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Is artificial intelligence a trustworthy route navigation system for smart urban planning?

Karima Kourtit [a,b]✉, Peter Nijkamp [a], John Östh [c], Umut Türk [d]
[a] Alexandru Ioan Cuza University of Iasi, Romania; [b] Open University, Heerlen, The Netherlands; [c] Oslo Metropolitan University, Norway, [d] Abdullah Gül University, Kayseri, Turkey

Abstract
In the age of smart or intelligent cities, the use of Artificial Intelligence (AI) presents a spectrum of new opportunities and challenges for both the research and policy community. The present study explores the intricate interplay between AI-generated content and actual choice spectra in urban planning. It focuses on the concept of 'city intelligence' and related AI concepts, underscoring the pivotal role of AI in addressing and understanding the quality of life in contemporary urban environments. As AI continues its transformative impact on communication and information systems in the realm of urban planning, this study brings to the forefront key insights into the challenges of validating AI-based information. Given the inherently subjective nature of AI-generated content, and its influential role in shaping user-perceived value, AI will most likely be a game changer catalyzing enhancements in the urban quality of life and inducing favorable urban developments. Additionally, the study also addresses the significance of the so-called 'Garbage-in Garbage-out' (GiGo) principle and 'Bullshit-in Bullshit out' (BiBo) principle in validating AI-generated content, and seeks to enhance our understanding of the spatial information landscape in urban planning by introducing the notion of an urban 'XXQ' performance production function.

Keywords: artificial intelligence, city intelligence, data quality, information systems, subjective content, smart cities, urban XXQ production function

Introduction

In the past decades, the concept of '*smart cities*' has gained much popularity (see Caragliu et al., 2011). This notion refers predominantly to the effective use of *digital technology* in urban planning. The benefits of smart cities are not only dependent on the singular application of individual ICT devices. A coherent localized concentration of system-wide urban ICT applications may significantly enhance the overall performance of cities. Clearly, in the modern era, as we recognize the complexities of

✉ Researcher, Alexandru Ioan Cuza University of Iasi, Romania; Open University, Heerlen, The Netherlands; e-mail: k_kourtit@hotmail.com.

urban life, the pursuit of enhancing the quality of life in cities and their neighborhoods has taken center stage. Nowadays, at the core of this pursuit lies the novel concept of '*city intelligence*'; we now find ourselves in an age where data holds the key to unlocking urban potential (Eden et al., 2012; Good, 1966; Tariq et al., 2023; Tegmark, 2017). Current discussions encompass a wide spectrum of concerns, ranging from dystopian visions of technical singularity to the broader labor market effects resulting from the 'disruptive' nature of Artificial Intelligence (AI) (Agrawal et al., 2019). Notably, the introduction of ChatGPT and of other Large Language Models (LLMs) has prompted heated debates on the practical, often value-laden implications of AI integration into both everyday activities and decision-making processes, especially in urban fields such as education, poverty, mobility and healthcare (Holmes et al., 2022; Martin et al., 2021; Nemorin et al., 2023). These debates underscore the dual nature of AI, with both advantages and disadvantages, i.e., the pivotal role of data analytics expertise and supervision as well as the sound need of adopting a critical stance vis-à-vis the great science-supporting potential of AI.

Digital technology has, indeed, dramatically changed the world. Not only have the industrial and administrative processes been significantly altered over the past decades, but also human-made operations and cognitive learning procedures have been affected by the great and unprecedented potential of ICT (Suchman, 2006). Its global pervasiveness has also changed the operational mechanisms of industrial products (ranging from cars to dishwashers), management procedures (ranging from automatic control systems to public procurement guidance), industrial and logistic processes (ranging from unmanned vehicles to real-time route guidance systems), or of cognitive capabilities (ranging from speech recognition to computational neural networks). Against the background of the advances in digital technology, various heterogeneous forms of artificial intelligence have, in recent years, gained an enormous popularity.

Artificial intelligence (AI) is based on human-machine interaction. It takes for granted that a computer is able to mimic and apply human cognitive functions (e.g. learning, adaptation, problem-solving), ranging, for example, from optical character recognition to playing complex games (such as Go or Chess). A wealth of studies on AI was published in the past decades (Kahneman et al., 1982; Neapolitan & Jiang, 2012; Russell & Norvig, 2009; Shapiro, 1992) while, in more recent years, the number of AI publications has shown an exponential growth rate. Machine learning, artificial neural networks, data mining and deep learning are just a few examples of the current differentiated trajectories in contemporaneous artificial intelligence research.

Digital technology, in general, and AI, in particular, is also increasingly entering urban planning and analytics all over the world. After the first wave of '*smart city*' interests (Caragliu et al., 2023 for a meta-analysis of a wide range of studies), nowadays, we observe the rise of '*intelligent city*' concepts, followed by intelligent industrial cluster concepts and even intelligent knowledge campus concepts (Nijkamp, 2024). A common feature of such concepts is the rich information orientation in these notions (e.g. 'big data'). This feature also prompts increasingly serious concerns on the reliability of heterogeneous and multi-scalar data (as witnessed, for example, in the past 'fake news' debates). And therefore, the requirement of accountability and verifiability of large pluriform information in combination with uncontrolled big empirical data is a serious concern.

The present paper seeks to offer an overview of the discussion on the use of imprecise or unverified data in the context of complex urban systems. We will, in particular, address the well-known and nowadays popular 'Garbage-in Garbage-out' (GiGo) and 'Bullshit-in Bullshit-out' (BiBo) dilemma. We will – after a critical discussion of such concepts – introduce the notion of an urban 'XXQ' production function in order to shed light on the limitations and caveats in using AI type of information for modern urban planning in smart or intelligent cities. First, we will present some ideas on intelligence in urban planning.

1. Smart planning for intelligent cities

An intelligent city is an integrated information and knowledge hub, driven by digital technology, in which both physical and virtual proximity and synergy play a pivotal role. It is not a single island system, but it makes up for an archipelago of (real and virtually) connected, accessible and actionable knowledge and innovation centers, which provide an open entry to scientists, clients and society at large. The effective influence radius of an intelligent city far transcends a local or regional territory. It is a network that mirrors global proximity, including academic, industrial and societal liaisons (Neal, 2012). The creative combination of hardware, software and humanware generates an open innovation arena with a global coverage, not only for industrial purposes, but also for the achievement of the Sustainable Development Goals (SDGs), as formulated by the UN.

In the rapidly evolving landscape of our modern digital society accompanied by AI opportunities, an intelligent city is a beacon for a transformative endeavour that modern smart cities all over the world are set to embark upon. It is, therefore, desirable to offer an insightful exploration of future endeavours and to map out the promising and collaborative efforts driving the promising trajectory of contemporaneous intelligent city initiatives. An intelligent city is not a goal in itself, but seeks to develop and favour knowledge-oriented and digitally-based insights for academia, industry, policy and society globally. Examples of key features of digital intelligence to realize sustainable future strategies or scenarios include:

1. *Intelligent Twin Cities:* Moving from single-point intelligence to platform intelligence, converging technologies to build an effective urban digital operating system;

2. *Creative Sensing Interaction:* Leveraging augmented reality (AR), extended reality (XR) and virtual reality (VR) for immersive human-human and human-machine interaction;
3. *Ubiquitous Intelligent Connectivity:* Converging communications and sensing to comprehensively improve intelligent sensing capabilities of cities based on integrated sensing, transmissions, and computing;
4. *Intent-Driven Ultra-High Bandwidth:* Providing on-demand network services relying on high bandwidth, high-density coverage, and deterministic ultra-low latency in modern cities;
5. *Security and Resilience:* Ensuring system security and resilience, including trustworthy components, secure devices, and secure connectivity across different systemic layers;
6. *Full Domain Zero Carbon:* Building a zero-carbon (or climate-neutral) system by reconstructing the ICT network/device architecture and making the city microgrid intelligent from an integrated sustainability perspective.

Such key technical features serve as a convergence trajectory for both scientific and innovation synergy, accelerating the evolution of digital technology fruits all over the world. Clearly, an intelligent city is not a static concept. It is forward looking, and also addresses long-range strategic options on an open future, like:

- *Personalized Learning Ecosystems:* Envisioning a future where digital technologies enable personalized learning experiences tailored to individual needs, fostering a dynamic and adaptive learning ecosystem supported by AI;
- *Integrated Data Analytics:* Harnessing (big) data analytics for insights into research performance, enabling proactive interventions and personalized support systems;
- *Smart Sustainability:* Implementing intelligent solutions for sustainable practices, such as energy-efficient urban infrastructure and environmentally conscious technology adoption (including green city features);
- *Blockchains for Science Integrity:* Integrating blockchain technology to ensure academic integrity, secure science credentials, and transparent verification processes, fostering a trustworthy educational ecosystem in cities;
- *AI-Powered Learning Systems:* Implementing AI-powered learning assistance that offers personalized guidance to knowledge workers, adapting to their learning styles and providing real-time feedback;
- *Quantum Computing for Research:* Leveraging quantum computing capabilities to propel scientific research within urban environments, unlocking new possibilities for data analytics, simulations, and problem-solving abilities;
- *Immersive Language Learning Platforms:* Creating immersive language learning platforms that utilize virtual reality (VR) and language processing technologies to enhance language acquisition on the basis of AI-empowered possibilities;

- *Smart City Suprastructure:* Transforming urban digital infrastructure into a smart environment, utilizing the Internet of Things (IoT) for efficient urban resource management;
- *Renewable Energy Integration:* Expanding the zero-carbon system to include the integration of renewable energy sources, creating energy-efficient urban districts powered by sustainable solutions;
- *Circular Economy Initiatives:* Fostering a circular economy within educational and research institutions, promoting waste reduction, recycling, and responsible consumption;
- *Smart Transportation Systems:* Implementing intelligent transportation systems that optimize commuting in and between cities, utilizing data analytics to enhance optimal traffic flow and reduce environmental impact.

In all such ambitious cases, the use of AI will be inevitable. But will AI be a reliable tour guide? This will be discussed in the next section.

2. AI on stage

While AI raises not only ethical concerns on privacy matters in urban planning, it is worth noting that modern media technology increasingly automates content curation by using complex algorithms, thus replacing the cognitive tasks of human decision-makers. This automation has raised concerns about long-term societal inequity impacts, such as information reliability, polarization, and the formation of information bubbles (Bak-Coleman et al., 2021). In AI utilization, one of the prominent challenges is the inherent variability in the quality of AI-generated content, making scientific validation a complex task (Levinstein & Herrmann, 2023). Traditional statistical validation methods are, therefore, increasingly inappropriate for AI-generated text, as these texts neither strictly conform to objective truth nor prominently fabricate falsehoods. Instead, AI-generated content relies on probability-based estimations, prioritizing persuasiveness over factual accuracy, echoing even the concept of *'bullshit'* recently discussed in the context of language and communication (Schick, 2020; West & Bergstrom, 2021).

Accountability and verifiability are basic ingredients of solid scientific research, as clearly testified in the current discussion on open data access and replicability of research. Complete and transparent reporting of the research methodology adopted, including detailed description of data collection procedures, analysis tools, and adjustments made during the course of a study, is a guarantee for reproducibility. Researchers are expected to document and share their empirical findings, including negative or inconclusive results, so as to provide a solid and unbiased contribution to the cumulative knowledge in a given science domain. Open data practices and public availability of research material, whenever possible, can enhance transparency and facilitate replication studies. By considering these principles in research endeavours, researchers can ensure robustness, reliability and integrity of their work.

A major caveat on AI, often mentioned in current debates, is the actual reliability of the information underlying statements by ChatGPT, for example. In this context, frequently, reference is made to the '*Garbage-in, Garbage-out*' (GIGO) discussion in the information sciences. We just mention a few studies here. Arkhipova et al. (2017) have investigated the relevance of high-quality input data in generating accurate electron density maps in crystallography. Precise input data appear to be critical here. In a different area, Poksinska et al. (2002), Kilkenny and Robinson (2018), Trinh et al. (2017), Bittner and Farajnia (2022) and Teno (2023) explore the significance of data quality and the impact of the GIGO principle from a data collection and analysis perspective, while the author highlights the severe effects of poor data quality (Munyisia et al., 2017). High-quality data are to be preferred, and the authors offer several suggestions. In a study on the application of GIGO in the field of metabolisms, Miggiels et al. (2019) advocate for the use of quality control measures and reliable data preprocessing to obtain meaningful insights from large-scale metabolomic datasets. Again, in a different science area, viz. forensic science, e.g., Stanovich (1992), Carroll (2003), Shermer (2002; 2003), Snook et al. (2007; 2008) highlight the dangers of relying on pseudoscientific methods and unreliable information in criminal investigations. And finally, from a more general perspective, e.g., Wang et al. (1995), Davenport and Prusak (1998), Redman (1998), Kim (2002), Kim and Choi (2003), Eppler and Helfert (2004), Knolmayer and Röthlin (2006), Vayghan et al. (2007) discuss the importance of data quality in various economic sectors, in particular how organizations can turn low-quality ('garbage') data into valuable insights through professional and effective data management procedures and data preprocessing techniques.

The general findings from the data management and information science literature are that due attention to data accuracy and fit-for-purpose data characteristics are a sine qua non for solid scientific investigations (Haug et al., 2009; 2011; Lederman et al., 2003; Wand & Wang, 1996). The recent rise of AI has now prompted the question whether these lessons also hold for AI data applications. We will address this question, in particular, from a smart city or intelligent city perspective, in which digital technology (including AI) plays an increasingly important role. This will be discussed in the next section.

3. AI and information reliability

It is undoubtedly true that AI is able to collect more data or information than the human brain can. But quantity is not necessarily equal to quality (Holbrook & Hirschman, 1982). In this context, the term '*bullshit*' has come to the forefront in the last decade. 'Bullshit' is not a zero-one feature of data in terms of low or high reliability, but refers to the assumed collective plausibility of non-numerical information or statements. Drawing inspiration from Harry Frankfurt's (2005) earlier work on the concept of 'bullshit', we can apply its methodology to AI-generated texts, focusing not only on the truthfulness of statements, but also on their capacity to persuade the audience. In AI-generated output, the information obtained relies on likelihood estimations, effectively reshaping common perceptions or opinions on various subjects.

The widespread dissemination of non-factual information, metaphorically termed 'bullshit', in AI-driven societies, prompts media consumption and influences public trust in science, media, and policymakers. While AI-generated content often transcends the binary categorization of true or false, it serves as a persuasive tool that reshapes existing textual statements. This persuasion, rooted in probabilistic textual output, aligns with the concept of 'argumentum ad populum', where the validity of a statement is presumed based on the majority's belief (Ferraro, 2020; Holbrook & Hirschman, 1982; Rosnow & Fine, 1976). AI-generated text acts as a vehicle for persuasive output, drawing from pre-existing textual content. Clearly, if our primary concern is not only factual accuracy, but also the persuasiveness of statements, AI-generated content becomes a potent instrument in economic valuation studies related to market behavior. In particular, the complex market estimation of use values of the attributes or constituents of a composite good or service in a city, especially in the real estate and housing market, may benefit from AI approaches, specifically on hedonic pricing (Hu et al., 2019). The *'deep learning'* potential of AI regarding textual information, based on pre-trained exercises on vast amounts of numerical or textual data, is clearly reflected in Large Language Models (LLMs). This algorithmic capability is capable of dealing with text related to the queries on which the LLM was trained, often comprising subjective information and non-verified opinions about various subjects, such as attributes of commodities and places.

Incorporating this idea into an urban price market framework, LLM-generated content can enhance our understanding of pricing dynamics, for instance, through the concept of 'city intelligence', which strives for the highest possible multi-dimensional quality of urban life. Just as AI is transforming the urban landscape, it is essential to explore the implications of AI-generated content through the lens of recently developed *BiBo theory* (Bullshit-in, Bullshit-out) (Costello, 2023). BiBo theory, originating in the field of control systems, postulates that the quality output of a system is determined by its non-numerical inputs, with both inputs and outputs constrained within certain realistic bounds (Franklin et al., 1994; Kuo & Golnaraghi, 2010; Ogata, 2010; Phillips & Harbor, 1996). In the context of data science and computer science, BiBo theory may provide a useful framework for assessing the limitations and potentials of AI-generated content, posing critical questions about the plausibility or reliability of information systems when AI plays a mediating role in content creation (Åström & Murray, 2008; Chen, 1970; Khalil, 2002; Nise, 2004). The interplay of AI and urban development also prompts an important research question: "To what extent does AI-generated content conform to the bounds of BiBo theory, and how does this conformity affect data quality, information systems, and communication?" It seems plausible that AI-generated content often operates within the bounds of BiBo theory, albeit with some variability. The degree of conformity to BiBo theory significantly impacts data quality, information system performance, and communication effectiveness. The integration of AI concepts with urban development perspectives showcases the transformative potential of data in both domains. This sets the stage for a comprehensive exploration of AI's impact on urban development, data quality, information systems, and communication effectiveness in the modern age.

Next to the AI-inspired content concern, we also note that, in the contemporary digital era, our exploration of the complexities of urban life influence by AI has initiated a rising pursuit of enhancing the quality of life in cities and their neighborhoods through the concept of 'city intelligence'. It is a multi-faceted perspective on future urban development, often referred to as the 'XXQ-principle', which aims to achieve the utmost quality for urban life (Kitchin, 2015; Nijkamp, 2008). This vision involves a data decomposition process, founded on a 'cascade principle', establishing a hierarchical governance system for multi-scalar city intelligence (Bosker & Snijders, 2011; Kourtit, 2021). This system leverages the fruits of the current digital age, incorporating 'big data' analytics, machine learning, artificial intelligence, data mining, and IoT applications. These have also become the new buzzwords for urban management and policy.

In this digital age, the pervasive use of modern information systems has prompted a reassessment of how we approach urban development. It provides a unique cognitive opportunity and actionable capability for urban policymakers, actors, and stakeholders. Large volumes of multidimensional data, often referred to as 'big data', have paved the way for structurally improved quality of life, enhanced overall health and safety conditions, and a wealth of knowledge. The transition from fuzzy, disconnected dimensions to reliable information systems and data-driven strategies is the driving force behind this transformative era of digital technology. By becoming more accountable, efficient, and actionable, urban systems aim to gain a strong competitive edge on a supra-regional or even global scale (Kourtit & Nijkamp, 2018).

Digital technology empowers various stakeholders within the urban system, providing them with up-to-date information for intelligent decision-making and spatial strategies. This helps city leaders to manage new types of applied data analytics, progressing from "policy analysis to policy analytics". These innovations enhance evidence-based, accountable policymaking, enabling the development and evaluation of cognitive-based alternative policy options, conditions, and criteria. It is important to note that data-driven smart urban policy does not aim to acquire the maximum volume of data. Instead, it focuses on filtering massive data to create a useful, systematic, and fit-for-purpose database. This is the essence of what we term "digital city intelligence" (Kourtit, 2021).

4. The broader perspective of city intelligence

4.1. Scope

In light of the confluence of AI concepts and urban development perspectives, the present study seeks to provide a comprehensive understanding of how AI-generated content influences data quality, information systems, and communication effectiveness within the urban context. Our study seeks to bridge the gap between the evolving landscape of AI and the dynamics of modern urban living, with a particular focus on the hospitality sector. The primary scope of this research encompasses a multi-dimensional complexity analysis. We will investigate how AI-generated content, which often prioritizes persuasiveness over factual accuracy, interacts with urban dynamics, particularly in the context of the quality of life in cities and neighbourhoods. This investigation extends to the realm of information systems, where the rise of AI requires a re-evaluation of content reliability, source credibility, and its impact on data quality. Our research will explore the core components of data science and computer science, drawing from the conceptual framework of BiBo theory. By examining the boundaries of BiBo theory in relation to AI-generated content, we aim to identify the limitations and potentials of this content in shaping urban environments. Through empirical analysis, we will explore the extent to which AI-generated content aligns with BiBo theory within the urban landscape, and how this alignment affects data quality, the performance of information systems, and the effectiveness of communication in an increasingly data-driven urban ecosystem. This study will provide insights into the evolving interplay between AI and urban development, offering actionable knowledge for policymakers, urban actors, and stakeholders.

The research also sets a broader context by emphasizing the importance of understanding the dynamics of AI in the digital age. It recognizes that just as AI-generated content can influence public opinion, it can also impact urban decision-making and policy formation. The implications extend not only to urban practitioners but also to educators and teachers, who play a crucial role in preparing individuals to navigate the digital age. Ultimately, our aim is to empower cities to harness the advantages of AI while preserving data quality and ensuring effective communication in the contemporary urban environment.

The integration of AI into modern media technology, where algorithms automate content curation, enhances our comprehension of societal implications in the city. While Bak-Coleman et al. (2021) offers valuable insights into long-term societal effects, including echo chambers and polarization, it is essential to consider the broader implications of modern media technology for cities. Ensuring responsible AI integration necessitates us to consider the work of scholars advocating for decisions that prioritize societal well-being and minimize the risks of creating information bubbles.

Modern media technology automates content curation using algorithms, replacing human decision-makers, which can lead to the formation of information bubbles and polarization (Bak-Coleman et al., 2021). These automated algorithms curate content not based on factual accuracy but on likelihood estimations, prioritizing persuasiveness over accuracy, echoing the concept of 'bullshit' as discussed in the context of language and communication (Baker & Walker, 2019).

4.2. AI-generated content and validation challenges

The challenges associated with validating AI-generated content are multifaceted and dynamic. Levinstein (2023) highlights the inherent variability in the quality of AI-generated content and emphasizes the need for innovative validation methods. Traditional validation approaches are often ill-suited to the probabilistic nature of AI-generated content. This aspect of AI aligns with Frankfurt's concept of 'bullshit' (2005), elaborated on by Schick (2020) and West and Bergstrom (2021). The extensive literature on this topic provides a rich source of insights to effectively frame our research.

In the context of validating AI-generated content, a substantial challenge arises. The probabilistic nature of AI-generated content means it neither strictly conforms to objective truth nor conspicuously fabricates falsehoods. Instead, it relies on likelihood estimations, prioritizing persuasiveness over factual accuracy, echoing the concept of 'bullshit' discussed in the context of language and communication (Schick, 2020; West & Bergstrom, 2021). Traditional validation methods that rely on binary categorizations of true or false statements are inappropriate for AI-generated text. This challenge calls for innovative validation techniques to ensure the reliability of AI-generated content.

4.3. AI-generated content and subjective information

AI-generated content extends beyond objective facts and frequently incorporates subjective information, such as opinions about commodities and places in urban agglomerations. Integrating this multifaceted nature into our research framework is crucial for a comprehensive understanding of the impact of AI-generated content on urban dynamics. To deepen our knowledge in this area, we explore additional sources that cover the complexities of AI-generated content, especially its interaction with subjective elements.

In AI-generated content, the incorporation of subjective information is notable. AI language models like ChatGPT often produce text related to the query on which they were trained, comprising subjective information and opinions about various subjects, such as commodities and places. This introduces a layer of complexity to the study of AI-generated content, particularly in the context of urban dynamics and the quality of life in cities and neighborhoods. It is clear that AI may act as a game changer in smart planning of modern cities. This calls for both new professionalism in intelligent urban planning and for advanced methodological and data-analytic contributions. This will be further elaborated in the next section.

5. An urban XXQ production function

In computer science, a machine is only intelligent, since it follows pre-determined rules in a complex choice environment. So, in general, AI mimics logically structured cognitive operations termed learning and problem solving, based on a rational and consistent interpretation of information. AI essentially originates in a multi-dimensional statistical toolbox, including neural networks, mathematical optimization, probability theory, computational intelligence, search algorithms, soft computing, data mining, and logical inference (McCorduck & Cfe, 2004). A machine can do this much faster than the human brain. Consequently, AI will have a great future for *problem solving* situations. However, for *problem prevention* needs – especially under great contextual uncertainty – a machine is less suitable, as it does not have the ability of unsupervised human creativity.

In the context of urban planning, a considerable part of daily operations has a routine character and hence, can be easily tackled by standardized AI-inspired support tools (e.g., in the form of interactive computerized planning-support dashboards). However, in the case of unexpected risks or complicated trade-offs (often of a political nature), human intervention is usually necessary, as was clearly witnessed in the recent corona time. Furthermore, in case of strategic development issues, often of a wicked nature with fuzzy demarcations, human, social, legal and political considerations may play an even more pivotal role; such 'unknowables' are difficult to programme in advance and do not follow a pre-defined logic. And this holds even more so in case of *prevention* strategies, in which the external environment is largely a black box. In such cases, interactive strategic scenario experiments may be more meaningful (Heijden, 2005).

Urban planning takes place in a complex volatile environment; it is goal-oriented and seeks to get a maximum performance (in terms of socio-economic and political targets), given a set of limited resources. Thus, the goal of urban planning is to generate an XXQ (maximum quality of the urban system) for the city as a whole – and its districts – (Nijkamp, 2008). In a traditional urban production function, the output – or achievement levels – is shaped by a combination of scarce resources (e.g., infrastructure, man-power, financial resources, land use configuration). In our information age, the efficiency of urban policy operations, is also determined by available information and accessible data. Thus, an urban quality production function may generally be described as:

$$XXQ = f\,(\text{manpower, finances, land use, information})$$

As mentioned above, information is not a simple quantitative index; it comprises millions of time-space varying multi-scalar data constituents, often too big for the human brain to capture simultaneously. And therefore, data mining and machine learning may be helpful tools. A major problem in taking solid decisions, however, is the question on the reliability and verifiability of the information concerned. Above, this has been referred to as the GiGo or BiBo phenomenon. This means that information is not an ambiguous variable; its relevance in an urban XXQ production function context is determined by: (i) the credibility (both objective and subjective) of the information content; (ii) the user's awareness and ability to access and employ the perceived information quality for taking decisions (either routine or more structural). Thus, we may define *information value* (IV) in an urban planning context as:

$$IV = f\,(\text{credibility, user ability})$$

which essentially means that XXQ is co-determined by IV.

We will illustrate the relevance of the IV production model by referring again to the GiGo and BiBo phenomenon. If a certain urban planning issue (e.g. traffic safety) is characterized by a high degree of uncertainty (i.e. a low level of information credibility), the resulting IV is very low as well, unless the user of this information is familiar with this uncertainty and decides or acts accordingly. In other words, the degree of substitutability between information reliability and the information management capacity is decisive for the outcome of urban performance policy. This phenomenon bears some resemblance to Leibenstein's (1978) X-efficiency principle, which posits that the efficiency of production units is co-determined by fuzzy or soft factors such as working environment, social atmosphere or managerial empathy.

Finally, by inserting the IV production function of information value into the overall XXQ 'master' equation, we obtain a nested production function for urban performance planning, in which existing, perceived and managed information quality plays a critical role. The consequence of this argumentation is that the GiGo or BiBo principles are not necessarily uniformly valid, and depend on the information quality awareness and information handling capacity of the user.

Conclusion

AI is a useful and – in the future – a necessary complement to urban planning. However, it does not create miracles and needs to be used with great care. A critical view on the concept and implication of Garbage-in Garbage-out and Bullshit-in Bullshit-out can be framed within the context of information dynamics, knowledge production, and social, political, and cultural factors. This perspective questions – as argued above – the assumption of objectivity and neutrality in data collection, analysis, and the interpretation of results.

From a critical standpoint, the GiGo concept can be seen as reinforcing a reductionist and positivist approach to knowledge production. It assumes that data, once collected, can be objectively processed and analysed to generate accurate and reliable results. However, this view neglects the way in which data can be influenced by various biases, policy differentials, and societal structures. Similarly, the notion highlights the vulnerability of information systems and research processes to manipulate and to be subjected to distortion. However, a critical perspective question is who gets to determine what constitutes low credibility (bullshit) and who has the authority to label certain information as unreliable or false. It acknowledges that the categorization of information as ‘bullshit’ can be subjective and may be influenced by power dynamics, vested interests, and ideological biases. This has been illustrated by using the urban XXQ production function presented above.

Furthermore, it should also be recognized that the construction of data and knowledge in urban planning is not unambiguous. Data is not a neutral reflection of reality, but is shaped by the social, cultural, and historical contexts in which it is produced and will be used. This perspective calls for an understanding of the political dimension and social dynamics that influence the collection, interpretation, and dissemination of data.

To address the caveats inherent in GiGo and BiBo principles, a more reflexive and contextual stance to research may be needed. This involves acknowledging and interrogating the underlying assumptions, biases, and values that shape the research process. It also calls for engaging in interdisciplinary and collaborative work in smart urban planning processes, recognizing the importance of diverse perspectives and voices in producing more nuanced and socially relevant knowledge to create XXQ cities.

In summary, this paper has challenged the assumption of objectivity in data collection and analysis in the pursuit of intelligent urban planning, in the era of AI. It has emphasized the need to critically address the social, economic, political, and cultural factors that shape knowledge production and distribution, and has questioned the power dynamics inherent in the GiGo and BiBo paradigm.

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