CHAPTER 9

Enabling Inclusive Urban Transport Planning Through Civic Artificial Intelligence

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Abstract We recommend enabling inclusive urban transport planning through civic artificial intelligence. To achieve this policy recommendation, we propose the following: (1) Encourage and provide resources for experimentation with new technologies that enable local community participation in urban transport planning; (2) Recognize the potential of Artificial Intelligence (AI) to assist in complex urban transport planning decisions; (3) Acknowledge that AI is embedded in society, instead of

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treating it as a neutral technology; and (4) Foster community engagement in transport planning and evaluation, via a Civic AI framework that directly integrates preferences and feedback into planning.

Keywords Artificial intelligence · Public transport · Participatory planning

Introduction

Transport networks, such as bus and metro lines, are the foundation of urban living (Martens, 2016). Investing in expanding public transport lies at the core of the European Union's Green Deal initiative, which aims at reducing transport emissions towards a climate neutral Europe. However, planning new or expanding existing transport networks requires overcoming physical, socio-economic, political, and legal challenges. This represents a problem that demands innovative solutions. Recent advancements in Artificial Intelligence (AI) have opened up possibilities for understanding and addressing some of these challenges (Michailidis et al., 2023), making urban transport an area where AI, combined with policies, can be pivotal in contributing to the European Green Deal (Fetting, 2020).

Artificial Intelligence was initially perceived as aiming at constructing computers with equal (or superior) mental capacities to the human

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brain (Simos et al., 2022). By now, however, AI is connected to the so-called "smartness mandate", a social drive to make everything, from individual artefacts to broader networks and infrastructures, smart (Halpern et al., 2017).

Critical histories of technology suggest that AI, like all other technologies, is not neutral. Social, economic, and political interests are advanced through certain AI configurations (Garvey, 2018; Simos et al., 2022). In response, the field of AI Ethics has emerged, alongside special studies from the interdisciplinary field of Science and Technology Studies (STS), which aim at opening the black box of AI. STS focuses on biases that may be advanced through the opaque design of AI (Burrell, 2016; Pasquale, 2015). Comparatively, AI Ethics focuses more on the issues emerging during the use of AI after the design stage—with privacy, fairness, and accountability being some of them (Müller, 2020). Alongside STS and AI Ethics, additional concerns are being studied, including the hidden labour required to operate AI (O'Neil, 2016; Pasquinelli, 2023).

Within this context, AI has been specifically presented as a solution to transport-related challenges (Dia, 2023). Here too, issues regarding the opaqueness and unethical use of AI have arisen, as they may perpetuate social biases. Other issues are related to privacy and safety (European Commission: Directorate-General for Research and Innovation, 2020), and issues of accountability and responsibility (Blackett, 2022). Here, we instead focus on the problem of planning public transport lines, a problem in which considerable benefits can emerge from ethical and participatory usage of AI.

Many of the challenges faced by AI systems today stem from their globally oriented, top-down governance. A prime example involves language models, like ChatGPT, which are controlled by big corporations with the necessary resources for data collection and training (Schneier & Waldo, 2023). This process poses significant risks in terms of power concentration and ethical issues of these systems (Konstantis et al., 2023).

In this chapter, our interdisciplinary team, comprising researchers from AI, STS, economics, law, and human rights backgrounds, presents a framework for a locally oriented, bottom-up approach to transport planning policy (Forum for the Future, 2017). Our aim is to propose a method that involves communities in the decision-making process. Initially, we examined recent AI models proposed for transport planning. While these models offer significant potential to aid planners in making better decisions, we observed a predominant top-down approach in their development, neglecting the input of affected communities. Subsequently, we analysed large commercial models like ChatGPT and Gemini, identifying two techniques applicable to local transport planning: Reward Shaping and Reinforcement Learning from Human Feedback. Adapting these techniques requires ensuring representative and fair participation. To gain insights, we investigated participatory methodologies used in other fields, particularly in STS and economics. Through iterative discussions and knowledge exchange, we identified essential aspects to expand upon in our policy recommendation. We integrated these insights with our expertise to develop a framework for Civic AI-based transport planning, emphasising community engagement and inclusivity. We cover the technical components of the system, methodologies for fostering community engagement in a safe, collaborative environment, and potential European-level legislation to support its implementation. In the subsequent section, we elaborate on these key aspects.

With this chapter, we aim to encourage the European Commission to support research and experimentation with innovative technologies—such as Civic AI—that enable local community inclusion in decision-making processes. Through technology that integrates preferences and feedback into the process, we emphasise the potential for AI to contribute to the European Green Deal initiative, by promoting more sustainable and inclusive urban transport networks.

Transport Network Planning

Transport network planning involves an authority that decides where to build new transport networks or expand existing ones. Traditionally, it follows a process where, firstly, the future travel demand of a city is forecasted based on predicted demographics and economic activity. Subsequently, the current network is evaluated, identifying areas that may face capacity challenges. Following this assessment, potential projects of new lines are proposed and evaluated to determine their ability to meet the forecasted demand, alleviate congestion, and fit within the available budget. Finally, a shortlist of qualified projects is extracted and planned (Martens, 2016).

This process does not address a fundamental dimension: the fair distribution of benefits of the new lines. Furthermore, it follows a strict top-down approach, ignoring the input of affected urban communities. By emphasising efficiency, it aims to alleviate congestion, neglecting other fundamental considerations, such as environmental sustainability and access to opportunities (hereby referred to as accessibility) (Martens, 2016). New planning concepts have emerged to address the gap, considering evaluations based on factors such as CO_2 emissions and the number of accessible facilities.

Introducing additional factors into decision-making creates two challenges. First, planning transport projects becomes increasingly complex. Second, given the needs of different communities, determining the relative importance of the different factors for prioritisation is difficult. Hence, one possible solution is to develop AI-driven systems to facilitate informed decisions considering the needs of different communities.

Civic Artificial Intelligence

Our policy framework is grounded in Civic Artificial Intelligence (Civic AI), which promotes the participation of citizens in public decisions using AI (Duberry, 2022). Civic AI applies the Civic Studies framework to the challenges of rapid technological development and revolves around the fundamental question: "What should we do?" (Levine, 2022; Ostrom, 1990). In Civic AI systems, citizens are not passive consumers of technology, or mere data points to be used in models; rather, they are included as co-designers, actively contributing to their creation (Hsu et al., 2022). To achieve this, AI systems should be advanced from a globally oriented, top-down, to a locally oriented, bottom-up process.

Local community involvement can be achieved in different ways, including participatory design workshops that shape research questions, community-led data collection, or survey-based system evaluation (Hsu et al., 2022). By actively engaging with AI systems, citizens enhance their technological proficiency, while researchers gain a better understanding of societal requirements. Ultimately, this paradigm cultivates greater confidence among citizens that their needs are being addressed (Hsu et al., 2022).

In the prevailing top-down planning paradigm, users are treated as data-generation artefacts. For instance, recent AI-based tools employed for predicting future mobility demand rely on mobile phone GPS data to estimate current movements (Michailidis et al., 2023). These data sources are notorious for exhibiting biases against those who do not own latest-technology phones (Coston et al., 2020). In contrast, in our proposed bottom-up approach, citizens actively engage in the planning and evaluation of the system's output. Specifically, the AI agent learns to adapt its behaviour to user preferences. Users actively assess the agent's output throughout the training process, ensuring their involvement at every stage.

Bringing together community members and technological providers is difficult and requires actions in bridging the gap in terminology and facilitating co-creation. Translational activities can prepare communities for professional interactions with technological providers for a mutually rewarding engagement, with insights into social innovation tools and challenges (Khutsishvili, 2024). Ethical considerations come to the forefront, especially when engaging vulnerable and marginalised groups (such as older people, disabled, refugees, low-literate people), emphasising the "do no harm" principle (Khutsishvili et al., 2024). During co-creation, the biggest risk is community disappointment, stemming from factors like unaffordable final solutions, inability to immediately benefit from the solution, or feeling undervalued or unheard. Expectation management is a crucial tool to mitigate these risks. Initially, it is important to acknowledge the asymmetry of information and power disparity, prioritising translational activities and motivational frameworks aimed at balancing the co-creation setting.

Various EU rules provide the basis for the inclusion of citizens and communities in a Civic AI framework. Article 11 of the Treaty on European Union (TEU) states that institutions "shall, by appropriate means, allow citizens and representative associations to make known and publicly exchange their views in all areas of Union action" (TEU, 1992, Art. 11(1)), as well as participate in the democratic life of the union (TEU, 1992, Art. 10(3)). Additionally, one of the objectives of the Better Regulation agenda concerns involving citizens, businesses, and other stakeholders in decision-making, with the ultimate goal of enhancing the legitimacy of the democratic process (Bunea & Chrisp, 2023).

The recent framework for regulating Artificial Intelligence by the European Parliament (AI Act) forms the basis for citizen inclusion in AI systems design. Title V stipulates the creation of regulatory sandboxes for testing the new AI technology before its introduction to the market (European Commission, 2021). Article 55 provides specific measures for users and small-scale providers, including priority access to the sandbox, awareness-raising activities, and dedicated channels for communication (European Commission, 2021). Another example is the General Data Protection Regulation (GDPR) that focuses on the "protection of natural persons with regard to the processing of personal data and rules relating to the free movement of personal data" (European Parliament, Council of the European Union (2016), Art. 1). Although the GDPR does not require direct engagement of impacted parties (Skoric et al., 2022), it is a step towards fostering active involvement.

The AI Act and the GDPR represent some mechanisms adopted at the European level that include enhancing the participation of citizens, communities and civil society. In conjunction with general EU law, it shows that the union considers these stakeholders' roles, albeit further efforts are needed.

Civic AI for Transport Network Planning

In Fig. 9.1, we present the proposed framework for inclusive transport planning. Its key technical component is the transport planning agent. An agent is an AI model that iteratively learns to make decisions within a virtual environment. In the context of transport, such an environment is established by creating a grid of the city, with each area represented by a grid cell. Various layers of crucial metrics are encoded in this environment, such as forecasted travel demand, accessibility, and emissions.

The agent aims to generate transport lines that effectively balance a combination of these metrics. A fundamental AI paradigm for implementing such agents is Reinforcement Learning (RL). An RL agent learns through trial-and-error, by taking actions, receiving feedback from the

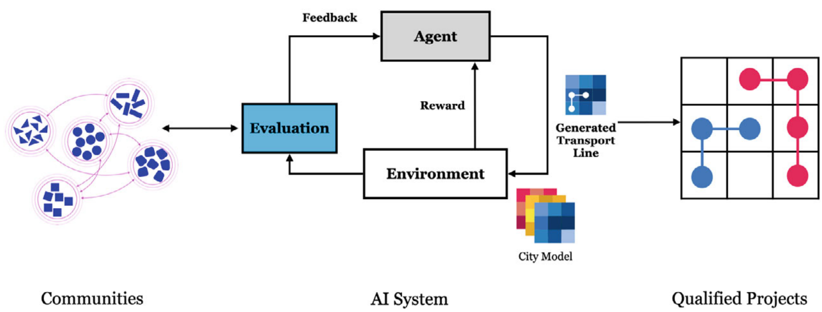

Fig. 9.1 A framework for inclusive transport planning, in which communities actively engage in the design and evaluation of the system used to generate transport projects

environment in the form of a reward, and adapting its behaviour to maximise it. Through this training process, the agent continually improves its decision-making.

For a transport planning agent, actions involve sequentially connecting areas in the city to form a transport line. Traditionally, this is automated and without interference, with domain experts deciding beforehand how to combine various metrics into a single reward. However, under the Civic AI framework, this process involves non-experts that influence the training process.

There exist various processes to incorporate community feedback into Reinforcement Learning (Kaufmann et al., 2023). We outline two classes that policymakers can utilise: Reward Shaping and Reinforcement Learning from Human Feedback (RLHF).

Reward Shaping draws from insights from social choice theory, which concerns the aggregation of individual preferences into collective decisions. In this process, communities collaborate to co-design the reward function that will train the transport planning agent. The agent thus learns to maximise the collective reward formulated by the communities.

Reward shaping occurs through direct data collection. Citizens, through an interface, provide their most important journeys or their preferred transport lines, based on their needs. The data can subsequently be utilised by experts to incorporate the relative community importance of various aspects (e.g. accessibility, emissions) into the reward function. This can lead to a reward that expresses the desirable compromise between the traditional objectives and the citizens' preferences. This is a process that enhances citizens' agency, as they are asked to directly submit their preferences. However, one drawback lies in the potential variety of the gathered data, making it challenging to reach an optimal compromise that satisfies everyone. Additionally, it requires substantial community input, making it crucial for policymakers to ensure the collection of a diverse dataset.

In Reinforcement Learning from Human Feedback (RLHF), communities are engaged throughout the entire training process, not solely during the reward-shaping phase. RLHF can be used alongside Reward Shaping, as a final tuning step. In contrast with Reward Shaping, citizens here evaluate generated lines by the agent. At various intervals during training, the agent generates alternative extensions, which are then assessed by citizens. In RLHF, this evaluation commonly takes place through direct comparison. Citizens are provided with a set of alternative lines, and they are asked to rank them from most to least preferable. This preference is then fed back to the agent to update the reward function.

This process requires fewer data and can be effectively implemented in a small, co-creative space. Additionally, it is less sensitive to specific individual needs, as the generated lines for evaluation align better with metric-based objectives. A drawback of this approach is that it limits citizens' evaluations to lines already considered good by the agent, thereby affecting their agency in the decision-making process. Nevertheless, it can lead to a meaningful compromise between the traditional planning approach and the Civic AI framework.

The training process of the agent concludes when it stops improving. This is a straightforward procedure in the system, which keeps track of the received feedback. Upon completion, the agent can be used to generate the eligible transport projects. Optionally, another layer of evaluation can be incorporated, for example via a final voting on the projects, or by expert planners.

A Hypothetical Example

Let us consider an example where a city plans to expand its public transport network by building a new metro line. In addition to traditional mobility forecasts and budget constraints, the planners decide to use the Civic AI framework to incorporate citizens' feedback. Workshops are organised to gather input from representative community members.

Citizen feedback occurs in two phases. Initially, citizens provide factors such as commuting preferences and environmental concerns. Transport planners use this input to shape the reward function of the planning agent. They aggregate preferences into factors like demand and travel ease, then use Reward Shaping to weight these factors accordingly.

The planner agent is then trained in a simulated environment to draw the metro line by maximising the given reward function. The second phase of citizen feedback begins, via Reinforcement Learning from Human Feedback, where citizens rank the generated metro lines based on their preferences. The agent adjusts its outputs to reflect these preferences. When it stops improving, qualified transport projects are extracted. These may undergo a final round of evaluation, either through participatory or expert assessment, to ensure alignment with city goals and values.

Conclusion

In this chapter, we combined our interdisciplinary expertise to propose a framework for Civic AI-based transport planning. Through discussions, knowledge sharing, and reviews, we have reached a recommendation that encompasses technical, social, and legal aspects of the framework. While practical implementation requires further experimentation, workshops are already underway across Europe to address how to incorporate diverse perspectives into decision-making. We outline the next steps required to advance the proposed framework.

Firstly, it is important to recognise Artificial Intelligence (AI) as a powerful, specialised tool rather than an omniscient, neutral technology that can take unbiased, universal decisions. By doing so, policymakers acknowledge its potential to assist in the complex decision-making process of planning public transport inclusively, while at the same time understanding its limitations.

Encouraging research and experimentation with innovative technologies that promote community inclusivity is crucial. The European Commission should allocate resources and funding towards initiatives that support the development and experimentation of AI solutions tailored to local contexts. This should focus on transitioning from a globally oriented, top-down approach to a locally oriented, bottom-up approach in decision-making. Resources could include funding pilot projects, offering technical assistance, and facilitating knowledge sharing among member states. Through these initiatives, AI can be leveraged for the benefit of local communities and to advance inclusive decision-making processes in transport.

Finally, to foster community engagement, we propose implementing processes that integrate preferences and feedback into AI systems' training and evaluation, via the methods we outlined in the chapter. By actively involving the community in the planning and evaluation of transport projects, we can ensure that the resulting infrastructure aligns with the needs and desires of those it serves, ultimately leading to more sustainable and equitable urban transport networks.

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References

Blackett, C. (2022). The ethics of AI in autonomous transport. In M. C. Leva, E. Patelli, & L. Podofillini (Eds.), Proceedings of the *32nd European Safety and Reliability Conference (ESREL 2022)* (pp. 3390–3397). Research Publishing. https://doi.org/10.3850/978-981-18-5183-4_J03-05-453-cd

Bunea, A., & Chrisp, J. (2023). Reconciling participatory and evidence-based policymaking in the EU better regulation policy: Mission (im)possible? *Journal of European Integration, 45*(5), 729750. https://doi.org/10.1080/07036337.2022.2144848

Burrell, J. (2016). How the machine 'thinks': Understanding opacity in machine learning algorithms. *Big Data and Society*, *3*(1), 1–12. https://doi.org/10.1177/2053951715622512

Coston, A., Guha, N., Ouyang, D., Lu, L., Chouldechova, A., & Ho, D. E. (2020). Leveraging administrative data for bias audits: Assessing disparate coverage with mobility data for Covid-19 policy. arXiv:2011.07194 [Cs, Stat]. http://arxiv.org/abs/2011.07194

Dia, H. (Ed.). (2023). *Handbook on Artificial Intelligence and transport*. Edward Elgar.

Duberry, J. (2022). AI and civic tech: Engaging citizens in decision-making processes but not without risks. In *Artificial Intelligence and democracy* (pp. 195–224). Edward Elgar Publishing.

European Commission. (2021). *Proposal for a regulation of the European Parliament and of the Council laying down harmonised rules on artificial intelligence (Artificial Intelligence Act) and amending certain Union legislative acts* (COM/2021/206 final). https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A52021PC0206

European Commission: Directorate-General for Research and Innovation. (2020). *Ethics of connected and automated vehicles: Recommendations on road safety, privacy, fairness, explainability and responsibility.* Publications Office of the European Union. https://data.europa.eu/doi/10.2777/035239

European Parliament, Council of the European Union. (2016). *Regulation (EU) 2016/679 of the European Parliament and of the Council of 27 April 2016 on the protection of natural persons with regard to the processing of personal data and on the free movement of such data, and repealing Directive 95/46/EC (General Data Protection Regulation)*. https://eur-lex.europa.eu/eli/reg/2016/679/oj

Fetting, C. (2020). *The European Green Deal*. ESDN Office, Vienna. https://www.esdn.eu/fileadmin/ESDN_Reports/ESDN_Report_2_2020.pdf

Forum for the Future. (2017). *Citizens bringing the future forward*. Futures Centre Issuu. https://issuu.com/futurescentre/docs/fftf_citizens_bringing_the_future_f

Garvey, C. (2018). Broken promises and empty threats: The evolution of AI in the USA, 1956–1996. *Technology's Stories, 6*(1). https://doi.org/10.15763/jou.ts.2018.03.16.02

Halpern, O., Mitchell, R., & Geoghegan, B. D. (2017). The smartness mandate: Notes toward a critique. *Grey Room, 68*, 106–129. https://doi.org/10.1162/GREY_a_00221

Hsu, Y.-C., 'Kenneth' Huang, T.-H., Verma, H., Mauri, A., Nourbakhsh, I., & Bozzon, A. (2022). Empowering local communities using Artificial Intelligence. *Patterns, 3*(3), 100449. https://doi.org/10.1016/j.patter.2022.100449

Kaufmann, T., Weng, P., Bengs, V., & Hüllermeier, E. (2023). A survey of reinforcement learning from human feedback. arXiv:2312.14925 [Cs, LG]. http://arxiv.org/abs/2312.14925

Khutsishvili, K. (2024). *Guidelines for translating frameworks, methods, tools and principles of local innovations for marginalised and vulnerable communities—2023*. Open Research Europe. https://open-research-europe.ec.europa.eu/articles/4-36

Khutsishvili, K., Pavicic, N., & Combé, M. (2024). The challenge of co-creation: How to connect technologies and communities in an ethical way. *Proceedings of the ETHICOMP 2024. 21st International Conference on the Ethical and Social Impacts of ICT*. https://dialnet.unirioja.es/servlet/articulo?codigo=9333577

Konstantis, K., Georgas, A., Faras, A., Georgas, K., & Tympas, A. (2023). Ethical considerations in working with ChatGPT on a questionnaire about the future of work with ChatGPT. *AI and Ethics*. https://doi.org/10.1007/s43681-023-00312-6

Levine, P. (2022). *What should we do? A theory of civic life*. Oxford University Press.

Martens, K. (2016). *Transport justice: Designing fair transportation systems*. Routledge.

Michailidis, D., Ghebreab, S., & Santos, F. P. (2023). Balancing fairness and efficiency in transport network design through reinforcement learning. *Proceedings of the 2023 International Conference on Autonomous Agents and Multiagent Systems* (pp. 2532–2534). https://dl.acm.org/doi/10.5555/3545946.3598992

Müller, V. C. (2020, Winter). Ethics of Artificial Intelligence and Robotics. In *The Stanford Encyclopedia of Philosophy*. https://plato.stanford.edu/archives/win2020/entries/ethics-ai

O'Neil, C. (2016). *Weapons of math destruction: How Big Data increases inequality and threatens democracy*. Crown.

Ostrom, E. (1990). *Governing the commons: The evolution of institutions for collective action*. Cambridge University Press.

Pasquale, F. (2015). *The Black Box society: The secret algorithms that control money and information*. Harvard University Press.

Pasquinelli, M. (2023). *The eye of the master: A social history of Artificial Intelligence*. Verso.

Schneier, B., & Waldo, J. (2023, May 30). Big Tech isn't prepared for A.I.'s next chapter. *Slate*.

Simos, M., Konstantis, K., Sakalis, K., & Tympas, A. (2022). "AI can be analogous to steam power" or from the "post-industrial society" to the "fourth industrial revolution": An intellectual history of Artificial Intelligence. *ICON, 27*(1), 97–116.

Skoric, V., Sileno, G., & Ghebreab, S. (2022). *Legality, legitimacy, and instrumental possibility in human and computational governance for the public sector*. https://ceur-ws.org/Vol-3289/paper4.pdf

Treaty on European Union. (1992). http://data.europa.eu/eli/treaty/teu_2012/oj