of the Research Survey's Respondents

Parameter	Data Summary	Remarks
Gender	Female: 43.4% Male: 56.1% Non-Binary: 0.5%	The survey offered a non-binary option to be more inclusive. Two respondents identified as non-binary.
Age Range	20 to 29: 8.0% 30 to 39: 39.4% 40 to 49: 37.7% 50 to 59: 11.0% 60 to 69: 3.7% 70 to 79: 0.2%	The survey excluded the 10- to 19-year-old range as the research focuses on the adult population. It also excluded the 80-year-old and above age range as that group only accounted for about two percent of the global population (Ang, 2020).
Country of Birth	44 countries and territories	Australia, Bahamas, Brazil, Burkina Faso, Cambodia, Cameroon, Canada, Chile, China, Czech Republic, Congo, Egypt, Ethiopia, France, Gambia, Germany, Ghana, India, Indonesia, Iran, Kenya, Libya, Macao, Malawi, Malaysia, Malta, Mexico Netherlands, Nigeria, Oman, Peru, Philippines, Poland, Russia, Rwanda, Sierra Leone, Singapore, South Africa, Spain, Taiwan, Thailand, United Kingdom, United States, and Zimbabwe.
Country of Residence	42 Countries and territories	Australia, Bahamas, Cameroon, Canada, Chile, China, Czech Republic, Ethiopia, France, Gambia, Germany, Ghana, India, Indonesia, Iran, Japan, Kenya, Kuwait, Macao, Malawi, Malaysia, Mexico, Netherlands, New Zealand, Niger, Nigeria, Oman, Peru, Philippines, Russia, Rwanda, Sierra Leone, Singapore, South Africa, Sudan, Sweden, Taiwan, Thailand, United Arab Emirates, United Kingdom, United States, and Vietnam.
Level of Education	Pre-University: 4.5% Undergraduate: 31.4% Postgraduate: 64.1%	This breakdown represents respondents' highest level of education. The data suggests that there could be some selection bias, skewing towards those with higher education levels.

The respondents represent a broad range of geographical, sociocultural, and demographic backgrounds, such as age, gender, nationality, country of residence, and education level. However, it is noticeable that the respondents have a relatively high level of education, possibly because the survey link was sent through digital channels to this research group's networks which have high a proportion of well-educated individuals. Thus, this paper acknowledges a certain degree of selection bias. However, that should not significantly reduce the usefulness of this research because it is arguable that smart cities will house a sizable proportion of residents with high education levels. For example, economists found a growing trend in recent years for large cities in the United States to have disproportionately high proportions of highly educated workers (Brinkman, 2015). Hence, the survey's sentiments should be reflective of those of potential smart city residents.

Although the research aimed to distil insights from diverse geographies, it strictly followed the statistical rule of thumb to only consider subgroups with at least 30 responses for more meaningful comparative analysis. Consequently, only four regional subgroups meeting this criterion emerged within the overall sample population of 401 respondents. These subgroups are from Africa (31 respondents), China (31 respondents), the ENA region (32 respondents), and Singapore (185 respondents). The respondents in each subgroup were born in their respective regions and currently live in their respective regions. These subgroups reflect different sociocultural representations. Singapore represents a region with a unique hybrid of cultural mix predominantly from East Asia, which has embraced democratization to a large extent (Cheang & Choy, 2024). ENA is a region that – though far from monolithic – generally represents the Western world that has different sociocultural values from Asian countries and a greater degree of democracy, equality, and freedom (Bell, 2017). In contrast, China is a region with highly homogeneous Chinese socialist values, whereby the communist government shapes the social norms centrally to a large extent (China Daily, 2017). The African respondents bring in yet another set of sociocultural voices, including from some Least Developed Countries (LDCs), such as Ethiopia, Gambia, and Rwanda. Although a comparative analysis using four regional subgroups might not seem to reflect great diversity, it is arguably a good starting point for future research in a nascent field that has limited current literature. This section discusses four key insights from the comparative analysis on these four population subgroups.

Insight 1: The awareness of the SDGs seems highest in African countries and significantly lower in the ENA region.

The survey starts by asking respondents about their existing awareness of the SDGs. 70.3% of the respondents in the entire sample population indicated that they were already aware of the SDGs. As Table 2 illustrates, there are differences across the four major population subgroups. Notably, 100% of the respondents from the Africa were aware about the SDGs while the proportion of respondents who were aware from China and ENA were below the overall sample population average.

Table 2: The Four Major Population Subgroups' Awareness of the SDGs

Subgroup	Aware	Unaware	Significance Two-Sided p
Africa	100%	0%	< 0.001 versus China, ENA and Singapore
China	58.1%	41.9%	< 0.001 versus Africa 0.256 versus ENA 0.091 versus Singapore
ENA	43.7%	56.3%	< 0.001 versus Africa and Singapore 0.256 versus China
Singapore	73.4%	26.6%	< 0.001 versus Africa and ENA 0.091 versus China

There is statistical significance in the Africa subgroup's high awareness of the SDGs versus respondents from other regions (100% versus China's 58.1%, ENA's 43.7%, and Singapore's 73.4%, $p < 0.001$ in all cases). In addition, the ENA subgroup has a significantly lower proportion of respondents aware of the SDGs not only in comparison to the Africa subgroup, but also the Singapore subgroup (43.7% versus 73.4%, $p < 0.001$). These results suggest that there could be some regional contexts or sociocultural factors at play that have an association with the levels of awareness of the SDGs.

Insight 2: Less than half of the respondents say they have no concerns about using AI in general, suggesting a general sense of discomfort in using AI, especially in ENA.

Table 3: Whether Respondents Agree They Have No Concerns about Using AI

Subgroup	Agree	Do Not Agree	Significance Two-Sided p
Africa	35.6%	64.5%	0.409 versus China 0.135 versus ENA 0.387 versus Singapore
China	25.8%	74.2%	0.409 versus Africa 0.501 versus ENA 0.060 versus Singapore
ENA	18.8%	81.3%	0.135 versus Africa 0.501 versus China 0.008 versus Singapore
Singapore	43.8%	56.2%	0.387 versus Africa 0.060 versus China 0.008 versus ENA

Only 41.1% of the total respondents said that they "agree" or "strongly agree" that they had no concerns about using AI in general. According to Table 3, the difference between the Singapore and ENA subgroups is significant. The next section will further discuss if this difference could be associated with sociocultural differences.

Insight 3: People from the ENA region seems to be most skeptical about AI's ability to improve residents' quality of life in smart cities

Per Table 4 below, it is conspicuous that only the ENA region had less than half of the respondents in the subgroup who believed that using AI to address sustainable development challenges could improve the quality of life.

Table 4: Whether Using AI in a Smart City Could Improve Residents' Quality of Life

Subgroup	Agree	Do Not Agree	Significance Two-Sided p
Africa	77.4%	22.6%	0.263 versus China 0.003 versus ENA 0.449 versus Singapore
.China	64.5%	35.5%	0.263 versus Africa 0.058 versus ENA 0.479 versus Singapore
ENA	40.6%	59.4%	0.003 versus Africa 0.058 versus China < 0.001 versus Singapore
Singapore	70.8%	29.2%	0.449 versus Africa 0.479 versus China < 0.001 versus ENA

Compared with the Africa and Singapore subgroups, the ENA subgroup's low proportion of respondents who agree with the view that using AI to support sustainable development could improve people's quality of life is significant (40.6% versus Africa's 77.4%, $p = 0.003$; 40.6% versus Singapore's 70.8%, $p < 0.001$). The difference between the ENA and China subgroups is also almost significant at a 5% error limit level (40.6% versus China's 64.5%, $p = 0.058$). Therefore, it is apparent that the ENA subgroup not only displays graver concerns about using AI but also holds a higher degree of skepticism about how using AI to support the SDGs in smart cities could improve people's quality of life.

Insight 4: Africans seem to have a more inclusive mindset to support social cohesion

The survey presented respondents with a hypothetical scenario in which an AI solution suggested to relocate a low-income community nearer to the respondent's community to support socially sustainable development. The Africa subgroup have the highest proportion that is likely to adopt an inclusive mindset and support the relocation while the China subgroup registered the lowest proportion – this difference is statistically significant (51.6% versus 25.8%, $p = 0.037$).

Table 5: Respondents' Support for an AI-Generated Solution to Relocate a Low-Income Community Nearer to Them to Address Social Inequality

Subgroup	Supportive	Not Supportive	Significance Two-Sided p
Africa	51.6%	48.4%	0.037 versus China 0.101 versus ENA 0.060 versus Singapore
China	25.8%	74.2%	0.037 versus Africa 0.633 versus ENA 0.366 versus Singapore
ENA	31.3%	68.7%	0.101 versus Africa 0.633 versus China 0.757 versus Singapore
Singapore	34.1%	65.9%	0.060 versus Africa 0.366 versus China 0.757 versus ENA

4. DISCUSSION

These four key insights from this research are consistent with the results from a set of comparative case studies this research group previously published (Yap, Katterbauer, and Cleenewerck, 2024) that highlighted that sociocultural differences could influence how smart cities apply AI for sustainable development. These findings could be valuable in providing helpful guidance for urban planners and policymakers in making decisions about applying AI sensibly in smart cities for sustainable development, especially in terms of potential sociocultural considerations.

Insight 1 informs us that there is a high level of awareness of the SDGs in Africa. Follow-up interviews with some residents in Africa suggest that this could have an association with the fact that many African countries had previously aligned their national development plans with the Millennium Development Goals which preceded the SDGs. Consequently, a statistically significant higher proportion of Africans are likely to be aware of the SDGs compared to other population subgroups in the survey.

Since the SDGs is a global effort and an endeavor that everyone should support, Insight 1 also suggests that governments in smart cities in other regions, such as China, ENA, and Singapore, should step up efforts in raising the awareness of the SDGs. Otherwise, even if the governments implemented AI solutions to pursue the SDGs, the low awareness of the SDGs and the importance in supporting them may lead to poor utilization of the solutions which may thwart sustainable development efforts.

Insight 2 underscores that less than half of the total sample population agree they have no concerns in using AI in general. In other words, most of the respondents have some degree of discomfort using AI. Notably, the ENA region has the lowest proportion of residents who agreed they have no concerns in using AI (18.8%), while Singapore has the highest proportion (43.8%). This difference is statistically significant ($p = 0.008$).

Follow-up interviews with some residents in the United States suggest that a major concern about using AI is personal data security. From a cultural perspective, ENA has a prevalent culture reflective of the Western world that values individual human rights. Hence, this paper hypothesizes that such a sociocultural factor could have led to greater concerns about personal data security that might be associated with the particularly low proportion of people in the ENA region who agree they have no concerns in using AI. Relatedly, interviews also suggest that the East Asian culture, which feature greater trust and compliance with authority, could explain why the Singapore subgroup has the highest proportion of respondents who agree they have no concerns in using AI. Specifically, according to the Edelman Trust Report, Singapore ranks highly as a country where citizens trust their governments (Edelman Trust Institute, 2024). As a result, Singaporeans might tend to trust that their government has put in place necessary safeguards for AI applications. In sum, Insight 2 suggests that governments in most regions need to spend more efforts in educating citizens on the use of AI and its potential to support the SDGs before implementing them; the ENA region might need considerably more effort on this front due to its higher levels of discomfort in using AI, which could be due to sociocultural factors.

Echoing Insight 2, Insight 3 also shows that the ENA region has a significantly lower proportion of respondents who believe that using AI to support sustainable development in smart cities could improve the residents' quality of life. Collectively, Insight 2 and Insight 3 suggest that there could be considerable sociocultural considerations in the ENA region that local governments need to manage before they can apply AI sensibly for their smart cities to support the SDGs. For instance, if personal data privacy is a critical concern, then the governments would need to show how they have the necessary safeguards and engage citizens actively to alleviate concerns before implementing the AI solutions.

Insight 4 shows that there is a higher proportion of African respondents who has an inclusive mindset to welcome outsiders into their communities to support socially sustainable development compared to Chinese respondents. Follow-up interviews with some members of the African community suggests that this statistically significant difference could be associated with sociocultural differences. Africa has a supportive and strong family culture. Take the Gambia, where the locals typically live with their extended families. They generally have an inclusive mindset and are open to welcoming people outside their immediate family into their community. This African culture contrasts starkly with that in China, which had a long period of the one-child policy until recent years and where a nuclear family structure is prevalent. Consequently, the culture in China could have contributed to a high proportion of Chinese respondents having a less inclusive mindset. Hence, Insight 4 highlights that the Chinese government might need to step up efforts to encourage people to be more open-minded socially to support the social SDGs.

5. CONCLUSION

Table 6 below uses a "Build, Consult, Develop, Educate" frame to sum up significant insights and pertinent discussions in this paper which could better guide scholars and practitioners in making decisions and taking action for applying AI in smart cities to improve sustainable development outcomes.

Table 6: Summary of Research Insights and Discussions on Applying AI Sensibly in Smart Cities to Support Sustainable Development

Build	***Build better awareness of the SDGs and the importance to support them*** In an ideal world, everyone should be aware of the SDGs and contribute efforts toward them. However, based on this research, only about 70% of the sample population is aware of the SDGs, with some regions registering well below this average. Hence, there is a need to upkeep efforts to build better awareness of the SDGs and the importance to support them. Otherwise, efforts to use AI to support the SDGs might not be effective.
Consult	***Consult people on concerns they might have about AI in smart cities for sustainable development*** All regions need to put in effort to alleviate concerns about using AI in general. Beyond that, specific regions, such as the ENA, might have some sociocultural considerations associated with the perceptibly higher discomfort in adopting AI solutions. Governments should actively consult and engage citizens to better understand these considerations and address the concerns to enable more sensible application of AI in smart cities for sustainable development.
Develop	***Develop interventions that could address sociocultural concerns impeding efforts to use AI for sustainable development*** After gaining better clarity on sociocultural considerations that might cause concerns about using AI to support the SDGs, urban planners and policymakers can develop relevant interventions accordingly. For instance, in the ENA region, the local culture could lead to strong emphasis on personal data privacy, so authorities must develop relevant safeguards to address personal data security concerns.
Educate	**Educate citizens to imbue correct mindsets or dispel misperceptions** Sociocultural factors might lead to mindsets in some regions that are less conducive for supporting sustainable development. For instance, the culture in China might lead to a relatively less inclusive mindset that could hamper efforts to enhance social cohesion. Governments should correct mindsets that might be due to unnecessary cultural baggage and imbue correct attitudes to better support the SDGs.

Despite some limitations of this paper, such as the presence of some inadvertent selection bias and a comparison involving only four regions, this paper has made a significant contribution to academic research by plugging the gap in existing literature regarding the potential impact of sociocultural influences on applying AI in smart cities for sustainable development. Future research could consider devising approaches to minimize selection bias or enhance outreach channels to achieve a higher number of sociocultural subgroups with sufficient sample size for more robust analysis. Furthermore, as this is a nascent field, this research focused on establishing an introductory understanding on the potential associations of sociocultural considerations with attitudes and behavior toward applying AI in smart cities for the SDGs; it did not include advanced statistical analysis to test potential causation relationship. Building on the foundation of study, further research could delve deeper into more extensive statistical analyses in such aspects.

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