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Uses, opportunities and risks of artificial intelligence in participatory urban planning

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Abstract
Participatory urban planning is undergoing significant changes because of the rapid development of artificial intelligence (AI) tools. This study explores and compares the differences in the relational agency of Analytical, Generative and Humanised AI as perceived by urban planners. We consider relational agency with respect to the intended and unintended uses and perceived opportunities and risks of these technologies in participatory urban planning. A Delphi survey was conducted with 34 urban planners across municipalities in Finland with > 20,000 inhabitants, followed up by a focus group and survey to build convergence on respondents' views ($n = 13$). Respondents commonly used Analytical AI to summarise plan information and to report on environmental variables, and saw its potential to analyse and report on citizen feedback on draft plans, including survey responses. Generative AI is currently used to undertake more creative tasks than Analytical AI, including generating images and simulations, with the potential to use it to draft plan content and summarise expert reports on plan drafts. Risks centre around data protection problems, the outsourcing of decision-making to computer tools, and the potential to create misinformation or incorrect content. Humanised AI is rarely used in urban planning in Finland, but respondents saw potential to use it to respond to community feedback on urban plans and to communicate plans more effectively to the wider public through a cautious approach that addresses the potential for emotion and opinion influencing. We discuss the implications of these findings for participatory urban planning across Europe and elsewhere.

1 Introduction

Effectively engaging communities in urban planning is critical to address the interconnected biodiversity, climate and well-being crises in cities [1]. Participatory urban planning builds on communicative planning theory [2] and involves many actions such as identifying participants, determining stakeholder interests, identifying shared preferences and communicating with different stakeholders [3]. Local knowledge can be collected using interviews, surveys, focus groups and public hearings [4]. New participatory planning tools combine online participatory mapping, visualisation tools, crowdsource and collaboration platforms and connect values and behavioural patterns of individuals with the physical, social and cultural characteristics of the local environment [5].

Building on Habermas' [6] theory of communicative action, in communicative planning it is assumed that urban planning becomes more democratic and just through improvements in the communications between planning stakeholders such as planners, politicians, citizens and corporations . There are different views on how power is embedded in participatory urban planning from this starting point. Healey views power as embedded in implicit and explicit principles about how planning actions should be achieved [2]. Planners not only bring power relations, but they also have the choice to change them. In contrast, Innes [7] views communication itself as a form of action that changes planning realities, including power relations [8]. The rapid acceleration of artificial intelligence (AI) presents a potential new means for not only citizens to influence planning decisions [9, 10], but also to reconfigure power dynamics within planning organisations. AI broadly refers to 'intelligence' of machines to perform human-like tasks which would typically require human intelligence to solve [11, 12]. Recent research on AI-mediated communication shows the potential for AI to complicate the processes and outcomes of persuasion in communication, particularly when the involvement of AI is not apparent [13]. AI can have 'relational agency' in that the algorithms are communicative entities are interconnected with humans in a planning organisation, and are 'co-actors' in planning decisions [14, 15]. Agency emerges from interactions with humans, other systems and the environment, rather than being solely an inherent property of the AI itself.

There are various pathways in which AI can support relational agency in participatory planning. This includes building nuanced insights into community preferences for urban development, predicting the results of alternative plans, partially automating plan generation, facilitating communication between stakeholders and educating participants [3]. Yet, AI also carries multiple relational agency risks for urban planning, including ethical and equity issues, and associated issues of justice, fairness, safety, accountability and loss of privacy [16, 17]. Indeed, AI influences opportunities for public participation across various urban planning phases [18]. AI can also perform work and assess risks and opportunities in isolation of human intervention, highlighting their social and material power [19]. Recent studies have created characteristics of responsible AI in response to these risks, which includes commitments to reliability and accountability to preserve public support and trust [20].

Many different perspectives on 'intelligence' exist, which has led to different definitions of AI [21]. We categorise AI types as *Analytical*, *Generative*, and *Humanised AI*, aligning with our focus on AI for participatory urban planning. Analytical AI aids in data processing, analysis, and pattern identification [22, 23]. Generative AI creates synthetic data and simulates scenarios through interactive interfaces, natural language processing, and personalised recommendations [24]. Humanised AI, while not fully developed as yet, seeks to understand human emotions like happiness, stress, urgency, anger and pain when humans display them through speech, facial and other expressions, enabling them to predict mood in the future [25]. Humanised AI is heading towards artificial general intelligence, where a system can perceive, learn, memorise, socially interact, plan and motivate like humans [26]. However, there has been limited scholarly research considering the relational agency of different types of AI, here operationalised as the potential uses, opportunities and ethical risks of different forms of AI in participatory urban planning [27]. Understanding relational agency across different types of AI can help urban planners in partnership with citizens and AI experts to tailor risk management strategies to AI uses and technological domains [9].

In this paper, we address the research question of how relational agency varies across different types of AI in participatory urban planning. More specifically, we explore city planners' views on the actual and potential uses, opportunities and risks of Analytical, Generative and Humanised AI in participatory urban planning. We present the results of a 3-phase Delphi Survey and Focus group conducted with 34 city planners across Finland and then use the main points of convergence to generate a typology of opportunities and risks, which is complemented by factors in the peer-reviewed literature. A Delphi methodology was adopted in order to identify the level of convergence and diverse in urban planners' perspectives on the relational agency of different types of AI. First, we provide a theoretical background to known AI opportunities and risks. Such insights are urgently needed to assist city planners discerningly use AI tools when engaging with different publics. We draw on this theoretical background in the discussion to show new and emerging uses, opportunities and risks of AI based on the empirical results.

1.1 Opportunities and risks associated with analytical, generative and humanised AI

1.1.1 Analytical AI

Analytical AI is a technology that aims to discover new insights, patterns and relationships or dependencies in data and to assist in data-driven decision-making [23]. It typically uses machine learning to analyse data and make predictions and inferences about the future [22]. Numerous machine learning algorithms have been established to extract information about the urban form [28] from remote sensing datasets such as height of buildings [29]or the urban fabric [30], to name a few.

Analytical AI presents multiple opportunities for participatory urban planning. It can help planners to process big data about community concerns or preferences regarding zoning, transport or environmental designs. It can identify socio-spatial patterns and trends in planning-relevant processes such as energy consumption [31] or transportation networks [32]. The analysis of social networks has also seen strong developments with interesting data mining methods for analysing use of space [33]. Such techniques have also been integrated into proposals for a fully automated planner, which automates land-use configurations and can integrate human feedback [34].

Analytical AI also carries risks. While it produces observations or analyses from massive amounts of data, it can still make certain parts of the population invisible [35]. It can also lead to "black box" problems, where justification and rationales for the results are opaque. Outsourcing political decision-making to highly analytical machines can lead to situations where new types of social norms, institutional rules and stereotypes are created [36, 37], particularly by companies who are able to control not only the technological developments but also the discourses around it [38].

1.1.2 Generative AI

Generative AI is a technology that (i) leverages deep learning models to (ii) generate human-like content (e.g., images, words) in response to (iii) complex and varied prompts (e.g., languages, instructions, questions) [24]. While Analytical AI is focused on analysing data and making predictions or decisions based on that data, Generative AI is focused on creating new data or content that resembles human-created content [39]. Existing tools in the public can create human-level text (e.g., ChatGPT, Luminous, Bard, Bing), images (e.g., Stable Diffusion, DALL·E 2), videos (e.g., Synthesia), or audio (e.g., MusicLM) [40], and many others are being developed for specific professions such as architecture and land-use planning [41]. Collectively, these models allow AI to find patterns and relationships in data, generating new examples that are similar to the training data [40].

Generative AI presents multiple opportunities for participatory urban planning. It can be used to imagine and visualise alternative uses of space, supporting the automation of many planning processes [42] and enable users often with little expertise to generate designs in existing cases [43]. It can support rapid urban design prototyping [44, 45]; for example, creating architectural sketches with a specific theme in just a few seconds with different user-specified elements [41]. The large language learning models associated with Generative AI could be used to emulate, interpret and test public comments without using traditional social survey methods [46]. Such models could greatly expand exploratory modelling capabilities, such as creating urban plans across time and space [47], particularly in data-sparse areas and newly planned regions [48]. These models can also support iterative adaptation of designs as part of social learning processes [41].

Generative AI also carries many risks. Generative AI leads to more pattern recognition without deep understanding by the user, which may proliferate misinformation and could lead to irreproducible results [49, 50]. Like Analytical AI, decision-makers and the public are currently unable to inspect the assumptions and interactions used to derive the results of Generative AI [51]. Scholars of planning, ethics and law have argued that decision-making over land-use planning should not be left to Generative AI given this has risks for the accountability of decisions. Generative AI bears the risk of creating synthetic content, making it challenging to differentiate between real and fake information [40]. For example, public opinions, stakeholder perspectives, or societal positions may be generated artificially and may pose significant threats to distorting participatory processes, in particular, when participation is increasingly organised in online formats. This raises many questions as to 'which public' is presented in these AI processes, whether informed consent has occurred, and whether citizen's concerns will be transparent to researchers, politicians and the public at large [52].

1.1.3 Humanised AI

Humanised AI is a form of AI that learns and thinks on varied tasks like a human [53]. It also has the ability to influence human emotion, including joy, sadness, fear, and anger or related affective states like interest, alertness, or engagement [54] by drawing on machine learning to try and sense, learn about, and interact with human emotional life [55]. For example, BMW, Audi, and Honda, car makers, are upgrading their 'in-cabin' driving experience with sensors which can detect driver's happiness, anger, alertness, distraction, calmness, or agitation [56]. Microsoft's XiaoIce and Meta AI's Blender Bot are being developed to build empathy with humans through new forms of human-AI interactions [57]. More widely, researchers in healthcare are investigating how Humanised AI can enhance empathic awareness, empathetic response and relational behaviour [58].

Humanised AI holds much promise for participatory urban planning. It has the potential to help planners identify and predict new dimensions to a planning problem, such as citizen's likely emotional responses to planned development. Chat-bot messaging could be tailored to affected communities to build empathy with them about their concerns. It could also help build relationships with customers (residents) in difficult circumstances such as pandemics [59]. Humanised AI could iteratively code concerns and feed them into a set of new planning proposals e.g., drawing on edge-based, hyperlocal, and respectful methods to have rich-media, emotionally enhanced interactivity [55]. Humanised AI could also help create spaces for listening, learning and discussing how identities can be reframed or power can be redistributed to achieve meaningful and transformative change [60]. It could also collate affective responses to planned development, supporting subtle changes to plan implementation (e.g., collection of feedback about adverse impacts of noise, air pollution etc. - changes in work practices).

Humanised AI also holds multiple risks. Humanised AI could lead to unwanted policing of emotions (managing sentiments that are deemed to be harmful to a given institution) and attitudinal conformity (changing beliefs, attitudes or actions to align with accepted institutional norms), polarisation of public discourse, which is a threat to human privacy and autonomy [56]. It could enable urban developers to become extremely close to citizens, making citizens expose sides of themselves that they wouldn't normally reveal to a corporate organisation (ibid.). Subsequently, cities and companies could use Humanised AI to influence user thoughts, decisions and behaviours, affecting their awareness of consequences of given planning decisions [61]. There is potential for institutional actors and industries that surround algorithmic tools to take advantage of (often already marginalised) people's emotions [37]. Unconsented-to sensing of emotion using big data, and cloud logics could lead to further marginalisation of less heard groups in participatory urban planning [55].

2 Methods

2.1 Participatory urban planning context in Finland

The legislation governing land use planning in Finland has adopted a communicative planning approach. The law requires municipalities to involve citizens and other stakeholders in the preparation of plans at an early stage and to consult them at different stages of the planning process. However, the formal participation procedures require a limited amount of community engagement. Digitalisation has been driving a paradigm shift in Finnish urban planning already for decades, which is also reflected in the increasing use of digital participation tools in participatory processes over the past 20 years [62]. Digitalisation has raised challenges in terms of how to use written opinions from stakeholders in the planning process [63]and how to systematically analyse and process large data sets [62].

2.2 Sampling

We employed a snowball sampling technique which involved sending an invitation to land use planning team leaders and team representatives from all municipalities and associated planning organisations with more than 20,000 inhabitants, a total of 53 municipalities, to participate in a three-phase Delphi study. Invited participants could circulate the survey to a colleague within their organisation if they believed they had greater interest in the content of the survey. We chose this cut-off given that very small municipalities were unlikely to have the time to participate in the study and capacities to reflect, test and utilise AI tools. Each email contained a link to an online round 1 Delphi survey that took approximately 20 minutes to complete. To encourage response, we sent gentle reminder emails each fortnight over a six-week period (April-May 2024).

We reached 16 out of the 53 municipalities and received 34 responses to our survey. The majority of respondents were employed in city municipalities (79%) or private companies (12%), located principally in southern and mid-Finland. Most identified as being either strategic urban planners (12%), master planners (16%), detailed planners (37%), or communication/interaction planners (13%).

A similar proportion of men (42%) and women (55%) participated in the first-round Delphi survey, and 3% classified themselves as other. The majority of respondents were middle-aged (46% 30–44 years; 39% 45–59 years), but there were some younger respondents (9% 15–29 years) and older respondents (6% 60–74 years). All respondents were highly educated with the highest qualification of either a bachelor's or associate degree (9%), master's degree (78%) or Doctorate or Licentiate (13%). Most respondents had more than six years of experience with participatory urban planning (57%) with only a few having no experience (12%).

The majority of respondents had no or only moderate experience with AI. In total, 42% of respondents had 0 years of experience with the use of AI generally, 45% 1–2 years of experience, 9% 3–5 years and 3% 6–10 years, while 78% had 0 years of experience with the application of AI in participatory urban planning and 22% had 1–3 years of experience. Also, the majority of respondents were somewhat knowledgeable about the risks or opportunities and risks posed by AI on participatory urban planning (59%).

2.3 Delphi survey and focus group technique

The Delphi survey technique comprised of three activities: (1) a first round survey to structure group communication [64], allowing participants to reflect on the topic at their own pace, while avoiding the persuasively expressed opinions of others; (2) an online focus groups enabling participants to identify convergence in opportunities and risks identified in the first round survey, and; (3) a short post-focus group survey enabling participants to reflect on their main learnings (Fig. 1).

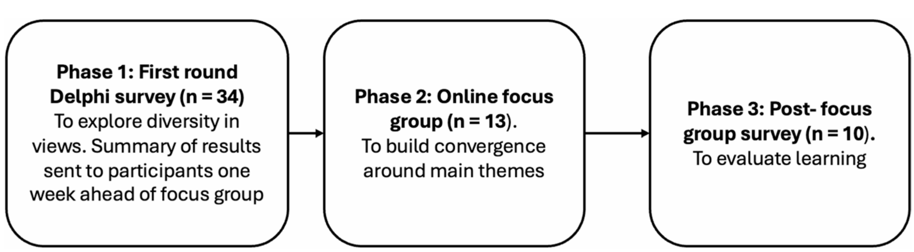

Fig. 1 Overview of the Delphi survey and focus group technique

The survey (Supplementary Material, SM1) included the sections of: (1) general knowledge about AI and participatory urban planning; (2) views on the potential uses of Analytical, Generative and Humanised AI, which was preceded by succinct definitions of each, and; (3) views on the opportunities and risks presented by Analytical, Generative and Humanised AI. Results were summarised and presented back to all participants one week prior to an online focus group so that they had an opportunity to digest the main results ahead of the meeting. Thirteen participants attended the focus group and 10 of them completed the post- focus group survey. The focus group consisted of a 20-minute presentation of the summary of the results, 30-minute break out group discussion enabling participants to expand on the survey results and a 25-minute plenary discussion enabling all participants to build convergence around the main opportunities and risks of the three types of AI in participatory urban planning. The post-focus group survey (SM1) included questions on their impressions of the focus group and what they learned from the deliberations.

2.4 Analyses

Delphi survey data were first analysed using descriptive statistics. Inductive coding of open-ended survey questions was conducted in Atlas.ti using thematic analyses [65] involving an iterative process of: (1) reading and familiarization of open-ended responses and (2) complete coding of uses (current, potential and inappropriate), opportunities and risks, and (3) clustering observations into broader thematic sets and combining similar codes. The thematic analysis resulted in 332 quotations classified into 74 codes, each divided into Analytical, Generative and Humanised AI. Responses to focus group questions and post-focus group survey was also analysed using inductive coding.

In the second analysis phase, a cross-tabulation was undertaken in Atlas.ti (using code-document analysis) to compare the findings of the thematic analysis (classified set of codings) among respondents with different levels of self-reported knowledge about AI (not knowledgeable, somewhat knowledgeable, more knowledgeable). Due to the low frequency of observations, it was not possible to assess the statistical significance of the results. However, it is possible to create some general conclusions that we report in each sub-section of the results.

3 Results

3.1 Attitudes towards the participatory urban planning functions of AI

We asked participants to rate their level of agreement or disagreement with respect to the potential participatory urban planning functions of AI. Participants generally agreed with all responses, although when comparing all respondents there was divergence of opinion with regards to whether AI can help local decision makers to make informed decisions about land-use plans (51.5% agree, 33.3% neutral, 15.2% disagree, Table 1), and whether AI can help urban planners to give feedback to residents (67.6% agree, 14.7% neutral, 17.6% disagree). Overall, the strongest agreement centred around AI being able to help urban planners analyse participatory data (97% agree). Respondents with no knowledge about AI were less certain about whether AI can help urban planners source development ideas from the public (12.5%, Table 1).

Table 1 Current, potential and inappropriate uses of Analytical, generative and humanised AI identified by survey participants (Observations ratio to number of respondents, %)

	All respondents (*N* = 34)
Analytical AI	
Current uses of Analytical AI	
Gathering, analysing and summarising participatory data	1–25%
Analysing plans	1–25%
Searching information	1–25%
Potential uses of Analytical AI	
Conducting different analyses	26–50%
Analysing participatory data	26–50%
Assessing and comparing plans	26–50%
Enhancing communication	1–25%
Processing and combining data	1–25%
Summarising information	1–25%
Creating conclusions and planning solutions	1–25%
Searching information	1–25%
Inappropriate uses of Analytical AI	
Economic optimisation	1–25%
Processing sensitive data	1–25%
Creating mis- or disinformation	1–25%
Making decisions	1–25%
Predicting or identifying the probabilities of phenomena	1–25%
Prioritisation based on population classification	1–25%
Generative AI	
Current uses of Generative AI	
Generating images and visualisations	1–25%
Generating text	1–25%
Processing images	1–25%
Translating languages and proofreading	1–25%
Drafting building blocks	1–25%
Potential uses of Generative AI	
Drafting content for plan documents	26–50%
Generating communication material	26–50%
Generating new planning proposals	26–50%
Co-creating future visions	26–50%
Programming and GIS	1–25%
Promoting sustainable development	1–25%
Inappropriate uses of Generative AI	
Intetional manipulation of behavior	1–25%
Generating voice and deepfake videos	1–25%
Generating text for plan reports	1–25%
Programming	1–25%
Using sensitive data	1–25%
Humanised AI	
Current uses of Humanised AI	
Communicating and storytelling future scenarios	1–25%
Potential uses of Humanised AI	
Planning and implementing communication and interaction	1–25%
Expressing empathy	1–25%
Pre-assessing plans	1–25%
Measuring and changing the atmosphere around community sentiments on proposed plans	1–25%
Inappropriate uses of Humanised AI	

Table 1 (continued)

	All respondents (N=34)
Opinion forming and manipulation of emotions	1–25%
Using for fraudulent purposes; creating deepfakes, dis- and misinformation	1–25%

3.2 Use of analytical, generative and humanised AI

The current, potential and inappropriate uses of AI (Table 1) were identified using thematic analysis of the open ended questions in the survey (phase 1) and the the focus group (phase 2). Respondents currently use Analytical AI to summarise plan feedback data and to analyse the environmental impacts and traffic data. Commonly used tools include Autodesk Forma which provides real-time analyses of environmental variables (e.g., wind, sunlight, noise); Perplexity – a conversational search engine; Howspace AI for summarizing and analysing participant conversations; Miro AI for generating content, synthesizing data and automating workflows; and Microsoft Copilot which are AI tools integrated within Microsoft applications. At the most basic level, respondents use Analytical AI to search information using Google and through GIS systems. Respondents currently use Generative AI to generate images and visualisations (e.g., sketching the visual appearance of the area, citizen-driven initiatives), generating text, translation and proofreading, drafting building blocks and the creation and simulation of future scenarios (Table 1). Tools being used include ChatGPT to generate human-like text responses, Stable Diffusion to turn text into images, Urbanist AI for visualizing ideas and reimagining neighbourhoods, Adobe Firefly to generate and manipulate images and a diversity of translation tools. No current software applications of Humanised AI were identified, although participants noted the use of Humanised AI in communicating and storytelling future scenarios through images, texts, sounds and videos.

We then compared the potential and inappropriate uses of Analytical, Generative and Humanised AI, as identified by participants. The most frequently cited potential uses of Analytical AI were linked to the analysis of participatory data and the assessment and comparison of plans (Table 1). Respondents saw potential in using Analytical AI to address issues of missing data in old plans, to combine data sets and interpret aerial images, to conduct optimisations and simulations, to compare plans with respect to their environmental impacts, and in knowledge management and communication. However, the processing of sensitive data, or the intent to create dis- or misinformation, or the prioritisations of community needs based on population registers were deemed inappropriate uses of Analytical AI.

Respondents identified more creative potential uses of Generative AI compared with Analytical AI. The most frequently cited potential uses were drafting content for plan documents, generating communication material, creating new planning proposals and co-creating future visions (Table 1). While inappropriate uses of Analytical AI stemmed from predictive modelling of existing data, inappropriate uses of Generative AI concern the generation of incorrect new text or the creation of deep fakes which misconstrue or blatantly undermine planning goals. Unlike Analytical and Generative AI, Humanised AI was deemed to have important potential uses for responding to angry feedback from community members in an empathic manner, and for supporting effective planning and implementation of communication and interaction. Yet again the creation of deepfakes, dis- and misinformation were seen as inappropriate uses of this type of AI.

Knowledge about AI was associated with identification of a greater variety potential and inappropriate uses. Respondents not knowledgeable of AI were less likely to identify potential or inappropriate uses of Generative AI, and respondents not knowledgeable or somewhat knowledgeable of AI were less likely to identify potential or inappropriate uses of Humanised AI.

3.3 Opportunities and risks of analytical, generative and humanised AI

The opportunities and risks of the three types of AI (Table 2) were also identified based on thematic analysis of the open-ended survey questions and focus group. The most frequently cited opportunities of Analytical AI were increased efficiency of planning processes and the ability to analyse large datasets (Table 2). However, respondents identified potential for errors and biases in results, as well as issues of transparency, uncritical and unethical use. For example, some respondents noted a general lack of engagement with diverse knowledge systems, leading to the voices of minorities being lost. Respondents identified multiple opportunities of Generative AI, including the potential for faster work, new methods of visualisation and automated communication, and the most frequently cited risk relates to unintentional errors stemming from the results and outputs of Generative AI (Table 2). The opportunities of Humanised AI were spread across multiple themes such as anticipating conflict and seeking consensus, enhancing participation experience and producing engagement content, and sparring in planning. The most frequently cited risks of Humanised AI were manipulation and opinion influencing, and dehumanization and unethical use stemming from, for example, the use of Humanised AI to emphasise disparities among people of different race and identity, which in-turn increases the potential for conflict in participatory urban planning.

Overall, respondents not knowledgeable about AI were able to identify some AI risks, but their responses were more narrow than those somewhat knowledgeable and more knowledgeable about AI.

Identifying opportunities and risks was more difficult for Humanised AI than for Analytical or Generative AI.

3.4 Main learnings and points of convergence during the Delphi process

The discussions at the workshop confirmed and complemented the results of the survey. Participants agreed that AI is a useful tool for some tasks, but there are risks associated with its use. One potentially beneficial application was to use AI for reviewing the planner's own deliverables, for example to bring a 'neutral', outside perspective to the analysis. Furthermore, the use of Generative AI to visualise the preferences of participants as part of the interactive activities was welcomed. In contrast, there were mixed views on the use of visualisations to illustrate the plans drawn up by the planner.

The risks of reliability and bias were perceived to be higher for Generative and Humanised AI than for Analytical AI. For example, Analytical AI processing of geospatial datasets was perceived to be more reliable than qualitative analysis or text generation using AI. There was also agreement on the problems associated with the use of personal data by AI in participatory urban planning. Datasets often contain personal or family-related information that cannot be processed by AI. On the other hand, the analysis of large

Table 2 Opportunities and risks of Analytical, generative and humanised AI identified by survey participants (Observations ratio to number of respondents, %)

	All respondents ($N=34$)
Analytical AI	
Opportunities of Analytical AI	
Increased efficiency and streamlined processes	26–50%
Ability to analyse large datasets	26–50%
Better results from data analysis	1–25%
Better communication and services	1–25%
Risks of Analytical AI	
Errors and bias in results	26–50%
Lack of transparency of analyses	1–25%
Uncritical use	1–25%
Unethical use	1–25%
Generative AI	
Opportunities of Generative AI	
Faster work	1–25%
New methods of visualisation	1–25%
Automated communication	1–25%
Facilitates opinion-forming and understanding	1–25%
Analysing feedback	1–25%
Optimised planning solutions	1–25%
Risks of Generative AI	
Unintentional errors	51–75%
Ethics	1–25%
Data protection problems and unethical use	1–25%
Quality of results	1–25%
Biases	1–25%
Increased volume of data	1–25%
Impact on thinking	1–25%
Inefficiency	1–25%
Environmental impacts	1–25%
Humanised AI	
Opportunities of Humanised AI	
Anticipating conflict and seeking consensus	1–25%
Enhancing participation experience and producing engaging content	1–25%
Sparring in planning	1–25%
Alleviating labour shortage in planning	1–25%
Separating emotional messages from analytical information, regulating and communicating emotions in interactions	1–25%
Understanding personality differences	1–25%
Risks of Humanised AI	
Manipulation and opinion influencing	26–50%
Dehumanization and unethical use; potential to emphasise disparities among people; increasing conflicts and lack of transparency	26–50%
Biases and misinterpretations	1–25%
Not suitable for urban planning and considered too challenging	1–25%
Intentional fraud and disinformation	1–25%

participatory datasets was seen as having potential benefits for participatory urban planning. Views differed on the use of AI for actual planning and impact assessment of plans. For example, it was not considered desirable for plans to be based on training data collected in other cultural contexts, making the solutions unsuitable for Finnish planning.

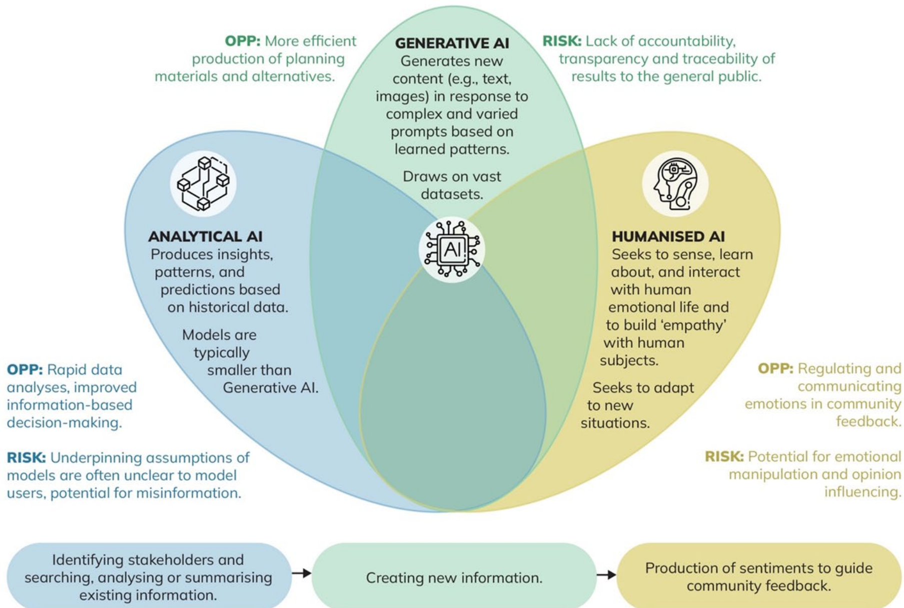

Fig. 2 Summary of the differences in the relational agency of participatory urban planning across analytical, generative and humanised AI

Conversely, the use of analytical tools to assess the environmental impact of the plans was considered useful.

4 Discussion

This paper explored and compared the relational agency of Analytical, Generative and Humanised AI in participatory urban planning. Unlike previous research focusing on the general opportunities and risks of AI in urban planning [3], we showed that uses, opportunities and risk vary across different types of AI. As AI advances from analytical to humanised forms, current or potential uses change from summarising, searching or analysing existing information to creating new information and the production of sentiments to guide feedback on the planning process (Fig. 2). This presents opportunities for faster and more 'efficient' planning processes, but at the same time increasing influence of AI systems on decision-making in urban governance creates further risks in terms of access, privacy, representation, accountability and legitimacy [27, 66]. The results also advance relational agency in communicative planning theory by showing that agency not only emerges from humans, other systems and the environment, but also decision contexts in which different types of AI are used, and the capacity and vested interests of stakeholders involved in interpreting and using the results in planning. In this discussion, we compare the opportunities and risk of the three types of AI, and then explore ethical implications and future research directions.

4.1 Comparison of opportunities and risks

Respondents somewhat knowledgeable and more knowledgeable about AI identified a greater diversity of appropriate uses, inappropriate uses and risks associated with Analytical and Generative AI compared with respondents not knowledgeable about AI. Respondents not knowledgeable and with some knowledge of AI had more difficulty identifying appropriate and inappropriate uses, opportunities and risks associated with

Generative AI compared to those with more knowledge about AI. While respondents with more AI knowledge may be more optimistic about the future of AI, they are also able to identify risks, suggesting that they are able to effectively discern the positive and negative consequences of AI in their planning practice.

Overall, responses demonstrate that AI can be a powerful tool in urban planning, offering new ways to partially or fully automate certain procedures or tasks in urban planning, while also recognising that planning involves human values and judgement requiring human planners to always have a role in decision-making (building on [16]). Participants noted that Analytical AI provided a more transparent approach to modelling big data, although issues of bias and accountability remain (supporting [37, 67]). New opportunities that emerged in the discussion that are rarely mentioned in the current planning literature include the ability to use Analytical AI to better understand stakeholders' needs and help explain and predict the impact of changing operational environments on their livelihoods. Generative AI's ability to analyse large amounts of community feedback and to provide automated and multilingual communication are new ways for improving participatory urban planning, and respondents feedback confirmed evidence that Generative AI leads to faster output generation and synthesis, as well as iterative development of planning outputs [42, 68]. However, there are fewer opportunities for the user to control how data are combined and analysed, creating issues of data verifiability and replicability [69] and the potential for 'fake' outputs on the other. While many of the opportunities of Humanised AI are untested, respondents saw potential in understanding personality differences and managing conflicts relating to urban planning.

Given the variation in relational agency across the three types of AI, one needs to question whether the different types of AI will lead to participatory planning ideals of genuine involvement of the public, meaningful deliberation, mutual learning, and the management of power imbalances [2]. Participants raised concerns regarding the financial and technical resources needed to develop and implement Generative AI [16, 70]. The expense of AI tools and the specialized knowledge needed to operate them can centralize power among those with large resources, leading to less-inclusive urban planning processes and smaller stakeholder groups having less influence on participatory planning processes (building on [66]). Developers and urban planners could use the AI outputs to not only reframe community sentiment in ways that support the interests of powerful interests over public good, but also emotionally target community members through 'empathy' building, leading to shifts in attitudes and behaviours aligning with dominant planning interests. Respondents with no knowledge about AI were less able to identify such risks compared with those with more knowledge of AI, particularly for Generative and Humanised AI sub-groups. Hence there is potential for misuse of AI when knowledge about their implications is low.

Respondents were also concerned that Generative and Humanised AI have the potential to spread misinformation or disinformation. If the underlying data used in AI systems is flawed, outdated or biased, the AI's outputs can be inaccurate or misleading, leading to misinformation. Sometimes AI systems are deliberately fed inaccurate data, leading to disinformation, which can hamper the ability of citizens to take informed decisions in urban planning [66]. Wider studies have identified similar risks in terms of the 'block box' nature of AI, complicating understanding and trust in AI-driven decisions, and the potential misuse of the extensive amount of data collected by AI systems [66, 70]. For example, over-relying on information from social media accounts that object against certain land developments could distort plan formulations [3, 71].

Protecting individuals and their data is foundational to any participatory urban planning process and needs more systematic consideration in AI and participatory urban planning practice [72]. Survey participants identified privacy concerns associated with Generative AI use, including the safety of personal information and data protection problems. Smart cities literature highlight that both data acquisition and the data transfer process pose risks to privacy and fairness [73]. For example, AI can use advanced machine learning algorithms to predict confidential information from non-sensitive data, such as one's emotional state, as well as analyse political views and general health based on activity logbooks, location data or similar [74].

4.2 Limitations and future directions

The study did not consider how opportunities and risks of AI vary across different stakeholder groups. Future research should focus particularly on the requirements of different urban actors towards transparency of the AI use in participatory urban planning, as these actor groups have different capabilities and resources to engage with AI based participatory planning. Future research could also explore the opportunities and risks of AI with stakeholders located in small municipalities, which were not investigated in this study. We also recommend using diverse datasets, implementing human oversight, and engaging communities to mitigate bias, and support [75] on the need to build convergence of artificial and human intelligence in urban planning. Furthermore, developing explainable AI models, establishing clear ethical frameworks, and promoting public education can enhance trust and transparency.

5 Conclusion

Drawing on insights from the peer-reviewed literature and the Delphi survey, we show that relational agency in participatory urban planning varies across different types of AI. As AI advances from Analytical to Generative and Humanised forms, there is increased potential for AI to move from a scenario planning and decision-support tool to producing new information based on sentiments and emotional needs of humans. In Analytical AI the risks and opportunities often pertain to questions about which data streams to integrate into the AI system while in Generative AI the end results of the AI assessment are more difficult to predict and to confirm accountability and legitimacy of the results. In Humanised AI, further challenges arise about how AI can genuinely empathise with planning stakeholders and the motives behind emotional engagement. Future research could consider how the risks and opportunities of each type of AI could be considered not only in participatory urban planning but also different phases of technology development and diffusion.

Supplementary Information

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Supplementary Material 1

Author contributions
C.R. and P.N. led the writing of the paper. M.K., T.v.W. and A.P. developed the conceptual basis of the paper. A.P. generated the figures. S.B., A.A., E.D., E.M.D., N.F., A.G-R., F.H., A.H., J.K., O.K., M.M., A.J.P., T.M., A.M., V.N., S.R., P.R., T.R., J.S., N.S., T.T. and F.V. contributed to the review of the literature and the body text.

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Data availability
The datasets generated during and/or analysed during the current study are not publicly available due to the possibility of identifying subjects, but are available from the corresponding author on reasonable request.

Declarations

Competing interests
The authors declare no competing interests.

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