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INVESTIGATING MIDR THROUGH AI: A CASE STUDY OF THE CITY OF MOST IN CZECH REPUBLIC

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Abstract. Urban planning, which is inherently multifaceted, requires the development of innovative tools to navigate its complexities. This study introduces a pioneering approach that presents an AI-driven framework tailored for urban data collection and analysis. The impetus for this framework is highlighted through the unique narrative of Most city, which is profoundly transformed by mining-induced displacement and resettlement. While most cities serve as a vivid illustration of the challenges cities can face, especially in the wake of industrial imperatives, this study focuses on the potential of AI in addressing such challenges. The proposed framework, while grounded in advanced computational methodologies, is designed with keen emphasis on real-world applications, ensuring its relevance and adaptability. By integrating Most city's detailed account with this AI-centric methodology, this study emphasizes the importance of a data-driven approach in understanding and addressing urban dilemmas. Importantly, this study is preparatory, laying the groundwork for the framework's future application, especially in contexts such as Most city. By bridging advanced AI techniques with tangible urban challenges, this research illuminates a path forward, suggesting a future in which urban planning is not only informed by data but also empowered by AI's analytical process.

Keywords: Mining-induced displacement and resettlement, artificial intelligence, relocation, Most city, urban planning.

1. Introduction

Urban planning, a discipline that shapes the fabric of cities and communities, continually faces multifaceted challenges. From demographic shifts to economic transformations, urban planners must anticipate and address myriad issues. One such challenge is mining-induced displacement and resettlement (MIDR), which is becoming increasingly prevalent in the wake of industrial development. MIDR not only disrupts the physicality of cities, but also reshapes their socio-economic and cultural landscapes, requiring innovative methodologies for understanding and intervention.

Mining operations can be found worldwide, with numerous countries relying on mining as a critical component of their economies. Australia, Canada, China, Russia, the United States, and various African and South American countries are all major mining countries. Each region's mineral resources and mining processes are distinct. It spans from artisanal mining on a small scale to large-scale industrial mining. Individual miners or local communities are often involved in small-scale mining in developing countries. Large-scale mining operations by multinational businesses necessitate extensive infrastructure and machinery [1].

Mining activities may have a positive or negative impact on urban areas. By understanding the global prevalence of mining activities and their impact, urban planners and policymakers can develop informed strategies to mitigate negative consequences, promote sustainable mining practices, and effectively plan for sustainable post-mining city transitions. On one hand, mining activities contribute significantly to economic development at both local and national levels; they generate employment opportunities and revenue while stimulating related industries, attracting investments, infrastructure development, and economic diversification in cities hosting mining operations. However, mining operations also have substantial environmental consequences, including habitat destruction, deforestation, soil erosion, water pollution, air pollution, and greenhouse gas emissions, which adversely affect the health and well-being of urban and rural populations [2].

Furthermore, mining can lead to population influxes, demographic changes, and increased social inequalities. The disruption of traditional livelihoods, cultural practices, and community cohesion caused by mining activities can give rise to social tensions and conflict. Additionally, extensive mining activities can strain existing infrastructure and services, resulting in inadequate healthcare, education, water supply, waste management, and transportation systems due to rapid population growth and increased demand. Abandoned mines also pose long-term challenges for cities, including safety hazards, environmental contamination, and visual blight. While architectural interventions have addressed the issue of abandoned mines in the past, the topic of expanding mining activities necessitating the relocation of entire cities still needs to be studied by urban designers and planners. This knowledge gap is of utmost importance as the growing demand for resources leaves cities with little choice but to contemplate the necessity of moving due to the escalating demands and constraints within their existing locations [1].

The term "Mining-induced displacement and resettlement" (MIDR) refers to the forced displacement of communities and individuals as a direct or indirect consequence of mining activities. It occurs when mining operations require the acquisition of land, which results in the displacement of people from their homes and livelihoods. This displacement often necessitates the resettlement of affected communities in new locations [3].

2. Historical context of Most city

In the Ústí nad Labem Region of the Czech Republic lies the City of Most, an urban area that serves as an intriguing focal point for scholars and practitioners interested in the dynamics of Mining-Induced Displacement and Resettlement (MIDR) [4]. The narrative of this city is intertwined with the themes of obliteration and rebuilding. It was not simply built but was effectively rebuilt following the mass displacement of its original population in the pursuit of brown coal mining [5]. Once known as Starý Most ("Old Most"), the old city was evacuated, and its inhabitants were resettled in what became Nový Most, or "New Most".

At first glance, the story of Most, the town that moved, seems very simple. With communist heavy industrialisation demanding ever-increasing amounts of energy, planners decided in the late 1950s to mine a rich vein of coal under Most, gradually constructing a new city to replace the old one. Cost analyses determined that the procedure would not only uncover 86 million tons of coal but also net a profit of over two billion crowns, including the expenses of demolition and building new housing and services for up to 20 000 people. Although construction and destruction proceeded in fit and started by the mid-1980s, the project was complete. The historic streetscape of Old Most was gone, except for that of the itinerant church. The efficient surface mine that took its place yielded the expected revenue, fuelling several nearby power plants and bringing promised profits. A new socialist town emerged amidst open coal pits. It was the communist planner's dream, with mass housing, modern architecture, and rationalised infrastructure [6].

All that remains of Old Most is a towering late Gothic church, conspicuously isolated on a sculpted plateau north of the new city. Beyond the church, the pit begins, miles and miles of hollowed-out landscape left for natural regeneration, a vacuous memorial to a vanished city and the coal that lay beneath it. If the juxtaposition of the church and coal pit seems surreal, consider this: the Church of the Assumption of the Virgin Mary used to reside 840 metres away, near the centre of Most's liquidated Old Town. In a triumph of communist engineering in Czechoslovakia in 1975, a team of scientists, preservationists and technicians transported the 10 000 ton church on custom-built rails to its new home. Although the church stands as a reminder of the lost old town, its miraculous journey has also rendered it a monument to modernity, to the ability of planners and ideologues to reconfigure the natural and human landscape in the name of industrial progress [5].

This deliberate reshaping of a populated area for resource extraction provides an invaluable case study for examining the complexities involved in MIDR within the context of urban planning and design. The City of Most offers a historical and spatial tableau to assess the immediate and long-term consequences of such an endeavour-sociologically, spatially, and psychologically. Unique in its history, Most presents a golden opportunity to explore how the abrupt changes inflicted by mining activities can morph not only the geography but also the very essence of an urban area [4]. The city's resettlement and subsequent evolution illuminates the grander themes of spatial perception, social resilience, and the ongoing impact of resource-centred decisions on urban settlements.

2.1. Purpose

While the historical intricacies of Most city provide a rich backdrop, the core thrust of this study diverges from conventional urban studies. It has been approximately 50 years since Most was resettled, providing ample data to understand the challenges and consequences of resettled cities. Although gathering this large amount of data can be very time consuming and intense, recognizing the burgeoning role of technology in modern research, this paper presents an artificial intelligence (AI) framework specially tailored for data collection in urban scenarios like Most. This paper does not aim to present specific data findings from Most as it is the initial stages of ongoing research, but to lay the groundwork for how AI can be leveraged to garner insights into significant resettlement situations in Figure 1. By bridging advanced computational methods with real-world urban challenges, we seek to illuminate a path forward for more nuanced data-driven urban planning interventions.

3. The role of AI in urban planning

3.1. Current applications

Artificial Intelligence (AI), with its computational prowess, is increasingly found in the realm of urban planning. Modern cities generate vast amounts of data daily, and AI offers tools to process, analyse, and interpret these data to make informed decisions. From traffic management and infrastructure maintenance to

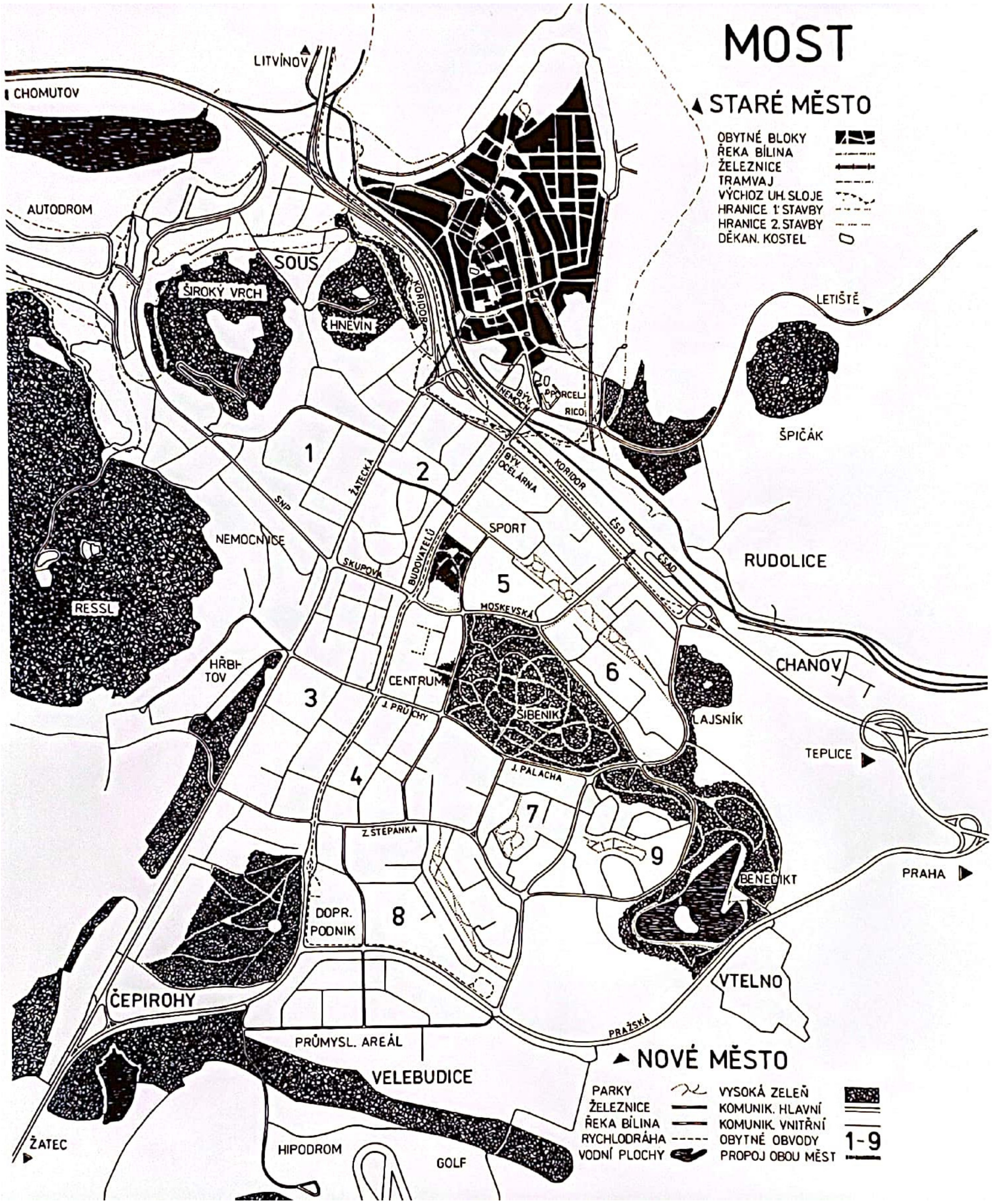

Figure 1. Map showing the resettlement from Starý Most to Nový Most [7].

the prediction of urban growth patterns, AI-powered algorithms assist in optimizing resource allocation and improving urban living conditions, facilitating more sustainable and informed planning.

Data Analysis: AI has the potential to efficiently analyze vast amounts of data, including socioeconomic data, environmental data, and spatial data [8]. This enables urban planners to gain valuable insights into the complex dynamics of post-mining cities, such as demographic changes, economic trends, environmental impacts, and social challenges. AI algorithms can be applied to diverse datasets, such as satellite imagery, sensor data, social media data, and surveys, to extract valuable information for decision-making, providing urban planners with valuable insights for effective planning and resource allocation [9].

Decision-Making Support: Using machine learning algorithms, predictive modelling and simulations, AI can generate scenarios, simulate the impacts of different policy interventions, and optimize resource allocation. This helps stakeholders make evidence-based decisions and assess strategies, potential outcomes, and trade-offs. With regards to MIDR strategies, AI tools could help identify suitable locations for resettlement, evaluate the economic viability of alternative livelihood options, and optimize the allocation of resources for infrastructure development [9, 10].

Community Engagement: AI-powered platforms and tools enable residents and stakeholders to participate in decision-making, provide feedback, and express their concerns. For instance, chatbots and virtual assistants can be used for community queries and providing information about the resettlement process in MIDR contexts. Moreover, natural language processing algorithms can analyze social media data and public sentiments, helping urban planners understand community perceptions and concerns [9, 11, 12].

3.2. Potential and limitations

The potential of AI to reshape urban planning is immense. By providing real-time insights and predictive modelling, AI empowers urban designers to make decisions that are both reactive and proactive. This forward-thinking approach driven by data can lead to more sustainable, efficient, and liveable urban environments. In addition, with the integration of machine learning, urban systems can continuously adapt and evolve based on incoming data, ensuring that cities remain resilient in the face of changing circumstances.

Predictive Modelling: By analyzing historical data and applying machine learning algorithms, AI-driven decision support systems can generate predictive models that help understand the impacts of various decisions on socioeconomic factors, environmental conditions, and community well-being. This assists urban planners in making informed decisions and evaluating the trade-offs associated with different strategies [13].

Optimization and Resource Allocation: Algorithms such as genetic algorithms, simulated annealing, and linear programming can optimize decisions related to land use, infrastructure development, and community services. These optimization techniques assist in maximizing efficiency, minimizing costs, and ensuring an equitable distribution of resources [14, 15].

Spatial Analysis and Visualization: By integrating GIS (Geographic Information System) data with AI techniques, urban planners can analyze the spatial distribution of affected communities, identify areas prone to environmental risks, and optimize the spatial layout of resettlement sites. Moreover, AI-driven visualization tools facilitate effective communication and understanding of complex spatial information [16].

Data-driven Decision-making: Through leveraging historical data, real-time information, and predictive analytics, urban planners can assess the impacts of different development scenarios and make informed decisions regarding land use, infrastructure investments, and service provision [9, 10].

Environmental Monitoring and Management: Combined with AI algorithms, remote sensing data can be used to analyze land use changes, vegetation health, and air quality in the city of Most. This information can help develop targeted strategies for environmental rehabilitation, identify areas of ecological importance, and implement measures to mitigate future environmental risks [17].

Community Engagement: Natural Language Processing (NLP) techniques can extract insights, sentiments, and concerns from community interactions and social media data, allowing urban planners to understand community needs and concerns. This fosters participatory decision-making and ensures the resettled community's voices are heard [9, 11, 12].

Infrastructure Planning: Machine learning models can assist in predicting future demands for housing, transportation, and community facilities through analyzing spatial data and infrastructure requirements. This could potentially help in designing well-integrated, sustainable infrastructure systems that cater to the evolving needs of the resettled communities [18].

However, the adoption of AI in urban planning remains challenging. Ethical implications associated with AI in urban planning strategies include fairness and bias, transparency and explain-ability, privacy and data security, and the need for human oversight and accountability [19]. Ensuring fairness requires addressing biases in data collection and algorithmic models to achieve equitable outcomes [20]. Transparency and explainability are essential to building trust and understanding the reasoning behind AI-driven decisions. Protecting privacy rights and ensuring data security are paramount when handling sensitive information. Lastly, maintaining human oversight is crucial to uphold accountability and ensure that AI

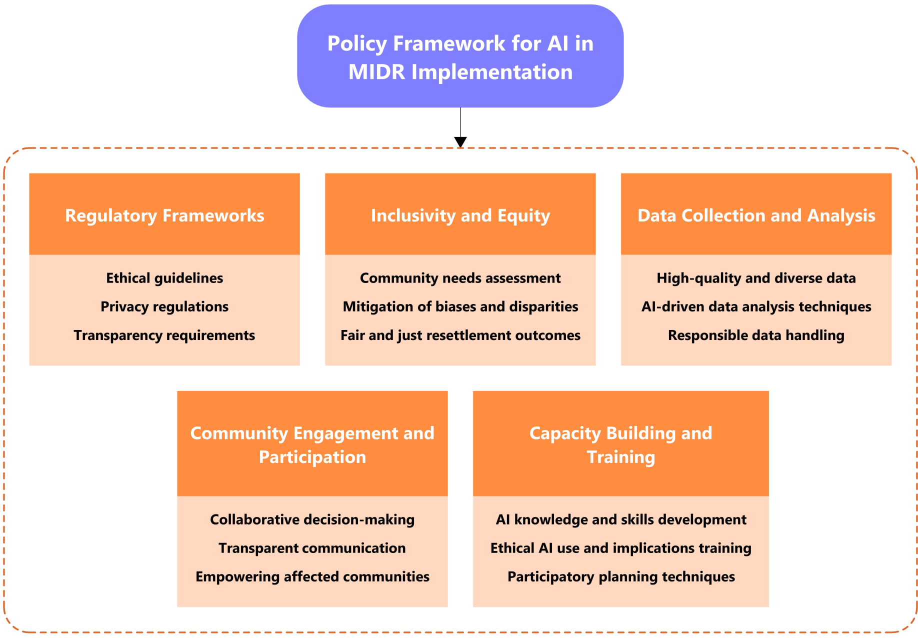

Figure 2. Policy framework for AI implementation in MIDR.

technologies are supportive tools rather than replacing human judgement in planning [21].

It's also worth mentioning that along with developing AI models, there are potential risks, biases, and limitations of such technologies. This could include data bias, overreliance on algorithms, limited generalization, and the potential for a technological divide and exclusion. Data bias can occur if the training data used for the AI model is biased or incomplete, which could exacerbate existing inequalities. Another risk is over-reliance on algorithms without human judgement, which can result in unintended consequences or inaccurate results, emphasizing the need for AI to be seen as a supportive tool rather than a replacement for human expertise. AI models may have limitations in generalizing the complexities of specific post-mining cities like Most, requiring cautious interpretation. Furthermore, implementing AI in urban planning may create a technological divide, leaving specific communities behind due to unequal access and digital literacy. Efforts should be made to address these risks and ensure equitable access to AI-driven tools and their benefits for all communities involved in MIDR initiatives.

In order to properly address these ethical considerations and potential risks, it is vital to establish clear guidelines, regulations, and ethical frameworks for using AI in urban planning. Transparency, inclusivity, fairness, and accountability should be at the forefront of AI implementation, ensuring the technology is harnessed to enhance decision-making processes while safeguarding the well-being and rights of the affected communities.

4. Proposed AI framework for data collection

4.1. Necessity

In the realm of urban planning, data are a cornerstone, shaping our understanding of cities and informing our interventions. The intricate challenges that cities face, especially those undergoing significant transformations such as Most city, necessitate a robust data-driven approach. Data not only capture the current state of affairs but also reveal patterns, allowing planners to anticipate future challenges. However, the sheer volume and complexity of urban data often transcends traditional analytical capacities. Herein lies the need for an AI-driven approach capable of delving deep into vast datasets, extracting pertinent insights, and guiding data-centric urban interventions.

4.2. Framework design

The proposed AI framework is tailored to address the unique challenges and requirements of urban data collection, particularly in contexts such as Most city. At its core, the framework employs advanced machine learning algorithms that are trained to process and interpret urban data. These algorithms are designed to handle a diverse range of data sources, from satellite imagery and urban infrastructure data to socioeconomic indicators. The framework also integrates real-time data-collection tools, ensuring that the insights generated are timely and relevant. Moreover, given the dynamic nature of cities, the framework is adaptive and evolving in response to new data, ensuring that the analysis remains pertinent as urban landscapes change.

In this diagram, see Figure 2, the policy framework for AI implementation in MIDR strategies is presented as a comprehensive system composed of five key components:

- Regulatory Frameworks: This component focuses on establishing ethical guidelines, privacy regulations, and transparency requirements to govern the responsible use of AI in MIDR initiatives.
- Inclusivity and Equity: This component emphasizes conducting community needs assessments, mitigating biases and disparities, and ensuring fair and just resettlement outcomes.
- Data Collection and Analysis: This component highlights the importance of collecting high-quality and diverse data relevant to MIDR, utilizing AI-driven data analysis techniques, and ensuring responsible data handling.
- Community Engagement and Participation: This component emphasizes collaborative decision-making, transparent communication, and empowering affected communities throughout the MIDR process.
- Capacity Building and Training: This component involves developing AI knowledge and skills among stakeholders, providing training on ethical AI use and implications, and utilizing participatory planning techniques.

Together, these components form a robust policy framework that promotes responsible and inclusive AI implementation in urban planning strategies for MIDR. The framework emphasizes ethical considerations, inclusivity, community engagement, data-driven decision-making, and capacity building, ensuring that AI technologies are used to enhance the MIDR process while addressing the specific needs and challenges of affected communities.

4.3. Potential applications

Although the framework is general in its design, its application to specific scenarios, such as the City of Most offers immense potential. Given Most city's rich history and the myriad challenges stemming from its resettlement, the framework can be used to collect and analyse data pertaining to their urban infrastructure, socio-economic dynamics, and cultural shifts. By doing so, planners and policymakers can gain a comprehensive understanding of a city's current state, anticipate future challenges, and design interventions that resonate with its unique context. Beyond Most, the modular design of the framework allows it to be adapted to other cities facing similar urban challenges, making it a versatile tool in the urban planner's arsenal.

5. Bridging the city of Most with the AI framework

5.1. Integration

The story of Most city, with its intricate tapestry of historical, socio-economic, and urban challenges, serves more than just a backdrop; it underscores the need for sophisticated data analysis tools such as the AI framework. Although technologically advanced, an AI-centric methodology derives its true value from its application to real-world challenges. Most city, with its unique trajectory of resettlement and subsequent urban challenges, exemplify the complex urban scenarios that demand a nuanced, data-driven approach. By integrating the detailed account of Most city's challenges with the proposed AI framework, the research aims to ensure that the technology is not viewed in isolation, but rather as a tool intricately linked with the city's narrative. This integration not only bolsters the relevance of the AI framework but also enriches our understanding of Most city through a data-centric perspective.

5.2. Future application

It is crucial to emphasize that the current phase of this research is preparatory. Although the AI framework is presented in detail, its application to Most city remains a future endeavour. However, this preparatory nature does not diminish the significance of this study. This study set the groundwork for imminent data collection and analysis by proposing a robust AI-driven methodology tailored for urban settings. The insights garnered from such future applications have the potential to revolutionize our understanding of Most city and provide actionable recommendations for its continued urban development. This study, therefore, serves as both a testament to the potential of AI in urban planning and a prologue to its practical application in cities like Most.

6. Conclusion

6.1. Summary

Urban planning, ever evolving in its complexities, demands innovative tools and methodologies to address multifaceted challenges. This research sought to highlight one such tool: an AI-driven framework tailored for urban data collection and analysis. Through the lens of Most city's unique narrative of mining-induced displacement and resettlement, we underscored the pressing need for such advanced analytical tools. The City of Most rich history and subsequent urban challenges, serves as a poignant reminder of the intricacies inherent in urban planning. While technologically sophisticated, the proposed AI framework is anchored in addressing real-world challenges, ensuring that its relevance extends beyond theoretical discourse.

6.2. Future directions

Although the current phase of this research lays the foundational groundwork, the journey ahead is both promising and demanding. The next step involves the actual application of the AI framework to Most city, embarking on comprehensive data collection and analysis. This hands-on application will not only validate the framework's efficacy, but also provide invaluable insights into the city's urban dynamics. Moreover, as with all technological tools, the AI framework will undergo iterative refinements, adapting to nuances unearthed during its application. Beyond Most city, the potential of this framework extends to other urban settings with similar challenges, positioning it as a versatile and impactful tool in an urban planner's toolkit.

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References

[1] H. Thorsteinsdottir, B. Chalmers, C. Waldmeier, et al. Sustainability reporting in the mining sector: Current status and future trends, 2020. United Nations Environment Programme and Group of Friends of Paragraph 47 (GoF47). [2023-05-01]. https://wedocs.unep.org/bitstream/handle/20.500.11822/33924/SRMS.pdf?sequence=1&isAllowed=y

[2] European Parliament. Directorate General for Internal Policies of the Union. *Social and environmental impacts of mining activities in the EU*. Publications Office, 2022. https://doi.org/10.2861/804163

[3] S. A. Wilson. Mining-induced displacement and resettlement: The case of rutile mining communities in Sierra Leone. *Journal of Sustainable Mining* **18**(2):67–76, 2019. https://doi.org/10.1016/j.jsm.2019.03.001

[4] B. Frantál. Living on coal: Mined-out identity, community displacement and forming of anti-coal resistance in the Most region, Czech Republic. *Resources Policy* **49**:385–393, 2016. https://doi.org/10.1016/j.resourpol.2016.07.011

[5] E. Glassheim. Most, the town that moved: Coal, communists and the "gypsy question" in post-war Czechoslovakia. *Environment and History* **13**(4):447–476, 2007. https://doi.org/10.3197/096734007x243168

[6] E. Glassheim. National mythologies and ethnic cleansing: The expulsion of Czechoslovak Germans in 1945. *Central European History* **33**(4):463–486, 2000. https://doi.org/10.1163/156916100746428

[7] V. Krejčí. *Most: zánik historického města, výstavba nového města*. AA 2000, 2008. ISBN 978-80-254-3157-3.

[8] S. C. K. Tékouabou, J. Chenal, R. Azmi, et al. Identifying and classifying urban data sources for machine learning-based sustainable urban planning and decision support systems development. *Data* **7**(12):170, 2022. https://doi.org/10.3390/data7120170

[9] M. Bielecka, J. Król-Korczak. Fuzzy decision support system for post-mining regions restoration designing. In *Artificial Intelligence and Soft Computing. ICAISC 2010*, pp. 11–18. Springer, Berlin, Heidelberg, 2010. https://doi.org/10.1007/978-3-642-13208-7_2

[10] M. Bielecka, J. Król-Korczak. Hybrid expert system aiding design of post-mining regions restoration. *Ecological Engineering* **36**(10):1232–1241, 2010. https://doi.org/10.1016/j.ecoleng.2010.04.023

[11] L. Wang, K. Awuah-Offei, S. Que, W. Yang. Eliciting drivers of community perceptions of mining projects through effective community engagement. *Sustainability* **8**(7):658, 2016. https://doi.org/10.3390/su8070658

[12] D. Ali, S. Frimpong. Artificial intelligence, machine learning and process automation: existing knowledge frontier and way forward for mining sector. *Artificial Intelligence Review* **53**(8):6025–6042, 2020. https://doi.org/10.1007/s10462-020-09841-6

[13] S. C. Koumetio Tekouabou, E. B. Diop, R. Azmi, et al. Reviewing the application of machine learning methods to model urban form indicators in planning decision support systems: Potential, issues and challenges. *Journal of King Saud University – Computer and Information Sciences* **34**(8):5943–5967, 2022. https://doi.org/10.1016/j.jksuci.2021.08.007

[14] M. Wang, C. Zheng. Ground water management optimization using genetic algorithms and simulated annealing: Formulation and comparison. *JAWRA Journal of the American Water Resources Association* **34**(3):519–530, 1998. https://doi.org/10.1111/j.1752-1688.1998.tb00951.x

[15] Y. Nian, X. Li, J. Zhou, X. Hu. Impact of land use change on water resource allocation in the middle reaches of the heihe river basin in northwestern China. *Journal of Arid Land* **6**(3):273–286, 2013. https://doi.org/10.1007/s40333-013-0209-4

[16] M. Breunig, P. E. Bradley, M. Jahn, et al. Geospatial data management research: Progress and future directions. *ISPRS International Journal of Geo-Information* **9**(2):95, 2020. https://doi.org/10.3390/ijgi9020095

[17] Y. Himeur, B. Rimal, A. Tiwary, A. Amira. Using artificial intelligence and data fusion for environmental monitoring: A review and future perspectives. *Information Fusion* **86–87**:44–75, 2022. https://doi.org/10.1016/j.inffus.2022.06.003

[18] L. McMillan, L. Varga. A review of the use of artificial intelligence methods in infrastructure systems. *Engineering Applications of Artificial Intelligence* **116**:105472, 2022. https://doi.org/10.1016/j.engappai.2022.105472

[19] A. Hagerty, I. Rubinov. Global AI ethics: A review of the social impacts and ethical implications of artificial intelligence, 2019. [2023-05-12]. arXiv:1907.07892 https://doi.org/10.48550/ARXIV.1907.07892

[20] E. Ferrara. Fairness and bias in artificial intelligence: A brief survey of sources, impacts, and mitigation strategies, 2023. [2023-05-05]. arXiv:2304.07683 https://doi.org/10.48550/ARXIV.2304.07683

[21] European Commission. Ethics guidelines for trustworthy AI, 2019. [2023-05-01]. https://ec.europa.eu/digital-single-market/en/news/ethics-guidelines-trustworthy-ai