Responsible AI for Cities: A Case Study of GeoAI in African Informal Settlements

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Biographical notes

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Abstract

Geospatial Artificial Intelligence (GeoAI) systems are increasingly used by local governments to manage urban planning activities. However, there is a lack of clear guidelines for responsible AI implementation. We address this gap by applying the task-data-user-technology fit theory. First, we create a conceptual framework that translates ethical AI principles into practical system requirements. Second, we apply this framework through a case study analysis. We examine the geospatial AI system that the city of eThekwini, South Africa, has deployed to monitor their informal settlements. Based on expert interviews, our analysis highlights the ethical trade-offs inherent in the interactions between fits, data, tasks, users, and AI interactions, especially in an inherently localized and multi-stakeholder field such as urban planning. Additionally, we show how these fits are interconnected and cross-dependent. For example, the technical skills and resources of users can influence all other fits. Our study also reveals how task reconfiguration, user adaptability, and data improvement can enhance or hinder alignment with technology. From these insights, we introduce practical and theoretical recommendations for responsible AI development, adoption, and use.

Keywords

Artificial intelligence; GeoAI; Ethics of technology; Responsible AI; Urban governance;

1. Introduction

Urban planning has reached a new evolutionary stage with GeoAI systems, which refer to the integration of Artificial Intelligence (AI), particularly machine learning and deep learning techniques, with Geographic Information Systems (GIS) and spatial data analysis (De Sabbata et al., 2023). GeoAI claim several benefits over traditional methods, such as greater geographic coverage, reduced data bias, enhanced accuracy and time efficiency (Marasinghe et al., 2024). These advantages have been demonstrated in various urban applications, for example high-resolution urban pattern monitoring, land and property mapping, and planning decision-making support (Son et al., 2023).

However, advancing the integration of these technologies to enhance city management and benefit citizens requires an understanding and respect for local conditions (Pereira and Prokopiuk, 2024): urban planning and governance systems should not only be more powerful, time and cost-effective, but also easy to implement and inclusive (Zevenbergen et al., 2016). In this regard, concerns persist about the ability of cities to manage the deployment, maintenance, and enhancement of these technologies (Yigitcanlar et al., 2021). The responsible use of AI in urban planning involves addressing three interlinked aspects: (1) the technical and administrative requirements of urban planning practices; (2) the ethical, social, and legal requirements of technology adoption; and (3) the specific needs of urban areas, their users, and their administrators (Peng et al., 2023). Unfortunately, current academic debates offer only abstract ethical principles, lacking in practical guidance for ethical decision-making and trade-offs (Morley et al., 2020). This absence hinders the responsible design and implementation of AI systems in the urban planning domain.

Against this background, our research addresses the following research questions:

- How can we translate responsible AI principles into practical requirements for urban planning systems?
- How do these requirements impact the development, adoption, and use of AI technology?

Our study makes a threefold contribution. First, we expand the academic discourse on responsible AI by structuring a conceptual framework that operationalizes broad ethical principles in urban planning. Leveraging task-user-technology fit theory (Jiang et al., 2020), this framework aligns ethical considerations with GeoAI system development, urban planning tasks, data, and user characteristics. Second, we apply this framework to a case study of an AI-based land-monitoring system in eThekwini, South Africa. Third, we build on the insights from the case study to offer both theoretical considerations and practical recommendations for the development of GeoAI systems.

The remainder of this article is organized as follows. Section 2 provides an overview of responsible AI research in urban planning and land administration, and it introduces our conceptual framework. Section 3 describes our case study and the methodology that we used to conduct the analysis. Section 4 details the findings of the study, while Section 5 discusses their theoretical and practical implications. Section 5 is also instrumental in exploring the limitations of our study and provide recommendations for future research.

2. Literature review

2.1 Responsible as useful: translating ethical AI principles into task-data-user-AI fits

The surge in research, development, and deployment of AI systems have sparked significant ethical discussions in academic, governmental, and industrial contexts (Hagendorff, 2020). As a result of these debates, several ethical guidelines have been introduced in recent years. These guidelines, together with research on technology ethics (Jobin et al., 2019 , Royakkers et al., 2018), demonstrate that the theoretical perspectives on “responsible AI” (Yigitcanlar et al., 2021:6), converge around a set of recurring themes, including transparency, responsibility, accountability, privacy, safety, human dignity, and trust. Research by Floridi and Cowls (2019) have distilled these themes into five main principles: *beneficence* (being beneficial to and respectful of both people and the environment); *non-maleficence* (ensuring robustness, privacy, and security); *autonomy* (upholding and respecting human values and agency); *justice* (maintaining fairness and diversity, avoiding bias); and *explicability* (being explainable, accountable, understandable).

However, Morley et al. (2020) highlight a gap in practical guidance for implementing these principles. Existing studies only focus on AI specifics, such as research on fair and transparent AI (Miller, 2019), or they attempt to address implementation from a more strategic perspective rather than introducing practical guidance (Sturm and Peters, 2020 , Traumer et al., 2017). More specific to the geospatial domain and urban planning applications, recent studies have attempted to identify responsible practices (Marasinghe et al., 2024), and exposed challenges in public perceptions and adoption (Son et al., 2023 , Yigitcanlar et al., 2020), as well as broader issues of urban AI governance (Cugurullo et al., 2023), but without sufficient details on technical aspects or other practical strategies.

To enhance our understanding of responsible AI in urban planning, we revisit the notion of *responsible* as traditionally portrayed in this domain (de Vries et al., 2021). For urban areas, this concept translates into the need for urban planning systems that are faster, more cost-efficient, straightforward to implement, and broadly inclusive. Consequently, when assessing AI technologies in urban planning, it is crucial to evaluate both their task performance efficacy and their appropriateness for the target user groups. In essence, this necessitates a proper alignment between the task requirements and the technology used, known as task-technology fit (TTF).

TTF theory is particularly useful for understanding how the interaction between tasks and technologies influences technology usage and its impact on performance (Goodhue and Thompson, 1995). This theory emphasizes that the effectiveness of a technology is closely tied to how well it aligns with the specific tasks it is meant to address. Moreover, it highlights the importance of the contexts in which technologies are deployed (Howard and Rose, 2019).

TTF theory has been widely applied in research areas related to AI. Various studies, such as those by Chang (2010) and Wongpinunwatana et al. (2000), have validated the relevance of this theoretical persepctive in assessing the performance, capabilities, and intention to use intelligent agents and expert systems at individual, group, and organizational levels. Additionally, TTF theory has also been instrumental in examining data usage practices (Karimi et al., 2004) including data analytics (Ghasemaghaei et al., 2017) and big data analytics (Muchenje and Seppänen, 2023). These studies have expanded the TTF theory by introducing a new dimension called *data-technology fit*. This dimension focuses on the compatibility between analytical tools and the data they process, which is crucial for effective and accurate data analysis (Ghasemaghaei et al., 2017).

TTF theory has been further developed with recent studies on decision support systems and planning support systems. Parkes (2013) found that in decision support systems, TTF positively influences outcomes when there is a match between technology features, employee skills, and their preferences for technological tools. Similarly, Pelzer (2017) showed that in planning support systems, success is not just about matching technology features with planning tasks, but also about aligning the capabilities of users with the functionalities of the technology. This connection is referred to as *user-technology fit*, which underscores the usability and applicability of a technology (Jiang et al., 2020 , Russo et al., 2018).

However, the unique attributes of AI, such as broader learning capacities, autonomy, and inscrutability, require expanding these studies and the contribution they offer, by introducing new definitions and research perspectives (Baird and Maruping, 2021). Accordingly, in the following sections we examine the key characteristics of AI systems, data, urban planning tasks, and users, and we extend upon the traditional theoretical constructs of technology-fit in urban planning, incorporating AI-specific aspects (Rzepka and Berger, 2018 , Sturm and Peters, 2020). This theoretical development will help us translate the ethical principles of AI into practical system requirements, emphasizing the criticality of matching tasks, data, and user characteristics for effective implementation.

2.2 AI Characteristics

The performance of AI systems is significantly influenced by computational time, which depends on model complexity, hardware efficiency, and the volume and complexity of the data being processed (Carter et al., 2020). GeoAI systems can be task-specific, that is, optimized for performing specific functions, or task-agnostic, designed to handle a wide range of tasks (Rolf et al., 2021). The latter, typically trained on large-scale datasets (Mai et al., 2022), require substantial data processing and computation power (Cowls et al., 2023).

Another notable feature is the level of automation. The literature typically interprets humans as either in-, on-, or out-of-the-loop entities, emphasizing their decreasing level of involvement (Traumer et al., 2017). Different interaction levels can either obstruct or boost AI efficiency (Grønsund and Aanestad, 2020).

The explainability of AI algorithms, or how understandable their decision-making processes are, is also crucial. Machine learning systems relies on data patterns rather than human-defined rules, leading to the perception of AI as a black box (Burrell, 2016). Current efforts in Explainable AI (XAI) aim to build-in features to clarify AI decision-making processes and analyses (Rudin, 2019), but usually require statistical and coding knowledge to be interpreted (Meske et al., 2022).

This challenge emphasizes the importance of considering user interfaces and the experience of users (Haque et al., 2023). For example, Automated Machine Learning (AutoML) approaches allow AI-model development with minimal coding knowledge (Li and Chau, 2022), but can be associated with a low level of transparency and control over algorithm design (Dwivedi et al., 2023).

2.3 Data Characteristics

AI algorithms are trained on existing data to create models that capture underlying patterns. These models are then used on new data to perform specific tasks. Therefore, the functionality of AI tools and the algorithms they apply are influenced by the characteristics of the data used to train them (Danks and London, 2017), including aspects such as quantity and variety (Agrawal et al., 2017). This means that it is crucial to consider not just the availability and accessibility of data, but also issues like data ownership and privacy (Janssen et al., 2020). In this regard, the growing ability to use GeoAI systems to collect personal data for completing planning tasks, like socioeconomic information and geolocations, introduces challenges for responsible AI usage. These include ensuring harm is not caused and respecting individual autonomy (Micheli et al., 2022). If data collection occurs automatically, without involving or informing people, it can lead to ethical concerns about justice, beneficence, and autonomy (Janowicz et al., 2022).

Data flows, from collection to application, assist in the implementation and maintenance of AI-based systems, as they continue to process data after their initial training phase (Jöhnk et al., 2021). However, data quality is the ultimate determinant of outcomes (Janssen et al., 2020). In geospatial data analysis, for instance, changing geographies, environmental conditions, and the heterogeneity of sensing instruments make it hard to select representative training data (Lunga et al., 2021). This could lead to computational biases in AI systems, especially if the datasets used for training are poor, limited, or biased. For example, in data-poor urban contexts, AI systems designed for land-use characterization may produce inaccurate results if they are not validated with local expertise and knowledge (Kim et al., 2021).

2.4 Tasks Characteristics

In the field of GeoAI, a task is the specific objective of using AI to predict or estimate a variable or feature, for example characterize land use or population densities from satellite imagery (Rolf et al., 2021). The complexity of tasks varies, depending on the level of cognitive resources and skills needed to implement it (Campbell, 1988). Some tasks are simple, leading directly to an outcome, whereas others may have multiple paths and numerous possible outcomes. The interaction between these paths and outcomes, such as balancing quality and quantity, along with the level of uncertainty and unpredictability, impacts on the complexity. Moreover, tasks with varying complexities also differ in their automation potential, which is associated with concerns over transparency and fairness (Vimalkumar et al., 2021).

Roth et al. (2023) highlight the importance of integrating values and principles into these tasks, as reflected in legal norms. Factors such as time constraints, participant involvement, and political sensitivities, which are influenced by planning and policy processes, are crucial in this context (Geertman, 2006 , Jiang et al., 2020). Furthermore, these tasks have various accountability implications—political, legal, organizational, and professional—in the context of modern urban planning, which also have wide-reaching societal effects (Bovens, 2007).

In this sense, in the deployment of AI for urban public services, openness and transparency can be features built around AI system rather than built in the system itself. This can be in the form of documentation and communication tools: for example, in Amsterdam and

Helsinki public algorithm registers offered insight on algorithm being used in urban services (Floridi, 2020). Additionally, in New South Wales, Australia, co-design practices allowed participation in early stages of the decision processes and addressed more explicitly accountability (Rittenbruch et al., 2022).

2.5 Users Characteristics

Indicators of digital divide highlight several AI-specific sensitivities (Carter et al., 2020). The need for increased computing power for AI tools poses a significant financial challenge, making access to digital technology difficult not only for underprivileged communities and developing countries but also for developed ones (Cowls et al., 2023).

Furthermore, even when access is available, factors like literacy, language barriers, and digital skills can hinder effective utilization of the technology (Bélanger and Carter, 2009). Specialized skills required by many innovative geospatial technologies (Ball et al., 2017) are often lacking in governments where such technologies are most needed (Haack and Ryerson, 2016). In this "capability divide" (Wei et al., 2011:170) the perceptions and beliefs of individuals become increasingly significant in the AI context (Yigitcanlar et al., 2020). Risk perception is notably high with AI, driven by widespread concerns over malicious applications in areas like surveillance and the black-box nature of many AI systems. This apprehension decreases the willingness of individuals to use AI systems, thereby widening the AI divide (Carter et al., 2020). Moreover, a lack of "AI awareness" (Jöhnk et al., 2021:11) can result in interpretation biases; users may not fully comprehend the intended use of an AI system or may misinterpret its capabilities (Danks and London, 2017). On the other hand, the current hype surrounding AI could result in excessive reliance and premature adoption of untested or inappropriate tools (Vered et al., 2023), diverting resources and attention from more suitable solutions (Gevaert et al., 2021).

2.6 Task, Data, and User-AI fit in urban planning

By combining the different characteristics of AI for urban planning tasks, we extrapolated a set of indicators to assess the fit and effectiveness of an AI systems for specific tasks and application contexts (Koumetio Tekouabou et al., 2022 , Yigitcanlar et al., 2020). The indicators are listed in Figure 1 and discussed in the following paragraphs. Additionally, this integration prompts critical discussions on the responsible deployment of AI in urban planning (see Table 1).

[Insert Figure 1 here]

Generalizability refers to the performance of the AI model across different datasets and tasks, beyond the ones it was initially trained on (Mai et al., 2022 , Rolf et al., 2021). It is a measure of both task-AI and data-AI fit (Sturm and Peters, 2020), which is necessary to avoid concerns about transfer-context biases (Danks and London, 2017).

Reliability focuses on the quality and timeliness of AI output, as well as the expert control required to train the system. Inadequate understanding of the local context can lead to the exclusion or misrepresentation of data used for urban planning purposes (Burke et al., 2021), limiting their effectiveness and usability (Gevaert et al., 2021). Simultaneously, if AI tools fail to perform their tasks in the required timeframes, the outputs they generate may become irrelevant or unusable (Sturm and Peters, 2020).

Contextualization refers to how sensitive an AI system is to its operational environment. It emphasizes the importance of designing AI in collaboration with its users, understanding their needs, methods of coordination, and the impacts of interventions (Floridi et al., 2020). By combining bottom-up perspectives with AI systems, urban planning is expected to become more inclusive, equitable, and responsive to the needs and priorities of diverse communities. Therefore, *contextualization* promotes justice and avoid perpetuating algorithmic and non-algorithmic biases in urban communities (Mitchell et al., 2021 , Räz, 2024).

Traceability involves transparency and accountability of an AI system. Therefore, it is affected by factors like the approach adopted by decision-makers to document procedures and responsibilities (Sanchez et al., 2022).

Comprehensibility concerns the trust and validation of the AI system's output (Berente et al., 2021 , Sturm et al., 2023), which is influenced by the level of information available on how the AI system function. This information is crucial to support effective adoption while preventing interpretation and automation biases (Vered et al., 2023).

Lastly, *accessibility* considers the human, financial, and technical resources needed to deploy and operate AI systems (Rolf et al., 2021). This indicator assesses whether an organization can quickly and effectively implement an AI system with its available resources. It also considers the requirements for ongoing operation and maintenance, as well as the potential for future improvements.

[Insert Table 1 here]

3. Research Methods

3.1 Case description

We applied our conceptual framework to a single-case study (Yin, 2009), focusing on eThekwini Municipality and the implementation of the Building & Establishment Automated Mapper (BEAM) Project. Established in 2000, the eThekwini Municipality is a metropolitan authority that encompasses Durban, the third-most populous city of South Africa, and a major African port. Since its foundation, eThekwini has emphasized digital technology in its long-term development strategy (Odendaal, 2011) and has now developed a well-established policy that links digital innovation to a comprehensive political agenda for urban sustainability enhancement (Söderström et al., 2021). However, the municipality struggles with rapid and informal urbanization. 314,000 households reside across 580 urban informal settlements[1], defined as "an unplanned settlement on land which has not been surveyed or proclaimed as residential, consisting mainly of informal dwellings".[2] Residents of these informal settlements are among the most vulnerable, facing significant risks from climate change, particularly increased flooding (Williams et al., 2019). To address these challenges, accurate data on the number, locations, and environmental hazards associated with informal structures is crucial. In response, the eThekwini Municipality initiated the Informal Settlement Information Management Solution (ISIMS) in 2018, supported by the UK Prosperity Fund.[3] This initiative is part of a larger effort to promote city-wide, evidence-based urban planning, with the objective to establish a comprehensive system of processes and technologies that enhance informed decision-making within the city.[4]

As part of these efforts, in 2021 eThekwini responded to a call for proposals seeking innovative technological solutions for urban issues. The call was launched by the United Nations Innovation Technology Accelerator for Cities (UNITAC), which is jointly managed by the United Nations Human Settlements Programme (UN-Habitat), the United Nations Office for Information and Communication Technologies (UN-OICT), and HafenCity University. The Human Settlement Unit of eThekwini, dedicated to the planning and management of informal settlements, proposed developing a system to automatically identify informal settlements from aerial images, aiming to replace the labor-intensive manual marking process with GIS tools. This improvement was expected to eliminate a time-consuming workflow that was limiting the capacity of the city to efficiently address needs.

The response of UNITAC to this request led to the development of BEAM, a deep-learning algorithm designed for image segmentation that can detect building footprints in digital imagery[5]. When applied to aerial images collected annually by eThekwini, this GeoAI system was promising continuously updated records of informal settlements.

Since 2022, the integration and testing of BEAM within the city's infrastructure are ongoing. Therefore, the AI system has not yet reached its full operational state, and the results and impact of the project are not fully measurable at this stage. However, its analysis allows for the evaluation of task-user-fit requirements through the stages of algorithmic development—use case development, design, training, and deployment—offering valuable insights into process dynamics, pitfalls, and challenges (Morley et al., 2020).

3.2 Data collection and analysis

Our primary data collection included interviews with 13 project managers and technical officers from the eThekwini Municipality and UNITAC. When selecting interviewees, we aimed for a diverse representation across various organizational levels, from senior management to frontline staff, and balanced between participants directly involved in the BEAM project and those with an external viewpoint. Therefore, our sample includes project team members with technical expertise and a comprehensive understanding of the AI system's development and implementation, as well as officials knowledgeable in urban planning processes, innovation dynamics, and data management within eThekwini. We adopted a snowball sampling approach (Johnson and Onwuegbuzie, 2004) and stopped adding participants when interviews began to repetitively reflect previously gathered data, indicating that data saturation was reached (see Appendix A).[6]

Interview transcripts were analyzed using a thematic-coding approach inspired by Gioia et al. (2012). This involved assigning codes to sections of the interview transcripts to identify core concepts and patterns in the qualitative data (Gerli et al., 2022). Our analysis began by pinpointing first-order concepts in these excerpts, covering areas like planning tasks, data, AI, and user characteristics. From these, we derived second-order themes concerning the interplay of task-data-user-AI characteristics. We then iteratively examined how these first- and second-order categories interconnected, grouping them into theoretical dimensions that aligned with the task-data-user-AI fit indicators of our conceptual framework (see Table 2). Appendix B presents some of the most representative quotes extracted during the coding process.

To supplement and corroborate our findings from the interviews, we gathered secondary data (Johansson, 2007) from policy documents like eThekwini's integrated development plans, its city-wide strategy for incremental upgrading of informal settlements, and various official documents and reports on the development of ISIMS and BEAM. We also reviewed user manuals, news articles, and online presentations related to these two projects. Appendix C presents the sources of the secondary data used in our study.

[Insert Table 2 here]

4. Findings

4.1 Generalizability

Owing to the limited bandwidth of eThekwini's broadband network, data for AI model training took a prolonged time to reach UNITAC, which is based in Hamburg, Germany. Initial samples were shared via a third party to begin development of the tool, but the bulk of the database for a single year of imagery (approximately 200GB) had to be physically transported on a hard drive. Although the model achieved 94% accuracy for the year 2019, it soon became apparent that the data-task-AI fit was very limited in terms of *generalizability*. The images were affected by atmospheric conditions, seasons, and time of flight. Additionally, the quality was affected by the sensor used for image capture, as the company managing the collection process operates over a three-year contract, and every third year a LiDAR scan is performed instead of normal photography. Therefore, image sets vary significantly from year to year. As a result, the images collected in 2020 had already a significantly lower tool performance and required retraining of the model. One of the use cases envisioned by the Human Settlement Unit was running BEAM through decades-wide historical aerials in the municipality's archives. However, this solution would have required lengthy manual labeling and training for each image set. Project development on the eThekwini side also moved from the Human Settlement Unit to Corporate GIS Unit, the City's centralized spatial data storage unit. This handover was meant to provide better technical expertise and was aligned with the city's data management rationalization. However, it shifted the focus of the tool from informal settlements to the entire city: a building footprint layer is "foundational" (INT.05) because it provides the basis for accurate city-wide analytics, population studies, and resource allocation strategies. However, the handover altered the task definition without a corresponding retraining of the tool. This resulted in an algorithmic focus bias, where the model trained on informal dwellings struggled to identify different shapes and larger buildings in eThekwini's formal neighborhoods and industrial areas, altering the task-data-AI fit.

4.2 Reliability

Training on the tool required only a few instances of validation by local experts to distinguish between formal and informal settlements and to identify structures and objects to exclude from mapping, such as buses, tents, and other objects that could be mistaken for informal buildings. However, the detail of the output was low, for example, shapes were not contoured into angular shapes or realigned to nearby polygons as would have been done manually.

The task-AI fit in this case was very much dependent on the specific use case to which BEAM would be applied. In the originally intended use of detailed service planning delivery and household-level calculations "more detailed analysis can be undertaken" (INT.10). Due to its limitations, the application of BEAM proved more suitable when swiftness was prevalent instead of accuracy; for a wholesome estimation "what you're getting from an AI process is good enough" (INT.02).

Production timeliness was, in fact, highlighted in all interviews. Improving the efficiency and speed of workflows was, by inception, the very reason for launching the project and was imperative to keep pace with the rapid urbanization of the city. On the part of UNITAC, in our interviews and during public events and presentations, emphasis was on a total processing time of approximately 72 hours for the entire city, or rather 80 seconds for each of the approximately 3,000 tiles covering the city, assuming a hardware meeting certain technical expectation, as discussed below. The computation time was comparable to state-of-the-art approaches (INT.07). However, the fit had to be estimated against the available hardware and working routines in eThekwini. Considering working hours, network slowdowns, possible power outages—common in eThekwini and South Africa—and other factors, the entire process could be completed "within three or four weeks" (INT.05).

4.3 Contextualization

Most interviewees did not see the need to involve the communities of the settlements being mapped as the end receivers of the intervention. The tool was described as "relatively basic" (INT.01) and conceived for a straightforward task, with no *contextualization* needed in terms of transparency of purpose or inclusion of a bottom-up perspective. Some level of community engagement was maintained through public presentations, but as one of the interviewees pointed out, “We didn’t feel that it was particularly useful to bring community members in to discuss this piece of technology, which is assisting us to do a function that we’re already doing, but just in a much more expensive and time-consuming way” (INT.04). Additionally, the high-altitude perspective of aerial imagery made it difficult to identify individual personal data during analysis, thus avoiding ethical concerns (INT.05).

4.4 Traceability

UNITAC raised some concerns about the potential use of the AI tool to target illegally occupied areas and use the information to enforce evictions, although this issue is already regulated by South African laws.[7] Existing rules, practices, and processes at the local and national levels were also highlighted to guarantee the *traceability* of the task regardless of the tool. Urban planning, as an inherently political process, is “entrenched” in the organizational structure of the municipality, and “it’s difficult to remove the people” from the accountability chain of a decision-making process” (INT.06).

4.5 Comprehensibility

Rather than delving into the workings of the algorithm, people were more interested in understanding the confidence level of a prediction and the overall quality of the result. However, there is a clear difference between expectations at the managerial level of eThekwini and a grounded understanding at the technical level. The former created the concept but found “limited” (INT.10) and “annoying” (INT.09) the need to retrain models for new contexts and different images. The latter were more aware of the challenges and opportunities offered by machine learning algorithms and were conscious of being part of an ongoing development process (INT.12) and that a more capable tool would “depend on a lot of time and resources” (INT.05). They praised the tool for having a very simple and straightforward user interface (UI) for image analysis but lamented the lack of an embedded function or module for retraining the model, which now requires programming skills. Some noted BEAM's lack of integration with and limited advantage over GIS tools in use in the municipality, such as ESRI's products, which also incorporate similar but more customizable AI tools.

4.6 Accessibility

eThekwini proved to have personnel with the necessary skills to operate the tool and to engage in dialogue with UNITAC developers, establishing a positive feedback mechanism. The move from Human Settlements to Corporate GIS, as the main counterpart of the municipality, was instrumental in achieving this goal. The importance of continued AI development expertise through all phases of algorithmic development emerged strongly when the project had a monthslong stop, as UNITAC's data scientist changed twice. Furthermore, like most projects led by an international organization, BEAM is tied to specific donor funding, and its development and maintenance will cease with that revenue stream. UNITAC plans to publish the code under an open-source license to enable eThekwini to further develop the tool through a third-party contractor or future in-house expertise that may develop along its innovation pathways.

However, the entire municipality lacked a computer with the minimum requirements to run BEAM, and they had to procure one for this specific purpose. UNITAC found this revelation "a little bit surprising" (INT.01); from their perspective, these technical requirements appeared ordinary. Conversely, eThekwini found these higher specifications "a big limitation" to using the tool (INT.04) and had expected at least "a discussion to understand whether the city had the capacity to immediately run it" (INT.06). Given the protracted procurement process of the municipality, the computer was transferred from Human Settlement to Corporate GIS upon project takeover. However, relying on a single machine to operate the tool will impact its sustainability. The city must secure a steady and appropriate influx of resources for tool dissemination. Online options have already been discarded due to the limited bandwidth at the city's disposal, but even the offline tool that was developed did not immediately fit the resources of its intended user in terms of *accessibility*.

5. Discussion and conclusion

The implementation of responsible AI requires value-based decisions and ethical considerations, an activity that implies trade-offs (Morley et al., 2020). Our study shows how these trade-offs reside implicitly in the data, task, user, and AI interactions and fits. Additionally, our findings reveal that these fits are interconnected and cross- dependent. This means that choosing a particular AI application involves balancing different task, user, and data characteristics, which extend beyond the specific features of a technology (Sturm and Peters, 2020). Specifically, as evidenced by our analysis, the technical abilities and resources of users can influence all other fits (Jöhnk et al., 2021). Inadequate infrastructure and insufficient skills not only make it challenging to set up and operate AI systems but also influence their *accessibility* and long-term sustainability. Dependence on resources can impede performance assessment and upgrade potential, thereby affecting *reliability*. These limitations also impact the development of AI tools before their deployment. Data accessibility and quality are crucially influenced by users; limited access to initial datasets and poor ongoing data flows can hinder the training and testing of the model, affecting its *generalizability*. Additionally, the nature of the task influences data sensitivities, which, in turn, determine the necessary level of *contextualization* and *traceability*.

Our study also highlights how task reconfiguration, user adaptability, and data improvement can either enhance or hinder alignment with technological systems. We observed that changes in the scope of eThekwini led to a redefinition of the task, which in turn negatively impacted *generalizability*. Consequently, the application area of the AI system was modified in response to its low *reliability*. This indicates that not only AI technologies can be refined for better outcomes and bias mitigation; tasks and user resources can also be adapted to the characteristics of AI. Effective communication among decision-makers, developers, and users is crucial for this adaptation process, which often occurs under tight deadlines and involves people with varying levels of technological expertise (Sturm et al., 2023).

Berente et al. (2021) stress the importance of tailoring tool explanations to the understanding level of the receiver, considering their familiarity with the technology and how it aligns with their beliefs, objectives, and values. This approach is essential, especially given that while there is a general focus on making AI approaches more explainable, most non-experts find even transparent (white-box) models difficult to comprehend (Miller, 2019). In the case of eThekwini, we found three types of receivers: city leaders and managers, local government employees, and the community. The disproportionate expectations of city managers resulted in low *comprehensibility,* which caused misunderstandings between the city and UNITAC (Riveiro and Thill, 2021). For local officers, *comprehensibility* was sufficient, as a general understanding of the algorithm was believed to support developers at UNITAC and the deployment of the tool. However, the re-training of the model was not possible without coding skills, affecting *reliability*, *generalizability*, and *accessibility*. A new user interface could have simplified AI training, enhanced the overall quality of the result, and facilitated the daily use of AI models (Li and Chau, 2022). For communities, the focus should be on *contextualization* and *traceability* for an accurate understanding of the potential risks of the outcomes of the technology being deployed, rather than on explaining the nature and behavior of the AI model (Floridi et al., 2020).

Based on these insights, we reflected on the contribution of these indicators to research on responsible AI principles for urban planning, and we elaborated on how they can offer practical guidance for designing, implementing, and adopting AI systems.

5.1 Theoretical implications

Our study shows how moving beyond the generic notion of responsible AI helps translating principles into more practical requirements. First, it advances our theoretical understanding of AI ethics within the specific task and application domain of urban planning. The fit indicators outlined in our model clarify the types of urban planning tasks involved and consider the rules and practices, of the planning processes into which the task is integrated. Through this, it is possible to identify the ethical risks associated with using GeoAI for these tasks and determine what checks and balances should be exercised over them. This does not suggest that certain AI tools can simply fit within pre-existing frameworks of well-tested and reliable urban governance guidelines (Floridi, 2020). Instead, AI ethics cannot function in isolation and must be integrated with existing regulations and policies that address individual and systemic risks in cities. This underscores that the endeavor to operationalize responsible AI should not focus solely on AI developers with little knowledge of the problem domain (Athey, 2017). Urban planning professionals, city leaders, and communities also play pivotal roles in what should be understood as a collective effort.

In connection to this, our study also offers insights on how responsible AI must situate algorithms and their tasks in the specific local cultural and socio-economic contexts of their users. This is particularly important in an inherently localized and multi-stakeholder field such as urban planning. However, just as AI systems advance, urban planning evolves and user's resources, need and challenges change dynamically. It derives that AI-fit is not fixed (Muchenje and Seppänen, 2023) but should be evaluated through the stages of algorithmic development (Morley et al., 2020). Responsible AI should consider evolving institutional structures and processes; cities, in turn, must understand AI as a technology and derive the right ambition for potential applications along their digitalization journey (Jöhnk et al., 2021).

Finally, in line with recent literature (Rzepka and Berger, 2018 , Sturm and Peters, 2020), our study contributes to TTF theory by adapting it to the unique technical characteristics of AI. In doing so, we included *user*- and *data-technology fit* (Ghasemaghaei et al., 2017 , Jiang et al., 2020 , Russo et al., 2018) in evaluating relevance and usefulness of GeoAI systems. Our results confirm these as crucial fit dimensions, at least in the context studied. Data availability, accessibility, and quality largely determine AI's suitability for given tasks. User characteristics impact task- and data-AI fit, especially as they affect data flow and planning processes. In addition, we identified the most relevant indicator for each construct. Future research could more systematically develop dimensions for the task-user-data-AI fit constructs.

5.2 Practical implications

The framework utilized in this study can help policymakers, AI developers, and urban planning practitioners harmonize technical functionalities with the environment in which they are embedded.

For example, the development of ever larger AI models, trained on vast datasets, promises to deliver both highly sophisticated (reliable) and highly adaptable (generalizable) outputs (Mai et al., 2022). For GeoAI, these models may not only be task-agnostic, but also able to work with images of different spatial or spectral resolutions, across a variety of environmental conditions and landscape structures, and aware of spatiotemporal variations (Li and Hsu, 2022). However, these models require major resource-intensive enterprise, making them increasingly unattainable (Ball et al., 2017). This accessibility gap is mostly addressed by focusing on the characteristic of the AI, for example reducing the need for specialized computational resources (Rolf et al., 2021) and improving diffusion through cloud-based service solutions (Lins et al., 2021). By defining *accessibility* as fit indicator, we point at the importance of considering also user's characteristics and needs. As seen in eThekwini, available infrastructure, network speed and bandwidth can be a limiting factor. Responsible AI should consider costs, but also technical resources for development and deployment, and processes for upkeep, upgrades, and scale up. For example, standalone custom software like BEAM may integrate less effectively within an existing corporate structure and be less upgradable compared to open-source GIS plug-ins, such as QGIS tools developed in Toulouse and Kumasi (Chen et al., 2024 , Touati et al., 2020). Accessibility also entails fostering AI skills and readiness (Jöhnk et al., 2021), and further research could specifically explore ways to improve capabilities in data preparation, data processing, and quality assurance in local governments (Engin et al., 2020).

Beyond purely technical progress towards *generalizability* and *reliability,* responsible AI must be flexible and responsive to the planning and policy processes of its application context. Expert reviews, community feedback loops, and validation with ground-based data collection support the *contextualization* of a tool (Blumenstock, 2018). For example, in Accra in situ observations and interviews with experts from local institutions integrated local knowledge and user requirements in geospatial analysis, addressing their impact on mapped communities (Owusu et al., 2021). Adopting inclusive approaches, collaboration and local ownership throughout the development and deployment stages of AI-systems ensure appropriate *traceability* and *comprehensibility* of a model for all stakeholders (Micheli et al., 2022).

5.3 Limitations and future research

The BEAM project was not finalized at the time of the study; therefore, user perspectives post-tool completion could reveal additional adoption barriers and enablers. This tool was also designed for straightforward tasks. Future research utilizing our framework should address advanced AI applications, supporting problem-solving and decision-making, which involve a wider range of users and stakeholders, and raise deeper concerns about ethics and their eventual societal desirability.

Additionally, our research relies on a single case study, and remarks some specific challenges and barriers associated with AI adoption in African cities, including infrastructure limitations, poor data availability, inadequate technical expertise and poor institutional readiness (Arun, 2020). As for many other digital technology, portrayed as “leapfrogging” conventional development patterns, AI promises to fix some of Africa's chronic problems through efficiency and optimal use of resources (Mengesha et al., 2024). By deploying models developed elsewhere and trained on data from different context, it also threatens to exacerbate existing vulnerabilities and disproportionately echo historical disadvantages (Ade-Ibijola and Okonkwo, 2023). Therefore, responsible AI in Africa deserves dedicated technical and ethical considerations for overcoming design, development, and implementation challenges (Eke et al., 2023) and our research offers contributions to this still emerging research stream.

While these challenges may vary in scale and urgency, they are not unique to African cities (Randolph and Storper, 2022). Examining how AI adoption challenges interact in different contexts can reveal ethical and policy issues that span cities globally and context-specific problems arising from the interplay of global urbanization forces and local factors. Comparative case studies from a wider range of geographical areas are essential to advance knowledge on AI adoption in urban planning and to generalize lessons from our study.

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Notes

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6. In the article, when discussing our findings (Section 4), direct quotations extracted from our 12 interviews are referenced with a code that links to each of the 13 interviewees (two experts were interviewed together). The codes are from INT.01 to INT.13. These codes are also used in Appendix A, which compares interviewees' characteristics, and in Appendix B, which provides a sample of the most significant coded passages. Verbal consent to reuse these data for publication purposes was obtained from all participants and recorded during the interviews.

7. For example, through the Prevention of Illegal Eviction and Unlawful Occupation of Land Act 19 of 1998.

Appendix A: List of interviews and Interviewees' characteristics

ID	Background	Role	Affiliation	Municipality Unit	Direct project involvement	Date
INT.01	Urban Planning	Manager	UNITAC	-	Y	28 March 2023
INT.02	Urban Planning	Technical officer	eThekwini Municipality	Spatial Planning	N	3 April 2023
INT.03	Data Science	Technical officer	UNITAC	-	Y	4 April 2023
INT.04	Geography	Manager	eThekwini Municipality	Human Settlement	Y	6 April 2023
INT.05	GIS	Technical officer	eThekwini Municipality	Corporate GIS	Y	13 April 2023
INT.06	GIS	Technical officer	eThekwini Municipality	Corporate GIS	Y	13 April 2023
INT.07	Technology	Manager	eThekwini Municipality	Economic Development	N	14 April 2023
INT.08	Data Science	Technical officer	UNITAC	-	Y	26 April 2023
INT.09	Urban Planning	Technical officer	UNITAC	-	N	10 May 2023
INT.10	Urban Planning	Manager	eThekwini Municipality	Data, Research and Policy Advocacy	Y	1 August 2023
INT.11	Urban Planning	Manager	eThekwini Municipality	Human Settlement Unit	N	3 August 2023
INT.12	GIS	Technical officer	eThekwini Municipality	Human Settlement	Y	10 August 2023
INT.13	GIS	Technical officer	eThekwini Municipality	Corporate GIS	Y	14 August 2023

Appendix B: Sample of the most significant coded passages

Concept *First-order coding*	*Representative quotations*
Data accessibility and flow	The most important thing in the beginning, of course, was to get some data to understand what we could work with in the first place. Problem was that the city had terabytes of data, but the issue was that according to them, due to Internet connectivity it was not possible to upload this data anywhere so that we could access it. So for months we were in talks of getting a hard drive that would be shipped to Europe from eThekwini. (INT.03)
	Some of the file size of the imagery was too big for us to send via email or via a cloud service, the upload time would have been quite long and with the issues of load shedding in South Africa it would not have sufficed. (INT.12)
Data quality	The idea that we worked based off of was that the images would be like the ones that we were given to train on, that that would be the type of image that it would later be run on. But we weren't told what and how the other images that this should also work on were, what their resolution was or so on. (INT.03)
	Durban has been flying the whole city boundary since the 1990s. Obviously the resolution has changed over time. So, we do understand that it might not be able to go back to say the 1995 aerial imagery or the 1990 aerial imagery, it might not be high enough resolution. (INT.04)
	The issue that we faced was that the image quality and the resolution of those images were far more different than the resolution of the 2021 and now the 2022 images. So they trained them on a lower resolution imagery and then we got higher resolution imagery after that. So that's where most issues came about. It was mostly logistical issues of sending the data, but you know also a delay on actually finalizing processing. (INT.12)
Variable project contributors	Our corporate GIS section has actually taken over from us in running the partnership from eThekwini side, so they're able to make more technical input than I could. But at the same time, the scope of the tool and the user journeys seem to have changed a little bit since they've taken over. (INT.04)
	I think there was mention of some shape files for formal areas that we could have done the testing on, but again we haven't really done anything systematic. We didn't really have time because I was focused on the handover and putting everything together for the person taking over. (INT.03)
Dynamic requirement	It was trained to pick up small structures, informal settlement structures, and now it's being trained to pick up all structures. So, it's moved out of the specific informal settlement focus. (INT.04)
	In commercial areas like our central business district, it does a poor job. Again, it's understandable that it was trained on the informal settlements, and it understands them well and it may not understand all the other different types of classifications. (INT.13)
Expert validation and local knowledge integration	Even with AI you need to use it by deduction, you need to take a human eye or a human assessment to look at it because you see in something that's normal or abnormal in it and you have concerns about it.(INT.02)
	What I think still needs to happen to ensure that data is reliable is to train the model further with our help. As you are aware, there's quite a lot of structures or phenomena that the tool picks which may not really be building structures. In some instances, it just picks up a big piece on the side of the road based on the shade, as an example. In some instances, it picks up buses, in some instances it will pick up many buses. (INT.13)
Output quality	To inform your decision making you need additional investigation, additional research. Or sometimes you'll be satisfied. Sometimes you don't need that detail. Sometimes what you're getting from an AI process is good enough. Depending on what you need to use it for. (INT.02)
	If you're looking at 300 and 14, 300 and 15,000 structures, if there is a 1% change higher or lower, that's acceptable, because once a project is selected or a settlement is selected and you zoom into it, that's when more detailed analysis can be undertaken. (INT.11)

	It's mostly going to be used for quantitative purposes. I'm not so much qualitative but more for as you said in numeration, entities and all those things. (INT.12)
	There may be issues in terms of reliability and confidence. People may have more confidence in what we've generated using a manual process because it gives out much more refined, much more accurate building footprints. (INT.13)
Automation Potential	I do not see us running that manual process of extracting building footprints using the LIDAR data with a few QA process that could take us one and a half year just to release a comprehensive data. (INT.06)
	I think officers were more than willing to use [the tool] because the current methodologies have proven to be time consuming and to some extent rather inaccurate at times. (INT.12)
	What we've been able to get out using different processes is of great quality, but we should also note and not forget that it's actually a very manual process and it takes extensive number of hours and human effort, while what we get out of beam is something that's quite quicker to get out and it doesn't really require that much human intervention in terms of generating the footprints.(INT.13)
Computing time	We are able to map all informal settlements in the city of eThekwini within 72 hours, so this is something that otherwise would take months and a huge team because they have been doing the whole mapping process manually beforehand. (INT.01)
	Obviously, we were then responsible to do all the technical and practical testing to prove that statement correct. One, we have to consider how many working hours we are here for during the day. Two, you had to consider other IT factors such as network speed etcetera, but I think roughly we're able to achieve that full process within three weeks or four weeks. (INT.05)
	This number comes from the 72 hours. Or actually I like the other number, which is 80 to 90 seconds per image depending on the complexity of the image. This is for the whole city. (INT.08)
Complexity	It's a very straightforward task and we can fulfill this task. (INT.01)
	I would say from a technical perspective it's not super complicated because this is a pioneer project, and the idea of segmentation or buildings is there since a long time. (INT.08)
Bottom-up perspective	At broad strategic level when you gather information for purposes of determining your overall backlog for determining funding at a high level, the actual accuracy down to getting it to 100% perfection is not going to happen in any case. So, it's only when, for example, a project becomes a reality, when people actually go on the ground to capture information from households that you would get a good idea of the exact number of people living there, because at the end of the day, that's what it boils down to: people and families as opposed to an account of the structures. (INT.11)
	Given the extent of the municipal boundary, given the magnitude of the backlog that we have, it would be impossible to have somebody on the ground, and covering such a large area and effectively over a short space of time. So, the best we can do is use such technology to assist us and to make very broad and informed assumptions based on maybe pilots or sample cases to determine the number of people or households or families residing in informal settlements and capture the growth that's occurring. (INT.12)
Data detail	It is assumed that when using a plane so many meters above the earth, privacy sensitivity cannot be breached. But if you're going to look at things like drone imagery, for example, a drone can fly very close. Yeah. Then I think that's only when we can have such conversations. (INT.05)
	It's a pretty transparent kind of data. It's transparent information. It's just an image, we're sure that the images were not manipulated or something. (INT.08)
Community engagement	We didn’t feel that it was particularly useful to bring community members in to discuss this piece of technology, which is assisting us to do a function that we’re already doing, but just in a much more expensive and time-consuming way (INT.04)
	Generally, when you're doing something like this, you also need to go to the ground and actually speak to those you think you will be assisting. It's no good just developing a model at this level and just assuming that it's basic function will be achieved right at the bottom. So, there was that need for that engagement, and it was done. (INT.06)

	The communities should be informed, I think this also helps with the understanding where data gaps could be. As an example, if you are running a AI model to pick up building footprints and some buildings are not picked up in the process and you're making decisions out of that, the communities need to be aware that there is that margin of error in the data that is generated. (INT.13)
Interface for image analysis	What [UNITAC] was able to deliver was a completely user-friendly solution. It's a literally a step one to three, once you've done all your prerequisites of downloading the different pieces of software that need to be there and installed the tool properly, running it very simple. (INT.05)
	It's definitely easy to use, so with that you have more people that will be able to use it because you have sort of guided process, a three-step process for you to run the tool. (INT.13)
Interface for model retraining	I don't currently have the understanding to do that. What we were hoping, and I'm not quite sure if it's gone that way, is that there would be a simple interface where when you load your aerial imagery, you can tell it whether it's just to analyze or whether it's to train. And then you could retrain the machine for each set ourselves. But I don't think that it's at that level (INT.04)
	Retraining is not something that's been automatically included in the process. It's something that happens in the back end. So that's the challenge I foresee with the tool, it's retraining it to use new assets of data. (INT.07)
	The difference [with corporate products] stays that you get something that is AI driven and much more simplified in terms of training your model, building your model, and running your model. (INT.13)
Developer-user dialogue	I can only tell you my feeling because I don't know what happened behind the scenes on their end. It did seem like most people had their main projects and this was kind of a side thing on top of their current work. It was always a bit like last minute and seemed a bit improvised. This was my main task. So I was, I felt much more invested in it than my counterparts because I could tell that this was just one of many things they had on their plate (INT.03)
	I'm not an IT specialist. The concept came from us, but I wasn't able to contribute towards the actual technological development, and I don't think UNITAC wanted that from us. I think they're had that best and the University of Hamburg. (INT.04)
	Without a doubt between the municipality and the team in Hamburg this issue should have been resolved when the project was handed over. But obviously that didn't happen. (INT.07)
	A planning tool needs to have a very deep internal component of people internally developing it and ensuring that it talks to the existing systems. (INT.10)
	We had some feedback loop from the corporate GIS because they obviously know better than us. They're the experts on the city. (INT.08)
Trust in technology	The opportunity that exists for African cities, particularly the big metros, is that they have a possibility of leapfrogging a lot of cities in the world because of the tools that are available (INT.10)
	If we can demonstrate to city officials the benefits of this tool [..] it would be key in in winning over officials to accept it (INT.11)
AI awareness	AI being Something that's new and growing, and we're definitely at the South of Africa, so everything tends to reach us last. Even the perceptions won't be the same. In an organization you'll have your technical staff right at the bottom, and then you'll have your senior management staff at the top. Your interactions technically are not the same, therefore perceptions will not be the same. And when new concepts like AI come across people can get excited and make assumptions about what it can do. But the technicals of it is something else. The science of it is something else. (INT.05)
	You either live with the option to consistently retrain for every single year, or you strengthen the algorithms and the development of the tool by familiarizing it more and more each time so that you wanted to automatically detect over years or you have the option to retrain every year. That depends now on a lot of time and resources. (INT.06)
	I feel that the tool has been oversold to outside the city while the reality is that it doesn't really function or do what it had promised to do. (INT.10)

Legal and policy framework	UN-Habitat has an MOU with eThekwini in place that this data can only be used for planning and not for eviction. It's really sensitive data now, if you provide data on informal settlement growing So it's actually data to see how our informal settlements growing, where they are densifying and where they need to go specifically with their upgrading measures and programs. (INT.01)
	We were told that in South Africa [evictions] wouldn't be possible. There are certain safeguards for people that have to be relocated from informal settlements and so on. So, I wonder, you know, how people when you tell them that the city now wants to automatically map their buildings from the sky, how they would feel about, it if they would even want to participate, if they would want to help. (INT.03)
	There are decision making structures, ten levels of decisions, that's how the reporting is done. Testing for approval. The reporting on the progress is unchanged, the decision making is entrenched in these systems and processes, so it's difficult to remove the people. This is how the structure works and how the accountability in the system is allocated (INT.07)
Existing practices and fora	The more effective way of bringing community closer to mapping is to do what we call enumeration or community-based mapping and profiling. We do that through other organizations like the Community Organization Resource Center. They have a lot of expertise in community-based mapping, enumeration processes, and we called them in the reference group for the BEAM. (INT.04)
	On algorithms and using algorithms for decision making and predicting certain things, we also have to be very transparent with that, because that creates a lot of challenges because it creates issues of exclusion. You exclude certain people if you are just using algorithms and trusting algorithms that they would pick up the differences and categories of people in certain ways. So I think for me that's extremely, extremely important that we look at how those processes are done. (INT.10)
	We did have a launch last year for the tool and we invited various stakeholders to participate at the top level management and counselors as well to see how the tool works and you know to see how it was developed, how it was done. So there has been quite a few stakeholders involved that represents the citizens of eThekwini municipality (INT.12)
Digital infrastructure	Hardware procurement was a little bit difficult. [..]) we just wanted them to procure one computer with higher resolution. For us it was a little bit surprising because it was not that much RAM and so on, and it was difficult to procure. (INT.01)
	Remember, we're sitting here in a third world country, so IT availability, fee, resources capacity, availability for funding might not be what you're used to. (INT.04)
	The team in Hamburg at least should have had in the discussion to understand whether the city had the capacity to immediately run [the tool]. You can also imagine that adding the cost of one computer in this project which would be able to run the tool would have just ensured that it's successful in terms of implementation. (INT.07)
	As we speak, we're trying to make use of the tool, but the city actually does not have in its possession a computer which is meeting the minimum requirements to be able to run that tool. Because the AI would require a machine with a very large GPU. So, you start to realize that on the technology infrastructure we are not as advanced. And also, the way the city is geared up it's not able to quickly respond to owning that tool. It means we have to now look for budget, we have to motivate for budget to be able to purchase a computer which is going to be able to run the tool .(INT.07)
Capacity for operating the tool	I think in terms of staff they have human resources, like with the corporate GIS and their Innovate Durban and so on, they have a lot of human resources. (INT.01)
	That was one of the reasons that I actually had it transferred to corporate GIS because I knew that I personally don't have the technical skill to interact with the tool at that level for maintenance or anything. But I'm hoping that our corporate GIS staff will be able to continue to refine and work with the tool given what's been set up so far by the UNITAC team (INT.04)
Capacity for retraining	We have the whole focusing on capacity building and knowledge transfer and there to enable people in antiquity or in other South African cities to train the modules themselves. For providing them with notebooks and training sessions. So, it's more like really tech driven capacity building to [...] train the models themselves for when they have new images, if they want to go back in time, if they want to train it for, for example, different use cases (INT.01)

	Our GIS technicians are fairly competent [...] but I'm not sure that they have highly got the capacity to retrain or do anything like that. Some people would probably be able to work with the source code, but even then, I'd be hesitant to just let him loose on it, unless we had somebody from UNITAC holding his hand. (INT.04)
	For training this model, unfortunately, eThekwini doesn't have that capacity. The idea that we came up with in the end is that maybe each year they would have to hire a freelancing or a very limited capacity of a data scientist or an expert to retrain the model for those images and then they can use it. (INT.08)
	There were still issues of training the model, whether the model could be trained using the new data without the intervention from UNITAC ambushing that process, where as a city we are able to utilize the whole data to be able to train the tool. (INT.10)
	Code had to be rewritten to train the model.So the skill is not really a skill that is easily available within the council at the moment. So in terms of training data sets, in terms of adjusting the tool in the back end, definitely the tool need either training of staff or identification and hiring of people that already possess those skills. (INT.13)
Editability and continued support	UNITAC will not employ this project for a longer period, so we hand over the tool, hand over the code (INT.01)
	If they've developed a tool, it is fine for them to hand over everything to us. Or do we just get the user version where we are just able to operate on the interface? Or are we able to go on the back end and do our own sort of inhouse development where we tweak and adjust one or two things, so they knew you bringing those conversations into play, so that just makes everything more complex. (INT.05)
	We like the fact that this tool is being developed on an open-source platform where we're not really requiring a lot of funding for us to purchase licenses and other things. The challenge with that is that the municipality is so used to proprietary software, and it hasn't really focused on ensuring that the skills to work with open-source software. (INT.13)
Scale up and new features	The idea was to have one work package "Enhancing the beam tool", training the model for different use cases and typologies in eThekwini, so that the model that we to have a good Output as well on on And the CBD area and so on. And then we had geographical upscaling in South Africa, and I think that's important (INT.01)
	There's a common question that does come up, it's the identification of objects. Whether the BEAM tool would now be able to automatically tag certain objects and identify them. The answer is no, we're not at that level yet. Well, I think we they still much more scope here in just the training of the data and making sure that the AI model does as best it can just to identify primary buildings as initial objects, so we're not at that level. (INT.05)
	There's new data or can it then predict and we don't have to prepare training data all the time? because of course that's frankly annoying when you're retraining the model each year. (INT.10)
	Those skills may not be skills that are present internally whether we make use of proprietary or open source, but in terms of the fuel chain what's more secure in the way I see it would be to make use of proprietary. We are exploring the AI capabilities within ArcGIS pro. (INT.13)

Appendix C: Secondary Data Sources

Author	Title	Year	Source
	City plans and strategies		
eThekwini Municipality	eThekwini Integrated Development Plan (IDP) 2017/18 to 2021/22. 2020-2021 Review	2020	Government Website
eThekwini Municipality	*Informal Settlement Incremental Upgrading City-Wide Strategy and Programme Description*	2022	Government Website
eThekwini Municipality	eThekwini Integrated Development Plan (IDP) 2023/24 to 2027/28. 2023-2024 Review	2023	Government Website
	Reports and Presentations		
eThekwini Municipality	Improved Data Integration, Collection and Analysis to Facilitate Informal Settlement Action	2021	Project Document
UN-Habitat	Durban City Context Report	2019	Project Document
Future Cities South Africa	Consolidated Principles for Data Management in the eThekwini Municipality	2020	Project Document
	Technical Documentation		
UNITAC	BEAM User Manual	2022	UNITAC Knowledge Hub
	News Article and Online presentations		
UNITAC	Building Smart Tools for Sustainable Cities: UNITAC Hamburg Projects	2022	Youtube
UNITAC	Using AI to Map Informal Settlements in eThekwini	2022	UNITAC
UNITAC	Building & Establishment Automated Mapper (BEAM)	2023	Youtube
Urban AI	Enabling Safe and Inclusive Cities in Africa - UN-Habitat - Mapping Urban AI Series	2023	Youtube

Tables and Figures

Figure 1: Indicators of Task, Data, and User-AI fit in urban planning

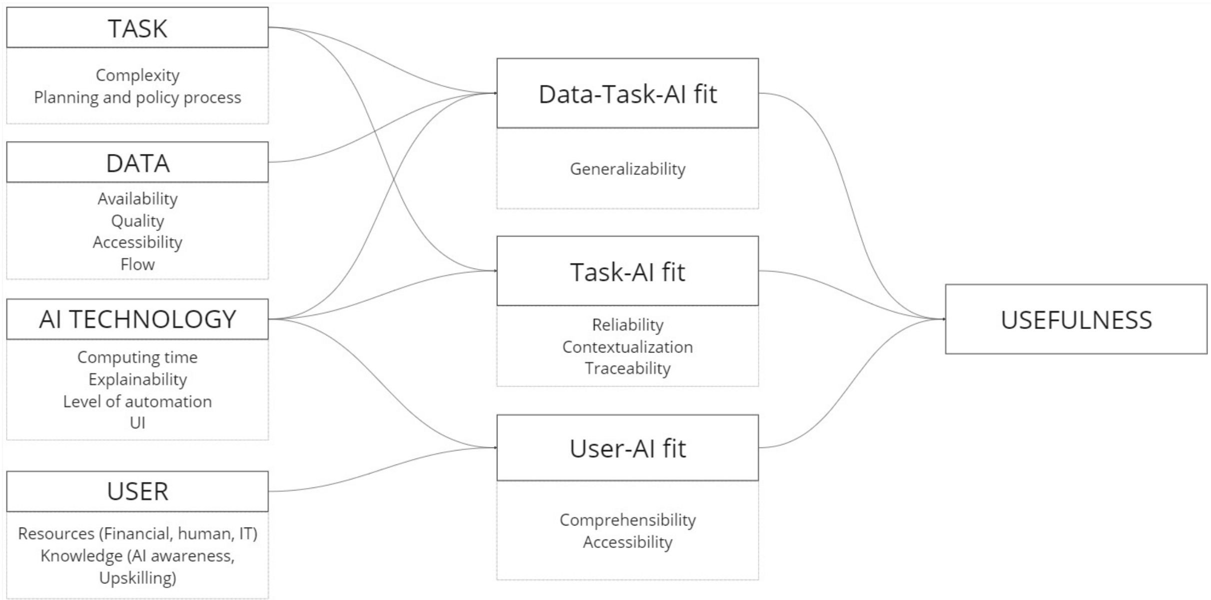

Table 1: Task-Data-User-AI fit indicators. Authors' elaboration based on Carter et al. (2020), Morley et al. (2020), Peng et al. (2023), Rzepka and Berger (2018), and Sturm and Peters (2020)

Indicator	**Description**	**AI Concepts**	**Ethical principle**
Generalizability	Input data of the tool are valid and appropriate to the selected task	Training data bias, algorithmic processing bias, transfer context bias, explainability	Justice; Beneficence; Non-Maleficence
Reliability	Output data of the tool are accurate, usable, and timely	Meaningful human control AI latency	Justice; Autonomy; Explicability
Contextualization	Process and outcome are sensitive to contexts	Bottom-up perspective privacy protection data subject consent	Justice; Beneficence; Non-Maleficence, Explicability
Traceability	The process is transparent and accountable	Algorithmic accountability	Justice, Beneficence; Non-Maleficence, Explicability
Comprehensibility	The tool, its functioning, and its output intelligible and utilizable	Interpretation bias	Explicability
Accessibility	Attainable, affordable, upgradable	AI divide	Justice, Autonomy; Beneficence; Non-Maleficence

Table 2: Data Structure

Concept *First-order coding*	**Theme** *Second-order coding*	**Theoretical Dimension** *Third-order coding*
Data accessibility and flow	Training	Generalizability
Data quality		
Variable project contributors	Task definition	
Dynamic requirement		
Expert validation and local knowledge integration	Accuracy	Reliability
Output quality		
Automation Potential	Production timeliness	
Computing time		
Complexity Bottom-up perspective	Transparent purpose	Contextualization
Data detail Community engagement	Privacy protection and data subject consent	
Interface for image analysis	User-friendliness	Comprehensibility
Interface for model retraining		
Developer-user dialogue	Expectations	
AI awareness		
Existing practices and fora Digital infrastructure	Accountability	Traceability
	Transparency	
Digital infrastructure	Using the tool	Accessibility
Capacity for operating the tool		
Capacity for retraining	Maintaining the tool	
Editability and continued support	Improving the tool	
Scale up and new features		