

Large Language Models for Synthetic Participatory Planning of Synergistic Transportation Systems

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Abstract

Unleashing the synergies of rapidly evolving mobility technologies in a multi-stakeholder landscape presents unique challenges and opportunities for addressing urban transportation problems. This paper introduces a novel synthetic participatory method, critically leveraging large language models (LLMs) to create digital avatars representing diverse stakeholders to plan shared automated electric mobility systems (SAEMS). These calibratable agents collaboratively identify objectives, envision and evaluate SAEMS alternatives, and strategize implementation under risks and constraints. The results of a Montreal case study indicate that a structured and parameterized workflow provides outputs with high controllability and comprehensiveness on an SAEMS plan than generated using a single LLM-enabled expert agent. Consequently, the approach provides a promising avenue for cost-efficiently improving the inclusivity and interpretability of multi-objective transportation planning, suggesting a paradigm shift in how we envision and strategize for sustainable and equitable transportation systems.

Keywords: Smart Planning; Generative Artificial Intelligence; Human-AI; Multi-Criteria; Explainable; Expert System

1. Introduction

Mobility systems worldwide confront escalating challenges—aging infrastructure, increasing environmental impacts from transportation emissions, and widening service provision gaps that exacerbate social inequalities. These challenges demand smart and adaptive planning strategies that effectively leverage both existing and emerging technologies—including autonomous driving, vehicle electrification, low-latency communication, and Mobility-as-a-Service (MaaS) platforms. Shared Automated Electric Mobility Systems (SAEMS), exemplified by on-demand autonomous electric bikeshare systems, autonomous transit and passenger car services, and unmanned aerial vehicle (UAV)

delivery services, present viable frameworks to potentially synergize these existing and emerging technologies to address the escalating challenges.

However, the potential of SAEMS to benefit diverse populations often remains underrealized amid environmental, technological, and socioeconomic uncertainties. This shortfall largely stems from the complexity of integrating a broad spectrum of domain knowledge and perspectives—ranging from charging systems engineering to urban policies, and from local business operations to residents’ daily experiences—into coherent planning processes. Therefore, an inclusive and anticipatory planning framework is crucial. It must be capable of synthesizing diverse technical and non-technical stakeholder inputs to ensure the comprehensiveness and inclusiveness of any proposed SAEMS to ensure that these systems evolve in a manner that is equitable and aligned with broader societal goals.

Traditional participatory planning, while valuable, often faces various barriers that limit its effectiveness and inclusivity, including the logistical and administrative challenges of coordinating meetings, the financial and organizational obstacles of providing adequate incentives for participation, and difficulty of reaching consensus (Gosling, 2018). Longer participatory sessions can also lead to participant fatigue, resulting in lower-quality outcomes, and participants may churn or be unable to participate continuously due to other life commitments.

This paper introduces a synthetic participatory planning approach that leverages generative artificial intelligence to create digital avatars representing diverse stakeholder groups in transportation systems planning and engineering. These avatars are powered by multimodal Large Language Models (LLMs) (Barreto et al., 2023; Li et al., 2024; Shanahan et al., 2023; Wang et al., 2024) and engage in virtual deliberations, significantly enhancing the inclusivity and efficiency of the planning process. This method facilitates comprehensive transportation planning by integrating diverse perspectives more effectively and cost-efficiently than traditional methods, allowing for multiple scenario simulations to refine system designs under various operational and strategic constraints.

Our approach utilizes a structured and parameterized workflow to create and utilize LLM-enabled digital avatars to represent the knowledge and interests of potential stakeholders in the city of Montreal when planning SAEMS, demonstrating the capabilities of aligning with stakeholders’ needs and opinions and improving service accessibility and sustainability metrics. By simulating the entire planning process—from identifying issues and setting objectives to conceiving and evaluating solution alternatives—our method offers a scalable,

adaptable, and interpretable framework that combines the insights of both real and virtual stakeholders. This creates a dynamic human-machine collaborative decision-making environment where each avatar can be calibrated to represent specific real-world attributes such as personality, socioeconomic status, and other relevant factors.

The synthetic participatory method proposed not only anticipates potential scenarios in the initial phases of planning but also integrates seamlessly into ongoing official processes. This is achieved through potential interactions between real stakeholders and their own or other stakeholders' digital counterparts, establishing a novel paradigm for artificial intelligence (AI)-assisted decision-making or human-AI teaming in transportation systems engineering and planning. Figure 1 illustrates how this integration facilitates the use of diverse data sources to evaluate and optimize transportation solutions in a risk-free simulation environment, paving the way for the development of interpretable and explainable AI-assisted decision support systems in transportation planning.

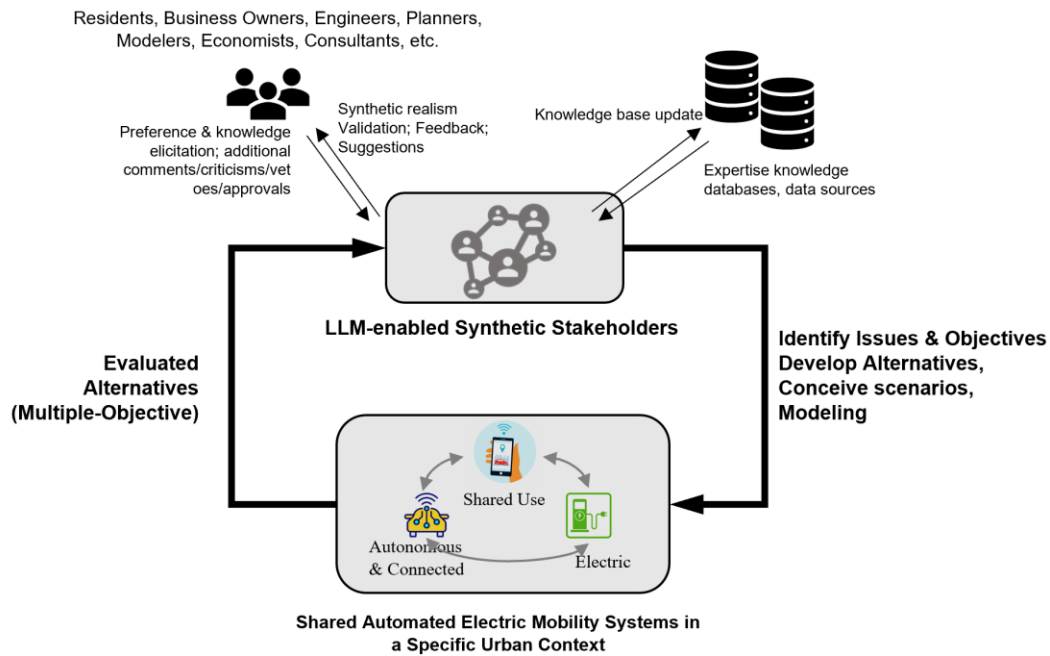


Figure 1: Conceptual illustration of the interaction between a planning agency and the corresponding urban systems.

The remainder of this paper is organized as follows: Section 2 offers a comprehensive review of the relevant literature, establishing the foundation for understanding the current landscape of SAEMS planning and the role of participatory decision-making and AI-enhanced transportation systems. Section 3 details the methodology, focusing on the architecture and

workflow of the synthetic participatory process involving digital avatars. Section 4 presents the context and settings of a case study in Montreal; this section specifies the background, prompting and output processing methods, baseline definition, and parameterizations for alternative scenario generations. Section 5 discusses the simulation results obtained from the case study, highlighting the effectiveness and implications of the synthetic participatory approach for SAEMS planning. Section 6 delves into the broader challenges and future prospects of integrating human-machine collaboration in urban mobility systems planning. This section also compares the synthetic participatory approach with conventional participatory methods, especially focusing on literature related to Montreal. Section 7 concludes the paper by summarizing the key findings, contributions, and implications for future research and practice in the field of SAEMS planning and synthetic participatory decision-making.

2. Literature Review

2.1 Technological Foundation and Planning of SAEMS

The transition towards sustainable urban mobility is increasingly characterized by automation, electrification, and large-scale coordination through online digital platforms. The convergence of these technologies offers promising solutions to challenges such as high human labor costs, low transport capacity utilization, and high emissions. Javed et al. (2022) underscore the transformative potential of such systems within the context of smart cities, highlighting the need for a holistic approach to urban mobility that leverages automation, connectivity, and electrification paradigms.

Automation plays a crucial role in SAEMS, particularly through the development of autonomous vehicles (AVs) such as autonomous bikes, buses, trucks, and surface and flying cars. The integration of AVs into shared mobility services promises to enhance efficiency, reduce human error, and improve accessibility. Planning for AV infrastructure (e.g., dedicated AV corridors and zones), as identified by Gomes Correia & Ferreira (2023), is critical to introduce and accommodate AV operations, covering domains such as physical infrastructure, communication systems, policies, and regulations. Yu & Chen (2021) suggest the importance of differentiating the installation rate and the usage rate when projecting the on-road AVs and emphasize the endogenous impact of AV infrastructures and traffic regulations on AV adoptions.

Vehicle electrification is considered an important strategy for zero-emission transportation systems, raising the need for charging infrastructure and subsidy policies to support the adoption of electric mobility services (Azin et al., 2021; H. Wang et al., 2019; Z. Wang et al., 2023). Huang et al. (2022) explore the joint planning of charging infrastructure and autonomous fleets, considering distributed renewable resources, underscoring the complexity of electrification planning in the context of SAEMS.

The planning and optimization of shared mobility systems, as explored by Chen & Liu (2023), highlight the integration of fleet management, charging infrastructure, and user demand. When the shared systems are on-demand or demand-responsive (rather than reservation-based), managing curb usage (e.g., static and dynamic pick-up and drop-off locations) and depot siting and capacity planning are critical (Dandl et al., 2019). (Vosooghi et al., 2020) assess the impact of charging infrastructure on the performance of shared autonomous electric vehicle services, providing insights into the operational considerations of shared mobility.

Although the individual technologies that enable automation, electrification, and shared mobility systems offer promising solutions to various urban mobility challenges, their combined effects on the overall sustainability, resilience, and efficiency are unclear, and hence deserve joint consideration. Sheppard et al. (2019) present a joint optimization scheme for the planning and operations of shared autonomous electric vehicle (SAEV) fleets serving mobility on demand. Miao et al. (2019) identify the need for a comprehensive system design approach that incorporates new emerging features of autonomous connected electric vehicle-based car-sharing system and addresses the limitations of conventional car-sharing policies and electric vehicle technologies, such as costly vehicle relocation, restricted vehicle range, and lengthy recharge times. Dean et al. (2022) highlight the potential synergy from careful coordination between charging activities and repositioning activities of operating SAEVs for reducing rider wait time, empty travel distance, and non-revenue operation time. Yu et al. (2023) propose the use of surface and aerial SAEVs to improve urban resilience. In scenarios such as hurricane-induced power outages, pandemics affecting vulnerable populations, and earthquake-damaged infrastructure, SAEVs can be deployed to evacuate and rescue at-risk populations, provide essential supplies and services, and transport repair crews and equipment. The authors present a modeling framework for feasibility analysis and strategic planning associated with deploying SAEVs for disaster relief.

Despite the emphasis on technical aspects of SAEMS planning, there is a notable gap in integrating social considerations, particularly through participatory approaches. The

integration of various constituent technologies within SAEMS underscores the complexity of urban transportation planning in the era of rapid technological change. A balanced approach that addresses both the technical and social dimensions of planning is essential for creating sustainable, efficient, and inclusive urban mobility solutions.

2.2 Participatory Planning

Participatory approaches in transportation planning are increasingly recognized for their ability to engage diverse stakeholders in the decision-making process, leading to more inclusive and sustainable urban mobility solutions. Becu et al. (2008) examine the potential of participatory processes for collective decision-making through the (computer simulation-aided) Companion Modeling (ComMod) approach. Applied to a watershed conflict in northern Thailand, their study highlights the challenges of making stakeholders understand the model as a representation of reality and the concept of scenarios as hypothetical situations. The research emphasizes the importance of stakeholder involvement in assessing model assumptions, interpreting simulation results, and suggesting scenarios for conflict resolution. Tatum et al. (2020) detail the Altona Mobility Lab, part of the "Cities-4-People" project funded by Horizon 2020, which implements locally developed mobility solutions through a co-creative approach. The lab serves as a model for urban living labs, demonstrating the process of community building, ideation, and implementation of user-centric mobility solutions. The analysis of this project offers insights into the potential successes and challenges of the Living Lab method for participatory development of sustainable mobility solutions. Acheampong et al. (2023) explore the use of participatory multi-criteria visioning and appraisal framework in the UK and Australia to envision and evaluate AV futures. This research underscores the critical role of participatory approaches in reconciling divergent values and competing visions in urban transport planning, especially concerning disruptive technologies like AVs. In the context of Montreal, Boisjoly & Yengoh (2017a) investigate the barriers and opportunities of local participatory approaches in transportation planning. They highlight the need for clear social equity goals and skilled facilitation to support the integration of diverse perspectives. Fouracre et al. (2006) argue for a more participatory approach to transport planning in developing countries, emphasizing the importance of understanding household activity patterns and the implications of travel on livelihoods. Their case studies in Harare, Accra, and Colombo illustrate how participatory methods can better support the needs of low-income populations and contribute to poverty alleviation objectives. Wang & Noe (2010) review knowledge sharing research, emphasizing the importance of organizational, interpersonal, team, cultural, and motivational factors in facilitating knowledge sharing.

Multi-stakeholder decision-making problems are often multi-objective or multi-criteria. Nalmpantis et al. (2019) evaluate innovative ideas for public transport proposed by citizens using Multi-Criteria Decision Analysis (MCDA). In their study, the Analytic Hierarchy Process method ranks ideas based on feasibility, utility, and innovativeness. The results highlight the importance of citizen participation in generating and prioritizing innovative solutions for public transport, demonstrating the value of participatory techniques in enhancing the attractiveness of public transport systems. Campisi et al. (2020) explore public opinion on personal mobility vehicle use in Palermo, Italy. Their study underscores the significance of participatory planning processes in understanding and addressing the real needs of road users, emphasizing the role of sociodemographic characteristics in shaping public opinion and transport planning. Schröder et al. (2019) advocate for a transdisciplinary research and stakeholder engagement framework to address consumption-based emissions and impacts in cities.

The Delphi technique, as discussed by Kezar & Maxey (2016) and Melander (2018), offers a structured approach to participatory research. Kezar & Maxey (2016) propose a change-oriented Delphi to create solutions for challenges in higher education, while Melander (2018) reflects on the method's application in transport scenario studies. Merfeld et al. (2019) conduct a four-stage Delphi study to uncover drivers, barriers, and future developments in carsharing with shared autonomous vehicles (SAVs). Their findings emphasize technological aspects, consumer acceptance, and legislative concerns, pointing out the secondary perception of sustainability and ethics in the context of SAVs. Schmalz et al. (2021) share lessons learned from a two-round Delphi-based scenario study, providing valuable insights for researchers applying the Delphi technique to prospective questions and other research settings. Beiderbeck et al. (2021) present technical recommendations derived from a Delphi study that was conducted amid the outbreak of the COVID-19 pandemic in 2020. These studies highlight the Delphi method's potential in exploring divergent ideas about the future and its adaptability to various research settings. The literature on participatory approaches in transportation planning underscores the importance of engaging diverse stakeholders, the potential of structured methods like the Delphi technique, and the need to address challenges related to governance, social equity, and technological uncertainties.

2.3 AI-Enhanced Decision-Making

Human-AI collaboration leverages the combined strengths of human intelligence and computing capabilities to enhance the design and operational efficiencies of complex sociotechnical systems. Studies such as those by Yin et al. (2015) and Gall et al. (2021)

underscore the importance of integrating human cognitive processes with AI systems, proposing a collaborative framework where humans and machines work together and learn from each other. This approach is essential for automating design tasks and fostering an upward-spiral cognitive process in decision-making. Yu & Jayakrishnan (2018a) discuss a cognitive framework that unifies human intelligence and artificial intelligence, highlighting the potential for synergistic decision-making in complex system simulations. Rafsanjani & Nabizadeh (2023) emphasize the need for human-centered AI in the architecture, engineering, and construction (AEC) industry, advocating for AI systems that understand and utilize human input to amplify human abilities and reflect realistic conceptions. They highlight the importance of integrating natural language processing and machine reading comprehension to create environments that satisfy human preferences and enhance collaboration, safety, and project management in the AEC sector. In the realm of freight infrastructure planning, Yu et al. (2021) demonstrate how machine learning algorithms, when paired with human expertise, can effectively analyze and interpret large datasets, such as truck parking behaviors. This collaboration not only improves the decision-making process but also ensures that outcomes are practical and closely aligned with stakeholder needs. Furthermore, (Zhang et al., 2022) explore the concept of integrated human-machine intelligence (IHMI) in civil engineering, discussing the fusion of AI's efficiency with human adaptability to advance decision-making in civil engineering projects in business-as-usual and emergent situations. They call for future studies to explore the value, methods, and challenges of applying IHMI in civil engineering, identifying knowledge gaps that need addressing to maximize the benefits of this integration. These insights showcase the versatile benefits of human-AI collaboration in managing and solving complex challenges in sociotechnical systems across various sectors, emphasizing the need for technologies that enhance human capabilities and respect human input and final decisions.

Role playing represents a cutting-edge application of LLMs that extends beyond traditional uses, venturing into dynamic simulations of human-like behaviors and decision-making processes. This approach leverages the advanced capabilities of LLMs to create interactive scenarios where artificial agents simulate complex social interactions and cognitive behaviors. Shanahan et al. (2023) discuss the risks associated with anthropomorphism in LLM role playing, emphasizing the necessity of maintaining clear boundaries between human-like and machine-driven behaviors. They argue for the importance of ensuring that the outputs and actions of LLMs are strictly interpretable and aligned with their intended applications, avoiding misrepresentations that could lead to incorrect or unethical uses of the technology.

Park et al. (2023) introduce the concept of generative agents that simulate human behavior within interactive environments. These agents are designed to perform daily activities, engage in social interactions, and respond to environmental cues, much like humans do. Ghaffarzadegan et al. (2024) explore the integration of LLMs in generative agent-based modeling, which is instrumental in mimicking human decision-making within diverse social systems. This methodology allows for the simulation of nuanced human interactions, providing insights into how individuals and groups might respond to various stimuli or changes within their environment. LLM role playing is an innovative field that offers significant potential across various domains; however, as this technology progresses, it is crucial to address ethical considerations and ensure the accuracy and appropriateness of the simulations to avoid potential misuses and societal harm.

3. Methodology

This section first introduces a synthetic participatory planning framework that integrates generative AI, particularly LLMs, for conceiving and planning SAEMS in the context of overall urban systems. The framework is grounded in the principles of participatory modeling and decision-making, the capabilities of generative AI for simulating complex human interactions, and the domain knowledge of transportation systems engineering and planning. We then present the workflow for utilizing such a framework in Sections 3.2 - 3.5.

3.1 Framework

The proposed decision support system consists of three main components: a set of digital avatars representing stakeholders that form a synthetic team, a multimodal LLM for generating and simulating participatory planning processes and outcomes, and a computational and data storage platform that enable participatory modeling and evaluates design and planning alternatives. The LLM enables the intelligence of the digital representatives and simulate their activities and interactions to identify problems and solution alternatives, and then collaboratively develop models and evaluate these alternatives. Figure 2 shows the procedure of how decision support system functions -- the three components interact in a three-step workflow that allows iterations. In the following subsections, we will present the details in each step.

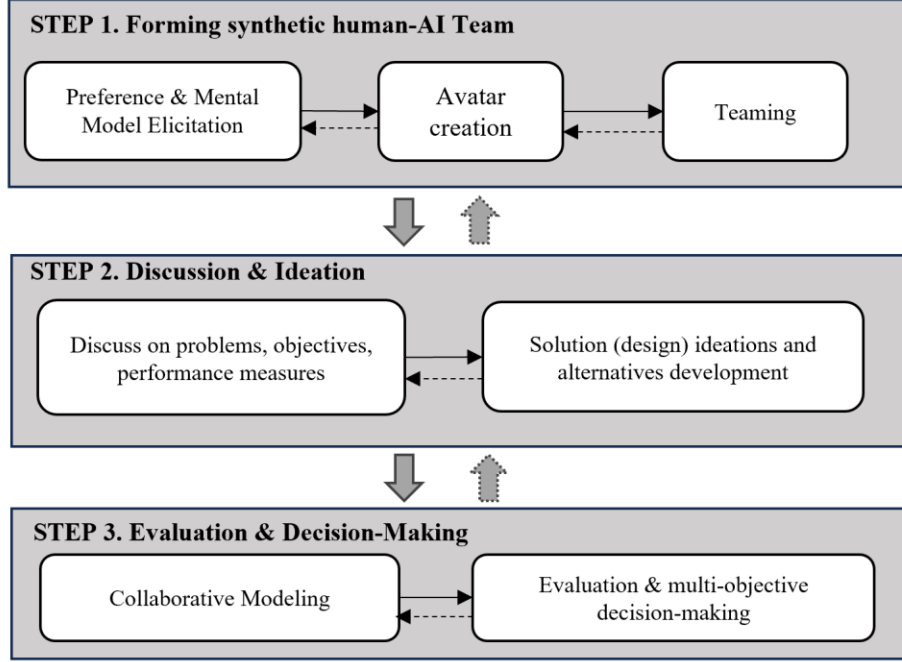


Figure 2. Synthetic participatory planning process of future mobility systems

3.2 Forming Synthetic Team

The workflow begins with collecting information from key stakeholders, which enables the creation of their digital avatars or digital representatives. The elicitation methods can be a combination of surveys, interviews, revealed preferences, observed behaviors, and biometric measurement. When conditions allow, we can even directly analyze the participatory procedures. We can then utilize the information to generate digital avatars of the participants. The training, validation, and testing of these avatars are crucial for ensuring their accuracy and reliability in representing stakeholder preferences, as in later steps these avatars will engage in simulated participatory processes for identifying urban problems and objectives and for envisioning and planning future mobility systems.

The elicitation process involves obtaining responses and observations from S stakeholders regarding their background, socioeconomic conditions, temperament, health conditions, and their views on identified problems, objectives, and performance metrics of SAEMS planning. This can be generally represented as a function:

$$Q: \Psi \rightarrow \mathcal{R} \quad (1)$$

where $Q \in \mathcal{R}$ represents a measurement (in natural language) or a set of measurements that maps a given mental state $\psi_s \in \Psi$ to a response or a set of responses $r \in \mathcal{R}$, where \mathcal{R} is the

semantic space. \mathcal{S} is the set of S stakeholders, with their corresponding mental states stored in a set $\psi = [\psi_1, \psi_2, \dots, \psi_s, \dots, \psi_S], \forall s \in \mathcal{S}$ and $S = \dim(\psi)$. ψ_s is a state vector (abstract construct) that contains all the information needed for the functional mapping of Q . A set of $Q^{train} \in Q$ produces all the necessary responses for (digitally) reconstructing a stakeholder in LLM (at least for the present planning purpose). From the perspective of the proposed synthetic approach, these attributes of a stakeholder become the parameters to be estimated. Note that, once we impose Q on ψ_s (or measure ψ_s with the operator Q), ψ_s might alter. We can denote the change of ψ (i.e., $\Delta\psi$) as an operator H on ψ , or simply $\Delta\psi = H(\psi, Q, \epsilon)$, where H describes how ψ evolves as a function of ψ , Q , and other factors ϵ that are considered as “noise.”

Suppose that all the information we need about a stakeholder s is in ψ_s , so the resultant responses is in $r_s = [r_s^1, r_s^2, \dots, r_s^n, \dots, r_s^N]^T$, where r^n (or r_s^n) is the n th response to Q^{train} (or simply Q^t), $N = \text{card}(Q^t)$. The expected response to a Q should approximate the observed response. That is, a new question $Q^{train,n}$ on the synthetic agent will produce a response, \hat{r}_s^n , similar to r_s^n asymptotically.

$$\hat{r}_s^n \leftarrow \mathbb{E}(\mathcal{LM}(Q^{t,n}|y_s)) \quad (2)$$

where $Q' \in Q^t$ and \mathcal{LM} is the mapping enabled by a LLM that is prompted by u as the system setting and Q' as the prompt question. y_s is a string of characters with a variable length capped by a maximum length that contains the information about the stakeholder s .

To ensure the reliability and validity of the data collected, the training process involves fine-tuning the prompt of LLM to accurately predict the response to any relevant $Q^{validate} \in Q$, or simply Q^v . Let a function f maps a response (a string) to a feature vector μ_s . The distance between the meaning of an actual response and a predicted response can then be measured as.

$$\mathcal{J}(f(r_s^n), f(\mathbb{E}(\mathcal{LM}(Q^{v,n}|y_s)))) = \frac{\hat{\mu}_s^n \cdot \mu_s^n}{\|\hat{\mu}_s^n\| \|\mu_s^n\|} \quad (3)$$

where $\hat{\mu}_s^n$ is the predicted feature vector and $\|\cdot\|$ is the Euclidean norm, and $y_s = y_s(\rho, \theta)$, where $\rho \in P, \theta \in \Theta$ are both parameters.

Let ρ be pre-determined information. The calibration process involves optimizing the parameters θ of the avatar model to minimize the difference between the avatars' responses and the actual responses of the professionals for both the training set (for $Q \in Q^t$), the validation set (for $Q \in Q^v, Q' \neq Q$), and, potentially, the test set (for $Q \in Q^{test}$). This

estimation can be expressed as an optimization problem that minimizes the loss function such as the following:

$$\min_{\rho_0, \rho_1, \theta_1} \mathcal{T} = \left\| \mathcal{J} \left(f(r_s^n), f(\mathbb{E}(\mathcal{LM}(Q^v|y))) \right) \right\|_2 \quad (4)$$

where \mathcal{T} is a loss function that measures the discrepancy (in Euclidean Norm) between the actual responses and the predicted responses across all the stakeholders. In other words, we want $\lim_{m \rightarrow \infty} \left(f(\mathcal{LM}(u_1|u_0, u_1, y_1)) \right) \rightarrow r, \forall s \in \mathcal{S}$, where m is the simulation round number.

Once have calibrated θ , we can start using LLM to simulate realistic stakeholder dialogues and interactions within the participatory modeling process. The model allows the digital representatives of the stakeholders to generate nuanced responses, enhancing the depth and realism of participatory simulations. Let denote the process of sending the initial with input (suppose the initial system instruction is already provided) as:

$$y_1 = \mathcal{LM}(u_1|u_0) \quad (5)$$

where $u_0 = u_0(\rho_0, \theta_0)$ and $u_1 = u_1(\rho_1, \theta_1, r)$. ρ_0 is the prompt template for the initial instruction which is a string with variable length (or a fixed maximum length) and with $\dim(r)$ number of blanks to be filled out by each string element in the vector $r \in \mathcal{R}$. The collection of the generated stakeholders is ψ which we can extract from y_1 . We use \mathcal{F}_ψ to denote the corresponding function that maps the input to the created set of digital avatars. That is,

$$\psi = \mathcal{F}_\psi(y_1) \quad (6)$$

In a group composed of digital avatars and perhaps also real human participants, each entity is informed of the motivations of the group and is aware of other entities and avatars to facilitate coherent interactions. The workflow leverages LLMs' prompting capabilities and includes mechanisms for synthesizing and retrieving information from other agents, leading to the generation of innovative ideas and ensuring logical coherence among agents. We can further add information about the team formation (e.g., who will be the facilitators, etc.) through adjusting ρ_0 and ρ_1 or through add-on instructions. We define the resultant output from this step as a tuple of all the inputs and outputs (with sequence preserved). That is $x_1 = (u_0, u_1, y_1)$.

3.3 Collaborative Visioning, Ideation, and Design under Constraints

This step involves utilizing the synthetic team to identify existing problems of the mobility systems, specifying planning objectives and the associated performance metrics (including their decision weights), and generating solutions (conceiving design alternatives and the associated implementation plans). Overall, we can denote the input-output relationship mapped by an LLM as

$$y_2 = \mathcal{LM}(u_2 | (u_0, u_1, y_1)) = \mathcal{LM}(u_2 | x_1) \quad (7)$$

where $u_2 = u_2(\rho_2, \theta_2)$. Where ρ_2 is a string with variable lengths that contains the background information about this stage of decision-making. Vector θ_2 provides the parameters in this stage that can be joint with the string ρ_2 to for a complete string (ρ_2 has at least $\dim(\theta_2)$ blanks).

This step starts with identifying the status quo, problems, objectives, and performance measures. This phase involves the synthetic participants identifying existing conditions, problems (including technical and financial constraints), objectives, and performance metrics, which form the basis for subsequent discussions and decision-making.

The prompt in this step needs to specify the soft and hard constraints that form a clear decision space, so that $p = \mathcal{F}_p(y_2)$, $\text{card}(p) = M > 0$, and $p = B$, where B is the complete set of M constraints. Similarly, we can elicit objectives and performance metrics. That is, $\mathcal{O} = \mathcal{F}_\mathcal{O}(y_2)$, $\text{card}(\mathcal{O}) = V > 0$, and $\mathcal{K} = \mathcal{F}_\mathcal{K}(y_2)$, $\text{card}(\mathcal{K}) = K \geq V$. Each element in \mathcal{K} is a two-dimensional tuple that contains the score of the performance metric and the corresponding decision weight. That is, the k th element of \mathcal{K}^k is (g_k, w_k) , $\forall k \in \{1, 2, \dots, K\}$.

The present step then generates solutions and develops alternative using the identified status quo and the specified objectives and performance metrics. In this phase, participants ideate solution alternatives *while* considering constraints and practicality. The process encourages creativity while ensuring that proposed solutions are feasible and aligned with the identified objectives. This can be specified as $\mathcal{D} = \mathcal{F}_\mathcal{D}(y_2)$. The final output from this step is a tuple $x_2 = (u_0, u_1, y_1, u_2, y_2)$.

3.4 Collaborative Evaluation of Alternatives and Continuous Improvement

Evaluating design alternatives with specific decision contexts requires evaluation models. We can directly utilize the mental models captured by the profile of each stakeholder (or their digital avatar) to evaluate alternatives in multiple rounds of participatory modeling sessions to build a common ground, though we can also instruct more specific evaluation mdoels. The

prompts need to be specific so that the model has the capability to evaluate all the design alternatives previously defined with outputs consistent and coherent with all the performance metrics. Insights from avatar interactions enrich these models, enabling a dynamic approach to planning that incorporates diverse perspectives and preferences.

Once we have determined an evaluation method that allows multiple stakeholders to perform multi-criteria Evaluation and Decision-Making, the third step of the prompt ensures that the selected alternatives are evaluated based on various criteria, reflecting the interests and concerns of different stakeholders.

$$y_3 = \mathcal{LM}(u_3|x_2) \quad (8)$$

where $u_3 = u_3(\rho_3, \theta_3)$. We can then obtain the final evaluation score vector E using a function (operator) \mathcal{F}_E that converts y_3 to obtain the attribute value vector, \mathbf{g} , and the corresponding decision weight vector, \mathbf{w} , for the K attributes. The results are $v_i = \sum g_{ik} \cdot w_k, i \in \mathbb{I}$. If $v_i > v_j$, the option i is more preferable than the option j . That is, $i \succ j, i, j \in \mathbb{I}$. Combining the previous information along with the new outputs, we have $x_3 = (u_0, u_1, y_1, u_2, y_2, u_3, y_3)$.

Figure 3 summarizes the proposed three-step process, where the inputs composed of strings and parameters are sent into an LLM for obtaining the output responses. Then all the prior inputs, outputs, and the new prompt (also composed of strings and parameters) are combined as the new input for the next step (note that each step might be composed of one or more prompting stages.) In terms of continuous improvement, we can run a real participatory process and compare the results with the statistical average condition from the simulated participatory processes. The proposal is scalable in more than three steps. It is also allowable to decompose a step into multiple steps. However, it is important to note that more steps lead to longer string x , which cost more token (a measure of the usage of a commercialized LLM) consumption and response time.

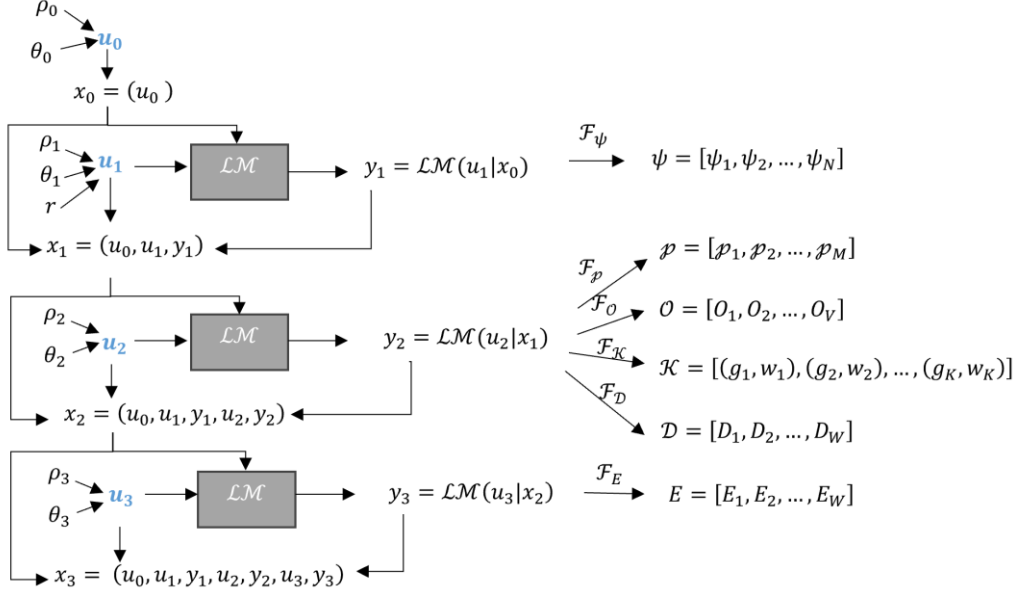


Figure 3. Illustration of the proposed multi-step simulation procedure of the synthetic participatory approach for planning SAEMS.

In our methodology, AI assistants, potentially augmented by external knowledge databases (such as official design guides and factsheets), enabled by the LLM can also play a pivotal role in facilitating different forms of participatory engagement, tailored to the specific needs of the discussion format. In open discussions, AI assistants can act as moderators or facilitators, guiding the conversation flow and ensuring that all stakeholders' perspectives are considered. In Delphi sessions, these AI tools are utilized as summary generators, synthesizing complex inputs into concise overviews that aid in progressing rounds of expert consultation. Our framework is versatile, accommodating various configurations from a single AI assistant to multiple agents. In scenarios where a single AI assistant simulates a discussion or Delphi process, the attention mechanism of LLM is crucial for simulating multi-agent cases. It selectively focuses on the profiles of each virtual agent from a new input prompt, drawing from historical outputs to simulate nuanced interactions. In multi-agent setups we still need a “master” LLM (the focus of the present paper) to coordinate the inputs and outputs from different “child” LLMs.

3.5 Prompt and Parameter Sensitivity Analysis

The sensitivity of the LLM outputs to inputs and parameters is analyzed by varying the prompts or wordings used in creating the avatars. This analysis is crucial for understanding how different linguistic formulations affect the calibration process (and hence, the output of a synthetic participatory planning process). Let $\theta = \{\theta_1, \theta_2, \dots, \theta_l, \dots, \theta_L\}, \theta \in \Theta$, be the set of

L LLM parameters corresponding to different prompts. The sensitivity of each parameter θ_i is evaluated by measuring the change in the output u_i with respect to the variation of θ_i :

$$\delta_{u_i:\theta_i} = \mathbb{E} \left(\sum_{i \in I} \sigma_i \cdot \frac{\partial \mathcal{LM}(u_i|x_{i-1})}{\partial u_i} \cdot \frac{\partial u_i}{\partial \theta_i} \right) \quad (9)$$

where $i \geq 1$. Similarly, we can obtain $\delta_{u_i:\rho_j}$ (the sensitivity of u_i with respect to the variation of ρ_j). As not all the directions of perturbation is feasible (e.g., changing one letter or word in a prompt sentence might not be a comprehensible or Grammarly correct sentence), the equation above might not be applicable, not to mention that the differentials might not exist. Therefore, we have σ_i being a dummy variable with 1 when the direction is differentiable, and 0 if not.

To perform sensitivity analysis, various techniques can be employed, depending on the complexity of the function and the availability of data. Due to the complexity of the internal mechanism of an LLM, even we have the complete information about the model architecture and parameters, it might still not be impractical to use analytical methods (direct calculation of sensitivity coefficients with closed forms). Therefore, numerical Methods (numerical techniques such as finite difference methods can be used to approximate the derivatives) and Monte Carlo simulations (especially when dealing with uncertainty in inputs or parameters) are recommended.

The results of sensitivity analysis provide valuable insights into the behavior of the proposed system and method. High sensitivity coefficients indicate that the function is highly responsive to changes in the corresponding input or parameter, which may require careful control or robust design. On the other hand, low sensitivity coefficients suggest that the function is relatively insensitive, allowing for more flexibility in design and operation.

4. Case Study

This case study delves into the application of the synthetic participatory approach within the urban mobility planning landscape of Montreal—a city renowned for its dedication to sustainable transportation and pioneering infrastructure initiatives. The goal of this study is to showcase the enhanced efficacy of integrating LLM-enabled digital avatars with multi-criteria decision-making strategies in SAEMS planning.

4.1 Background

Montreal, the largest city in Quebec, Canada, is characterized by its diverse population, extensive public transportation network, and various social events and tourism activities. The

city has been implementing sustainable mobility solutions, such as expanding its bike-sharing program, developing pedestrian-friendly streets, and introducing electric buses to its public transit fleet (Chehri et al., 2022; Damant-Sirois & El-Geneidy, 2015; Pelletier et al., 2019). The Réseau Express Métropolitain (REM) (Dent et al., 2021) is an automated (driverless), electric light metro rapid transit system that is partially operational and is expected to be fully complete in the Year 2027. Despite these efforts, Montreal faces challenges like traffic congestion, aging infrastructure, and balancing transportation demands with environmental sustainability goals. The city has set ambitious endeavor to reduce greenhouse gas emissions, increase the use of public and active transportation modes, and enhance urban mobility systems' efficiency and accessibility. It is an example of the city and region's effort on automating and electrifying the mass transit systems.

As the present paper is being written, the city is in the process of producing their 2050 Land Use and Mobility Plan¹, which recognizes the interactions of land use and mobility services and hence simultaneously plans for the two major aspects. There are six phases in this process. Phase I (Assessing the city's situation) and Phase II (Imagining possible futures) have been completed. It is now collecting public comments regarding the current city vision from Phase II. The city will improve the vision and the implementation strategy (Phase IV). In Phase V, the city council will provide additional comments and decide whether to adopt the plan. Phase VI will focus on implementing the plan and monitoring the progress (and adjust when necessary). The process started in around 2019 (and just finished Phase II in year 2024), indicating the heavy effort and cost of producing such a plan. The previous plan was released in 2008 with following five main objectives:

- Create optimal conditions for getting around the city
- Improve residents' quality of life
- Improve the environment
- Support the vitality of Montréal's economy
- Integrate the planning of transportation with that of land use

The SAEMS planning in the present case study has a narrower scope than that of the city's ongoing land use and mobility plan, as the case study focuses on planning the SAEMS (as a subsystem of Montreal's mobility system). However, the publicly available information

¹ Montreal's 2050 Land Use and Mobility Plan: <https://montreal.ca/en/articles/creating-2050-land-use-and-mobility-plan-15575>

released by the present planning process is likely to provide useful information. The rest of the case study will refer to the existing reports such as the report presenting the results of citizen focus group, the report on the city project ideation workshop, the sustainable mobility survey, and (Phase II's) *City Vision: Imaging the Montreal of 2050*. I leave the study of expanding the study scope using the proposed synthetic participatory approach to a broader transportation planning process to future research.

4.2 Prompting and Output Processing

Creating Human Agents and AI Assistants. The process begins with introducing the decision context and purpose to the LLM-enabled AI agent that will simulate the participatory planning process. For ρ_0 , we have:

“You are an expert in simulating a participatory planning process for the City of Montreal's future shared automated electric mobility systems (SAEMS). Suppose the planning activity occurs in the year 2024, and the planning horizon year is 2044.”

Then, we prompt to construct digital avatars representing Montreal's stakeholders such as residents, policymakers, urban planners, and transportation engineers (including modelers). Instead of using the prompt to detail their socioeconomic backgrounds, temperaments, and preferences, this case study directly prompts to request the generation of $S = \theta_1$ number of stakeholders. The profiles (and the associated probability distributions) of the generated stakeholder avatars are one main aspect of our research interest. For ρ_1 , we have:

“Create θ_1 stakeholder(s) as their digital avatar(s).”

Due to the stochasticity of LLM outputs, the LLM will respond by requesting additional details instead of directly generating digital representatives on rare occasions. In simulations, we drop these cases, though it is likely that further prompting can help utilize these cases.

Team Formation and Synthetic Participatory Process. In this step, we use two sequential prompts to guide the AI agent. We simplify the case by not introducing any real stakeholder participant in the participatory process. The team composed of (only) digital representatives of the stakeholders engages in a participatory process that includes identifying existing conditions, objectives, and performance metrics; then the team collaboratively generates solution alternatives (design alternatives and implementation plans). Various participatory methods, such as the Synthetic Delphi approach and Synthetic focus groups, are explored to determine their impact on the planning outcomes.

For ρ_2^1 , we have

“Concretely simulate the process and obtain the results from using a θ_2^1 -round Delphi method to let them collaboratively identify issues, objectives, performance metrics, and decision weights for each round. Then synthesize the information to form 5 issues, 5 objectives, 10 performance metrics (0-10 for each metric), and decision weights (sum up to 1.0). Be clear which performance metric is for which objective.”

For ρ_2^2 , we have

“Concretely simulate a θ_2^2 -min free-style brainstorming session to generate 3 mutually exclusive SAEMS alternatives with detailed specifications and the corresponding 20-year implementation plans with 4-year intervals (with a specific monetary amount for each interval) under a total budget of $\$ \theta_2^3$ million CAD (Net Present Value).”

Evaluation and Decision-Making. The synthetic participants collaboratively develop models to evaluate solution alternatives, using the multi-criteria evaluation and decision framework. For ρ_3 , we have:

“Evaluate the alternatives using the previously identified performance metrics -- make best guess about values about the variables and probabilities collaboratively. Compare the final scores and recommend the best alternative.”

4.3 Parameterization, Baseline, and Scenario Settings

The participatory process leads to the development of objectives, performance metrics, identifying key variables and their interactions within specific SAEMS. Key parameters, such as team size, participatory methods, and associated durations and efforts, are defined for different settings. The process results in identifying key issues, objectives, performance metrics, stakeholders, design alternatives, and final selection of the most suitable plan for Montreal's SAEMS.

The defined settings provide a structured approach to explore the impacts of different team compositions and participatory methods on the synthetic participatory planning process. This parameterization allows for a systematic analysis of how variations in the planning process influence the identification of problems, objectives, performance metrics, and the development and evaluation of alternatives for Montreal's SAEMS.

Key parameters include team size (θ_1), number of Delphi rounds for identifying problems, objectives, and performance metrics (θ_2^1), the duration of free-style discussion and ideation

(θ_2^2) in minutes, and the budget constraints (θ_2^3) in million Canadian dollars (net present value, NPV). We set the base scenario as $[\theta_1, \theta_2^1, \theta_2^2, \theta_2^3] = [10, 3, 90, 100]$. In the next section, we will first present the results (including the stochasticity) of the base scenario. Then we will explore the impact of perturbing the base scenario on the results of the synthetic participatory process. Note that in the case study, we essentially use words such as Delphi and free-style brainstorming or discussions as parameters rather than simulating the specific conversations or dialogues. We leave the study of varying the resolution of conversations or dialogues to future research.

5. Simulation Results

The simulation outcomes are discussed under two main subsections: base scenario results and sensitivity analysis of different scenarios based on various prompt settings. The simulations are performed using the OpenAI API version “gpt-4-turbo” in February and March 2024. The temperature is set as 1.0 (a median number in terms of the randomness of the LLM output). One complete round of simulation instance is shown in Appendix A.

5.1 Baseline Instance

In this subsection, we analyze the results of multiple runs of the baseline scenario, where each simulation generates a different set of five stakeholders. Table 1 shows the 10 generated digital representatives of the stakeholders in SAEMS. Each avatar has a unique perspective and stake in the successful planning and implementation of SAEMS, demonstrating the necessity of a collaborative approach that recognizes and addresses the wide range of concerns and objectives. We can further request additional detailing for each avatar, and we leave the investigation of the optimal prompting fidelity for a given SAEMS decision context to future research.

Table 1. 10 generated digital representatives of stakeholders and the summaries of their profiles.

Stakeholder	Profile
City Planner	An experienced urban planner specializing in transportation infrastructure, with a focus on land use densification and sustainable and efficient mobility solutions for marginalized communities.
Transport Engineer	A professional with expertise in the design and implementation of transportation facilities such as signal timing, intersection channelization, and roadside arrangement.
Policy Maker	A government official responsible for developing and enacting policies and investments that promote transportation systems that are in favor of their constituent.
Environmental Advocate or specialist	A representative from a non-profit organization dedicated to reducing carbon emissions and promoting environmentally friendly transportation options.
Community Representative	A respected member of a local community group, representing the interests and concerns of residents who will be directly impacted by the SAEMS.
Technology Entrepreneur or Innovator	The founder of a startup company specializing in shared autonomous vehicle technology and electric mobility solutions.
Academic Researcher	An academic or scientist conducting research on the impacts of shared automated electric mobility systems on urban environments.
Local Business Owner or Representative	Represents the interests of local businesses, focusing on how SAEMS can support economic growth and accessibility. Interested in how SAEMS can impact local commerce, potentially increasing foot traffic but also raising concerns about congestion and parking.
Public Transit Authority Representative	An official from Montreal's public transportation agency, focused on integrating SAEMS with existing transit networks.
Public Safety Official or Expert	Concentrates on the safety implications of SAEMS, including emergency response, accident prevention, and security measures.

The stakeholder avatars collaboratively identified and prioritized objectives for the potential SAEMS in Montreal, highlighting the importance of sustainability and accessibility as the leading concerns. The group collaboratively determines the performance metrics for concretely evaluating these objectives, with decision weights reflecting the collective priorities of this diverse group. Table 2 shows an instance.

Table 2: Final List of Identified Issues, Objectives, Performance Metrics, and Decision Weights.

Objective	Performance Metrics	Weight
Traffic flow improvement	Average travel time reduction, congestion reduction percentage, public transit integration level	0.15
Environmental footprint minimization	Greenhouse gas emission reduction, energy efficiency improvement, noise pollution reduction	0.15
Equity enhancement	Accessibility index for disadvantaged groups, affordability index for transportation	0.10
Infrastructure Integration	SAEMS network coverage, intermodal connectivity level	0.30
Technological innovation fostering	Adoption rate of new SAEMS features, collaboration level with tech companies	0.30

The brainstorming session yielded three distinct SAEMS alternatives focusing on comprehensive transit solutions, modular mobility integration, and environmental sustainability.

Alternative 1: The Eco-Friendly System focuses on minimizing environmental impact and promote sustainability. Specifically, the city will deploy SAEV fleets with high energy efficiency and low emissions and invest in installation of renewable energy charging stations powered by solar and wind energy, and promote the implementation of green roofs, permeable pavement, and urban green spaces to mitigate heat island effect and enhance biodiversity. The collaborative generated implementation plan is:

- Years 1-4: Pilot phase in downtown areas, deploying 100 SAEVs and 50 charging stations (\$20 million).
- Years 5-8: Expand to suburban areas, increasing fleet size to 300 SAEVs and 150 charging stations (\$30 million).
- Years 9-12: Integrate with public transit network, adding 500 SAEVs and 250 charging stations (\$40 million).
- Years 13-16: Enhance infrastructure resilience, with upgrades to 700 SAEVs and 350 charging stations (\$25 million).
- Years 17-20: Evaluate and improve system efficiency, optimizing fleet operations and adding another 800 SAEVs and 400 charging stations (\$35 million).

Alternative 2: The Equity and Accessibility System focuses on improving transportation access for all communities. Specifications: (1) Inclusive Design: Implement accessible vehicle designs and infrastructure to accommodate individuals with disabilities, (2) affordable Fares: Introduce fare structures that consider income levels and provide subsidies for low-income

users, and (3) accessible stations: Upgrade existing and new stations to be accessible to individuals with mobility challenges. The collaborative generated implementation plan is:

- Years 1-4: Accessibility upgrades in key locations, retrofitting 50 stations and 200 vehicles (\$15 million).
- Years 5-8: Expand service to underserved areas, adding 500 vehicles and 100 new stations (\$35 million).
- Years 9-12: Implement fare subsidies for low-income users, providing discounts and incentives (\$30 million).
- Years 13-16: Enhance accessibility features, adding 300 vehicles and upgrading 50 stations (\$25 million).
- Years 17-20: Conduct community outreach and feedback, engaging with stakeholders to improve accessibility (\$25 million).

Alternative 3: The Technology-Promoting System focuses on pioneering promising technologies and enhancing traveler experience. Specifications: (1) Deploy a fleet of SAEVs with advanced safety features and AI-driven capabilities, (2) Implement AI algorithms to optimize vehicle routes and minimize congestion, and (3) Upgrade infrastructure to support smart connectivity of civil infrastructure and facilities, enabling real-time communication between vehicles and infrastructure. The collaborative generated implementation plan is:

- Years 1-4: Pilot SAEV fleet, introducing 50 SAEVs and testing AI algorithms (\$25 million).
- Years 5-8: Expand the SAEV fleet and implement AI-driven real-time route optimization, adding 200 SAEVs and optimizing dedicated AV routes (\$40 million).
- Years 9-12: Upgrade infrastructure for smart connectivity, installing sensors and communication systems (\$30 million) to further improve the cybernetic capabilities of the Montreal's SAEMS.
- Years 13-16: Enhance user experience with app integration, developing user-friendly apps for trip planning and payment (\$20 million).
- Years 17-20: Evaluate and integrate emerging technologies, upgrading systems based on feedback and technological advancements (\$35 million).

The description, specification, and implementation plans (4-year intervals) are summarized in Table 3. Each alternative comes with a pragmatic 20-year phased implementation plan (with 5-year intervals), indicating financial implications to the stakeholders. Table 4 summarizes the collaborative multi-criteria evaluation of the three alternatives.

Based on the provided metrics and estimated scores, the “Eco” alternative emerges as the most favorable option in terms of both the total score (38) and the weighted score (7.75). This alternative is scored high in integration with emission minimization and its complementary nature to infrastructure such as public transit, factors that are critical to the successful and sustainable implementation of SAEMS. Although the “Equi” and “Techno” alternatives present compelling benefits in areas such as congestion reduction, accessibility and affordability, they fall slightly behind “Eco” in comprehensive fit, innovation, and public transit synergy. The “Eco” alternative also has a moderate requirement for financial commitment in the initialization phase (the first five years), allowing the public agency for lower risk (compared to the “Techno” alternative. Continued stakeholder engagement and detailed feasibility studies will be essential in refining and implementing this ambitious plan.

1 **Table 3:** Final List of Design Alternatives, Corresponding Implementation Plans

Alternative	2024-2028	2028-2032	2032-2036	2036-2040	2040-2044	Period and Cumulative Financial Commitment
“Eco-SAEMS”: Focus on minimizing environmental impact and promote sustainability. Specifically, deploy SAEVs, renewable energy charging stations, green infrastructure.						
	Pilot phase in downtown areas (\$20 million)	Expand to suburban areas (\$30 million)	Integrate with public transit network (\$40 million)	Enhance infrastructure resilience (\$25 million)	Evaluate and improve system efficiency (\$35 million)	
“Equitable-SAEMS”: Improve transportation access for all communities. Inclusive design, affordable fares, accessible stations.						
	Accessibility upgrades in key locations (\$15 million)	Expand service to underserved areas (\$35 million)	Implement fare subsidies for low-income users (\$30 million)	Enhance accessibility features (\$25 million)	Conduct community outreach and feedback (\$25 million).	
“Techno-SAEMS”: Pioneer new technologies and enhance user experience. Specifically, deploy SAEVs, AI-driven route optimization, smart infrastructure.						
	Pilot autonomous vehicle fleet in dedicated areas or zones (\$25 million).	Expand autonomous fleet and implement AI-driven route optimization (\$40 million)	Upgrade infrastructure for smart connectivity (\$30 million)	Enhance user experience with app integration (\$20 million)	Evaluate and integrate emerging technologies (\$35 million).	

Table 4: Evaluation Scores (By Metrics) and the Total Weighted Scores for Each Alternative

Objectives	Weights	“Eco”	“Equi”	“Techno”
Traffic Flow Improvement	0.15	7 (1.05)	5 (0.75)	9 (1.35)
Environmental Footprint Minimization	0.15	8 (1.20)	6 (0.90)	7 (1.05)
Equity Enhancement	0.10	7 (0.70)	9 (0.90)	4 (0.40)
Infrastructure Integration	0.30	9 (2.10)	5 (1.50)	8 (2.70)
Technological Innovation Fostering	0.30	7 (7.75)	5 (1.50)	8 (2.40)
Total Score (Avg Weighted Score)	1.00	38 (7.75)	30 (5.55)	36 (7.60)

5.2 Sensitivity Analysis

This subsection explores how the results of the synthetic participatory planning process change in response to different participation settings. The analysis aims to understand the impact of variations in team size, participatory methods, and the duration/effort allocated to different phases of the process on the planning outcomes.

5.2.1 Impact on Stakeholder Profiles

To analyze the synthetic stakeholder profiles generated across multiple simulations, we employ a time with bar charts for different parameter settings, where we visualize the frequency of each stakeholder type. This provides a clear view of which profiles are most commonly generated and how they change in response to the change of team size. Figure 4 shows the distribution of a stakeholder type to appear at least once from 150 simulations for each team size setting.

With the increase of the number of stakeholders, generated synthetic stakeholders that are fall in the same categories start to increase and the specifications of the stakeholder profiles start to also increase. For example, one simulation might generate a resident’s association leader, a senior citizen representative, and youth representative, all of whom fall into community representatives. The LLM also starts generating different types of urban planners and engineers. For example, the LLM starts generating different types of planners that focus on land zoning, public parks, transportation, etc. It is also noticeable that with the increase from 1 to 10 stakeholders, the coverage of stakeholders (at least by one stakeholder) start to increase, while from 10 to 20, most additional stakeholders fall into existing categories (i.e., there are more likely to have more than one stakeholder that in one category). This phenomenon implies the potential existence of an optimal team size and shows that explicitly requesting the LLM to generate more than one can avoid the agent directly assuming that the key decision-maker is a city or urban planner.

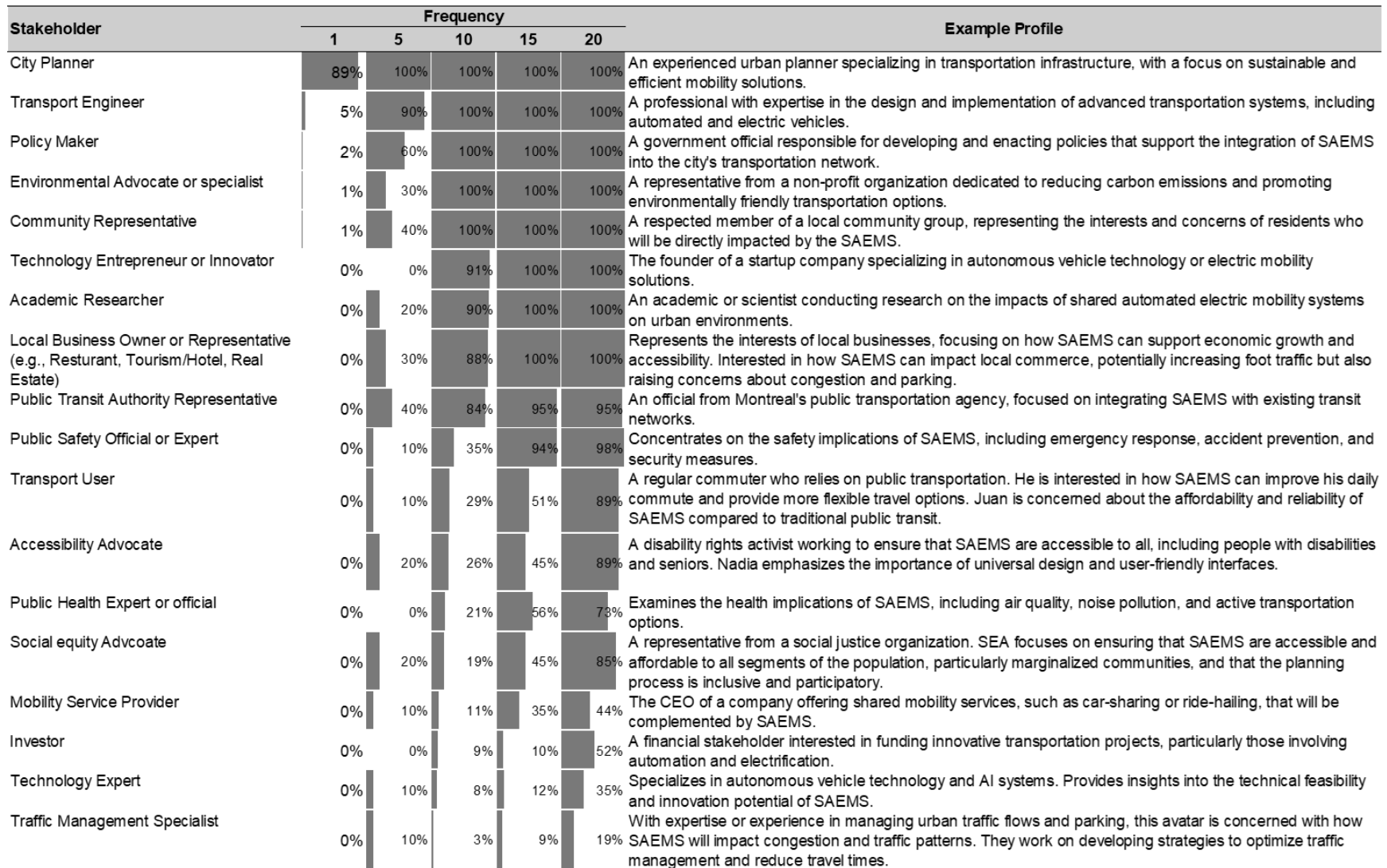


Figure 4. Histogram showing the frequency of different stakeholder profiles generated across simulations.

5.2.2 Impact on Objectives and Performance Metrics.

The influence of varying team sizes and the number of Delphi rounds on the articulation of objectives and performance metrics, including the assignment of decision weights, is critically evaluated through comparative analysis across multiple simulation scenarios. Simulations incorporating different numbers of stakeholder avatars are conducted to discern the effects of larger team compositions. While more extensive teams tend to offer a wider array of perspectives, they also introduce increased complexity in interactions and potentially protract the decision-making process (in terms of consensus reaching). To systematically analyze these dynamics, the objectives identified across simulations are categorized into ten distinct groups, as detailed in Table 5. Figure 5 presents a summary of the average decision weights assigned in each configuration along with their standard deviations (the total length of an error bar represents two standard deviations (2σ), reflecting the inherent stochasticity of the simulation outcomes. To simplify the notations, we denote a scenario with a team size 10 and the Delphi round number 3 as “S10R3.” A similar principle applies to other scenario settings.

As evidenced across various scenarios, the objectives concerning environmental and sustainability impact, congestion, safety, and accessibility consistently received higher decision weights. Interestingly, as the team size increases, the distribution of weights becomes more even, suggesting that the weights of less common concerns or objectives will be more important among a larger group of stakeholders. However, the impact of increasing the number of Delphi rounds appears nonlinear. Transitioning from one to three stakeholders tends to produce more specific objectives and lower variation in decision weights, possibly indicating the LLM's capacity for simulating a consensus-building effect. Conversely, expanding the team from three to five stakeholders does not yield significant changes, suggesting diminishing sensitivity to additional Delphi rounds. Larger groups may also require more rounds to achieve consensus, which seems consistent with the common experience where a large group tend to have more difficulties of reaching a consensus.

Moreover, the error bars that enter the 'negative' conditions suggest that when decision weights are low, they tend to be highly skewed. Specifically, certain alternatives are seldom selected (thus, often receiving zero weight); however, when these alternatives are chosen, their weights typically range from 0.10 to 0.20 rather than much lower but nonzero weights. This pattern underscores the importance of framing and participatory methods in replicating results for validation and mitigating common biases in participatory decision-making.

Table 5. Summary of commonly identified alternatives during participatory planning. The objectives identified across simulations are categorized into ten distinct groups

Acronym	Objectives	Generated Performance Metric Examples
ENRM	Environmental Impact and Sustainability	CO2 emissions reduction, energy efficiency
EFFIC	Congestion Reduction and Mobility Efficiency	Average Travel Time, Traffic Flow Improvement, vehicle kilometers traveled
SAFTY	Safety Enhancement, Regulatory Compliance	Number of accidents, comfort and perceived safety
ACCESS	Accessibility Improvement	Coverage Area of SAEMS, service availability, number of hospitals and libraries in 15 min buffer
PubTrans	Integration with public transit and other public services	Increase in transit coverage, multimodal transit usage, transit connectivity
Econ	Economic Viability	Cost-effectiveness, return on investment, employment stimulation
Pub-Adopt	Maximize public support and acceptance, market penetration	Public positive perception or acceptance rate. Potential user adoption rate, market share, user rating
R&R	Technology and infrastructure integration and reliability, cost effectiveness, Security, Resilience	System uptime, passenger feedback, tech innovation rate. Resilience to natural disasters, potential frequency and severity of cyberattacks, emergency response time
Equity	Equity and Inclusivity	Service Accessibility for disadvantaged groups, fair pricing, affordability
Infra Use	Efficient energy and infrastructure utilization	Existing facility and equipment utilization. Including promotion of urban green space, even charging station usage

Further analysis suggests that increasing the number of Delphi rounds beyond three yields minimal impact on consensus quality. Both small groups with fewer rounds and larger groups with more rounds tend to lead to more evenly distributed weights, posing an interesting question for real-world applicability. The exploration of a more diverse range of participatory methods—transitioning from structured approaches like the Delphi method to more free-form discussions—could provide insightful contrasts. Different methods likely influence the level of consensus, depth of discussion, and creativity of the solutions generated, shaping the dynamics of the planning process in distinct ways.

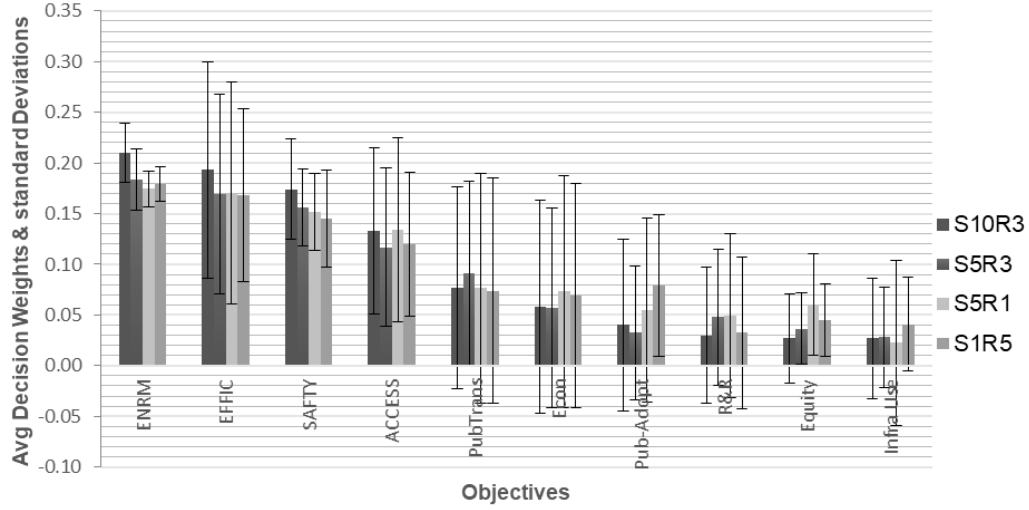


Figure 5. Decision weights for each category of objective and for each of the four parameter settings (team size and Delphi number of rounds).

5.2.3 Impact on Design Alternatives and the Evaluation

This subsection conducts a sensitivity analysis to evaluate the impact of team size, the duration of free-style ideation sessions, and budget constraints on the identification of issues and development of alternatives within the synthetic participatory process. We hypothesize that longer durations might allow for more in-depth discussions, while shorter sessions could necessitate more efficient and focused deliberations. Our results help assess the robustness of baseline scenario outcomes and identify potential areas for optimization. Settings that consistently yield better alignment with planning objectives might be favored in future simulations. We explore the diversity of design alternatives conceived by synthetic teams and their alignment with the identified objectives and performance metrics. The analysis focuses on several common design alternatives generated during the planning process, as summarized in Table 6. The frequency and distribution of these alternatives across simulations highlight trends and preferences among synthetic teams. For instance, a frequent selection of a particular alternative might indicate a strong emphasis on optimizing certain aspects like travel efficiency.

Each design alternative undergoes evaluation based on its alignment with established objectives and performance metrics. For example, an alternative might score highly on environmental impacts due to the integration of electric transit systems, while another might be favored for enhancing accessibility.

Table 6. Common design alternatives generated during the planning process

	Alternative	Example Description
1	Advanced/multimodal mobility network	Fully integrate SAEMS with public transit, bikesharing, offering seamless multimodal trip planning and fare integration.
2	Integrated MaaS platform	developing an integrated Mobility as a Service (MaaS) platform that offers a seamless and personalized mobility experience for users, integrating various modes of transportation including SAEMS.
3	Urban mobility hub	focuses on creating urban mobility hubs that serve as centralized locations for various modes of transportation, including SAEMS, public transit, cycling, and walking. These hubs are designed to improve connectivity and accessibility while reducing the reliance on private vehicles with sufficient charging (and discharging) capabilities
4	Automated shuttles	A network of automated shuttles providing first-mile/last-mile connectivity.
5	Basic System Upgrade	Implement a basic SAEMS with limited coverage and vehicle fleet size.
6	Sustainable Urban Mobility	Integrated SAEMS with green spaces and urban planning to create a more sustainable and livable city environment.
7	Smart transport infrastructure	Focuses on upgrading the city's road infrastructure with smart sensors and communication technologies to improve traffic management and enhance the efficiency of SAEMS. Use of AI
8	Urban Air Mobility System	Implement a network of autonomous aerial vehicles for passenger and cargo transport, reducing ground congestion and improving accessibility.

The variability in the evaluation results is analyzed through the distribution and scores for each performance metric. A radar chart (Figure 6) is utilized to visualize the variability in priorities among synthetic teams across simulations. This method allows us to identify common trends or outliers in planning outcomes. “ $S\theta_1$ - $R\theta_2^1$ - $D\theta_2^2$ - $B\theta_2^3$ ” representing team size θ_1 , θ_2^1 number of Delphi rounds, θ_2^2 -minute free-style discussion/brainstorming, and θ_2^3 million Canadian dollars budget (Net Present Value). We select the most representative cases for analysis instead of averaging for each scenario setting, to avoid obscuring trade-offs inherent in the planning process.

Smaller teams, exemplified by the scenario “S1-R3-D90-B100,” tend to favor alternatives that align closely with the expertise of urban planners, as when the team size is 1, an urban planner profile is the most likely one to be generated. Larger teams (15 members or more), exemplified by the scenario “S15-R3-D90-B100” do not exhibit significant changes in preference, suggesting a saturation point in the influence of team size on decision-making. The duration of free-style discussions for conceiving solution alternatives show that longer

duration tend to generate alternatives that balance performance metrics, as exemplified by the scenarios “S10-R3-D90-B100” and “S10-R3-D60-B100”. It is evident that budget constraint is an important factor. As shown in the case of “S10-R3-D90-B150,” the trade-off effect among different objectives is clearly lessened than the trade-offs in other settings that have lower budgets. I leave a more comprehensive analysis to study the interactions among parameters to future research.

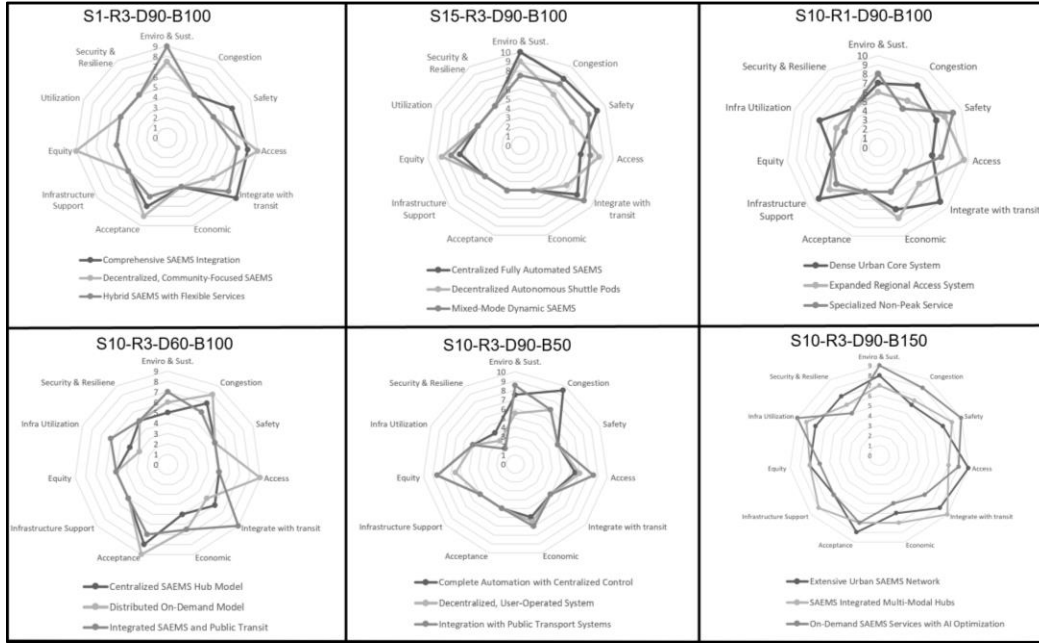


Figure 6. Radar chart comparison among the representative alternatives generated from six different settings.

6. Discussion

The results from the participatory modeling process for Montreal's SAEMS underscore the potential for significant improvements in urban mobility, environmental sustainability, and social inclusivity. This discussion section reflects on the implications of these findings, the challenges encountered during the modeling and simulation process, comparison with existing literature on Montreal's opinion elicitation and participatory planning effort, and the broader relevance of this study to urban mobility planning and policy.

6.1 Implications of Findings

The application of the synthetic participatory approach using LLM-enabled digital avatars significantly enhances the inclusivity and efficiency of the urban mobility planning process. By simulating a diverse range of stakeholder inputs, this approach ensures that

multiple perspectives are considered, reducing the risk of overlooking critical aspects of urban mobility. This method also streamlines the decision-making process, allowing for quicker iterations and adaptations to new information.

The findings suggest that varying team sizes and Delphi round numbers can influence the diversity and quality of planning outcomes. Smaller teams tend to produce more focused and efficient deliberations, which could be advantageous in early stages of planning when quick decisions are needed. Larger teams, however, provide broader perspectives, beneficial for comprehensive strategic planning where diverse inputs are crucial.

The synthetic participatory approach presents a cost-effective alternative to traditional methods by reducing the logistical and financial burdens associated with organizing physical meetings and managing stakeholder engagement over long periods. This aspect is particularly relevant for cities with limited resources but high aspirations for improving urban mobility.

6.2 Technical Challenges and Clarifications

One of the primary challenges encountered in the participatory modeling process is ensuring that digital avatars accurately and comprehensively represent real-world stakeholders. While the avatars are effective in simulating a range of perspectives, they may not fully capture the breadth of real-world experiences and concerns. Ongoing efforts to enhance the realism and depth of these representations are essential, as is continuous validation with empirical data to ensure that the avatars remain relevant and accurate over time.

Balancing the complexity of the models with the need for actionable insights presents a significant challenge. Overly complex models risk becoming impractical for decision-makers, as they can obfuscate clear paths to action with excessive detail. Conversely, overly simplified models may fail to capture essential dynamics of the system, potentially leading to suboptimal decisions. Finding the right balance to maintain both model utility and manageability is critical.

Integrating the outputs of simulations into a cohesive analytical framework can be challenging. Each simulation might generate varying design alternatives, and grouping similar alternatives for statistical analysis often requires manual intervention. Additionally, synthesizing qualitative insights from various rounds into a unified analysis presents further complications. Strategies to automate these processes and enhance the analytical capabilities of the simulation software are needed.

The introduction of digital avatars and synthetic participatory processes raises complex issues in their estimation, calibration, and validation. Yu & Jayakrishnan (2018) highlight the

challenges of modeling the difference between stated and revealed preferences and introduce a post-adjustment approach to bridge the difference effectively and conveniently; hence, the new approach can be used on prediction results from any decision model. Developing robust methods for accurately simulating and adjusting these avatars to reflect evolving stakeholder views is crucial. Although this paper recognizes these challenges, detailed solutions and methodologies are subjects for future research. The case study utilizes a single LLM for simulating the cases. The use of multiple Large LLMs simulate multi-stakeholder decision-making might introduce significant computational demands, and one might still need one more LLM to coordinate the interactions. However, comparing single-agent versus multi-agent configurations might reveal interesting differences in performance and feasibility. Launching multiple LLM instances to simulate individual agents and facilitating inter-agent communication can be computationally intensive but may offer more comprehensive insights by mimicking more dynamic and realistic interactions among stakeholders. I acknowledge the need for further clarification on the optimal use of single versus multi-agent approaches in synthetic participatory processes.

6.3 Relationship with Existing Literature on Participatory Planning in Montreal

The proposed synthetic participatory planning approach for SAEMS has the promise to be further developed on methods and findings from the existing literature on (public and expert) opinion elicitation and participatory planning in Montreal. The literature reveals a growing interest in understanding public preferences and involving diverse stakeholders in the transportation planning process, which aligns with the objectives of our proposed method.

Various studies such as (Damant-Sirois & El-Geneidy, 2015; Dent et al., 2021; Mildenerger et al., 2016; Thouez et al., 2007; Zapolskytė et al., 2022) highlight the importance of capturing public opinions and preferences to inform transportation policies and infrastructure projects. Our synthetic participatory approach, by integrating digital avatars representing diverse stakeholders, offers a novel way to incorporate a broad spectrum of opinions and preferences in the planning process. This inclusivity is crucial for addressing complex issues like climate change and urban mobility, where public support and acceptance are essential for successful implementation.

The literature on participatory planning in Montreal, including works by (Boisjoly & Yengoh, 2017b; Gauthier, 2005; Kold-Taylor & de Guerre, 2020) emphasizes the need for inclusive and participatory processes to develop sustainable and equitable transportation solutions. Our synthetic participatory method aligns with this emphasis by enabling a virtual

participatory process that can complement traditional public consultation methods. This approach can potentially overcome some of the limitations identified in the literature, such as the narrow contribution of local communities in the planning process and the challenges of integrating diverse perspectives.

By leveraging LLMs and digital avatars, our method advances the paradigm of participatory planning in several ways. First, it allows for more dynamic and iterative engagement with stakeholders, enabling the exploration of a wider range of scenarios and alternatives. Second, it provides a cost-efficient way to improve the inclusivity and interpretability of multi-objective transportation planning, addressing the call for more flexible and innovative policy responses highlighted in the literature (Lesteven & Godillon, 2020). Finally, our method contributes to the ongoing discussion on how to effectively integrate public opinions and participatory approaches into transportation planning, offering a new avenue for enhancing the sustainability and resilience of urban transportation systems.

6.4 Future Research and Broader Implications

Future studies should consider exploring the potential correlations between specific stakeholder profiles and the objectives and design alternatives identified in the planning process. For instance, if a strong correlation exists between 'Traffic Congestion' and the profile of 'Transportation Engineer', this would imply that transportation engineers are frequently generated in simulations where traffic congestion is a key issue. Conversely, a weak or negative correlation might indicate a lesser association of transportation engineers with traffic congestion problems. Such analyses could help in understanding how different stakeholder profiles influence the prioritization of various urban mobility challenges. However, the interaction among stakeholders and their influence on planning outcomes may not always be straightforward or additive, posing challenges in correlation analysis. Detailed investigation into these complex, nonlinear relationships is necessary to refine the synthetic participatory planning process, ensuring the most relevant perspectives are included in decision-making.

The synthetic participatory approach introduces the possibility for digital-real hybrid interactions, which can significantly enhance the learning and adaptation processes within urban planning. This method allows for adjustments in procedural details and can even reset or rewind deliberations, providing a dynamic platform for testing various scenarios and strategies. Future research could explore how these capabilities could be exploited to streamline the planning process, merging traditionally sequential phases into parallel activities.

This could potentially accelerate the overall planning cycle, from public opinion elicitation to plan development and feedback gathering.

With advancements in multimodal LLMs, there is a promising avenue for incorporating experiential learning into the synthetic participatory process. Future applications could include showing pictures and videos of infrastructure and urban environments to digital avatars, enhancing their understanding and responsiveness to real-world contexts. This multimodal interaction could further improve the realism and effectiveness of the synthetic deliberations, providing a richer, more immersive planning experience.

An intriguing aspect for further investigation is the impact of varying personalities and backgrounds of the digital avatars on the planning outcomes. Understanding how these characteristics influence the deliberation dynamics and decision-making processes could provide deeper insights into human-machine collaboration. Future research could explore how different configurations of avatar personalities and backgrounds affect the robustness and creativity of urban mobility solutions.

Another critical area of research is the examination of the nonlinear dynamics in stakeholder interactions within the synthetic participatory framework. The specific prompts and configurations of LLMs used in simulations may significantly influence these dynamics. Detailed studies on how these factors interact and affect the decision-making process could lead to more sophisticated and nuanced models, better suited to handle the complexities of urban mobility planning.

By addressing these areas, future research can significantly advance our understanding of the synthetic participatory process and its application to urban mobility planning. These efforts will not only enhance the methodology but also broaden its applicability and effectiveness in addressing the multifaceted challenges of urban environments.

7. Conclusion

This paper introduces a novel synthetic participatory approach to urban mobility planning, utilizing LLMs to generate digital avatars representing diverse stakeholder groups. The case study centered on Montreal's hypothetical planning of future SAEMS as demonstrated the potential of this method to facilitate and improve traditional participatory planning processes by enhancing cost-efficiency, inclusivity, and adaptability. The findings indicate that the synthetic participatory approach facilitates a more comprehensive integration of stakeholder perspectives, leading to robust and diverse urban mobility solutions. By employing digital

avatars, the method overcomes many of the logistical and financial barriers associated with traditional stakeholder engagement. Moreover, the flexibility to simulate various stakeholder interactions and scenarios allows for a more thorough exploration of potential outcomes and strategies, ensuring that urban mobility plans are both resilient and forward-thinking.

The study contributes to the field of urban planning and transportation systems engineering by illustrating how AI can be synergistically combined with participatory models to enhance the decision-making process. The use of AI not only augments the capacity to process and integrate large volumes of unstructured (mostly text) data but also enables the simulation of complex stakeholder dynamics that would be difficult to manage in real-world settings. This approach is particularly beneficial for cities like Montreal, where urban mobility challenges are compounded by diverse population needs and environmental considerations. The implications of this research extend to policy development and urban planning practice. By providing a clearer understanding of how different stakeholder inputs affect mobility outcomes, policymakers can make more informed decisions that align with broader social, economic, and environmental goals. Furthermore, the methodology outlined in this paper offers a replicable and scalable model that other cities can adapt to their specific contexts, promoting a more systematic and interpretable approach to urban mobility planning.

Despite its strengths, the synthetic participatory approach faces challenges, including the accuracy and authenticity of stakeholder representation through digital avatars, and the complexity of managing advanced AI systems. Future research should focus on refining these models to enhance their realism and applicability. Additionally, longitudinal studies are needed to assess the long-term impacts of decisions facilitated by this AI-augmented participatory process.

While challenges remain, the synthetic participatory planning process suggests a promising advancement direction in how cities can approach urban mobility planning. It offers a promising pathway toward creating more sustainable, efficient, and inclusive urban environments. As technological capabilities continue to evolve, so too will the opportunities to further enhance this approach.

References

- Acheampong, R. A., Legacy, C., Kingston, R., & Stone, J. (2023). Imagining urban mobility futures in the era of autonomous vehicles—insights from participatory visioning and multi-criteria appraisal in the UK and Australia. *Transport Policy*, 136, 193–208. <https://doi.org/10.1016/j.tranpol.2023.03.020>
- Azin, B., Yang, X. (Terry), Marković, N., & Liu, M. (2021). Infrastructure enabled and electrified automation: Charging facility planning for cleaner smart mobility. *Transportation Research Part D: Transport and Environment*, 101, 103079. <https://doi.org/10.1016/j.trd.2021.103079>
- Barreto, F., Moharkar, L., Shirodkar, M., Sarode, V., Gonsalves, S., & Johns, A. (2023). *Generative Artificial Intelligence: Opportunities and Challenges of Large Language Models* (pp. 545–553). https://doi.org/10.1007/978-981-99-3177-4_41
- Becu, N., Neef, A., Schreinemachers, P., & Sangkapitux, C. (2008). Participatory computer simulation to support collective decision-making: Potential and limits of stakeholder involvement. *Land Use Policy*, 25(4), 498–509. <https://doi.org/10.1016/j.landusepol.2007.11.002>
- Beiderbeck, D., Frevel, N., von der Gracht, H. A., Schmidt, S. L., & Schweitzer, V. M. (2021). Preparing, conducting, and analyzing Delphi surveys: Cross-disciplinary practices, new directions, and advancements. *MethodsX*, 8, 101401. <https://doi.org/10.1016/j.mex.2021.101401>
- Boisjoly, G., & Yengoh, G. T. (2017a). Opening the door to social equity: local and participatory approaches to transportation planning in Montreal. *European Transport Research Review*, 9(3), 43. <https://doi.org/10.1007/s12544-017-0258-4>
- Boisjoly, G., & Yengoh, G. T. (2017b). Opening the door to social equity: local and participatory approaches to transportation planning in Montreal. *European Transport Research Review*, 9(3), 43. <https://doi.org/10.1007/s12544-017-0258-4>
- Campisi, T., Akgün, N., Ticali, D., & Tesoriere, G. (2020). Exploring Public Opinion on Personal Mobility Vehicle Use: A Case Study in Palermo, Italy. *Sustainability*, 12(13), 5460. <https://doi.org/10.3390/su12135460>
- Chehri, A., Sharma, T., Debaque, B., Duclos, N., & Fortier, P. (2022). *Transport Systems for Smarter Cities, a Practical Case Applied to Traffic Management in the City of Montreal* (pp. 255–266). https://doi.org/10.1007/978-981-16-6269-0_22
- Chen, Y., & Liu, Y. (2023). Integrated Optimization of Planning and Operations for Shared Autonomous Electric Vehicle Systems. *Transportation Science*, 57(1), 106–134. <https://doi.org/10.1287/trsc.2022.1156>
- Damant-Sirois, G., & El-Geneidy, A. M. (2015). Who cycles more? Determining cycling frequency through a segmentation approach in Montreal, Canada. *Transportation Research Part A: Policy and Practice*, 77, 113–125. <https://doi.org/10.1016/j.tra.2015.03.028>
- Dandl, F., Hyland, M., Bogenberger, K., & Mahmassani, H. S. (2019). Evaluating the impact of spatio-temporal demand forecast aggregation on the operational performance of shared autonomous mobility fleets. *Transportation*, 46(6), 1975–1996. <https://doi.org/10.1007/s11116-019-10007-9>
- Dean, M. D., Gurumurthy, K. M., de Souza, F., Auld, J., & Kockelman, K. M. (2022). Synergies between repositioning and charging strategies for shared autonomous electric vehicle fleets.

- Transportation Research Part D: Transport and Environment*, 108, 103314.
<https://doi.org/10.1016/j.trd.2022.103314>
- Dent, N., Hawa, L., DeWeese, J., Wasfi, R., Kestens, Y., & El-Geneidy, A. (2021). Market-Segmentation Study of Future and Potential Users of the New *Réseau Express Métropolitain* Light Rail in Montreal, Canada. *Transportation Research Record: Journal of the Transportation Research Board*, 2675(10), 1043–1054.
<https://doi.org/10.1177/03611981211014528>
- Fouracre, P. R., Sohail, M., & Cavill, S. (2006). A Participatory Approach to Urban Transport Planning in Developing Countries. *Transportation Planning and Technology*, 29(4), 313–330.
<https://doi.org/10.1080/03081060600905665>
- Gall, T., Vallet, F., Douzou, S., & Yannou, B. (2021). RE-DEFINING THE SYSTEM BOUNDARIES OF HUMAN-CENTRED DESIGN. *Proceedings of the Design Society*, 1, 2521–2530. <https://doi.org/10.1017/pds.2021.513>
- Gauthier, M. (2005). La planification des transports et le développement durable à Montréal : quelles procédures de débat public pour quelles solutions intégrées ? *Flux*, n° 60-61(2), 50–63.
<https://doi.org/10.3917/flux.060.0050>
- Ghaffarzadegan, N., Majumdar, A., Williams, R., & Hosseinichimeh, N. (2024). Generative agent-based modeling: an introduction and tutorial. *System Dynamics Review*, 40(1).
<https://doi.org/10.1002/sdr.1761>
- Gomes Correia, M., & Ferreira, A. (2023). Road Asset Management and the Vehicles of the Future: An Overview, Opportunities, and Challenges. *International Journal of Intelligent Transportation Systems Research*, 21(3), 376–393. <https://doi.org/10.1007/s13177-023-00366-0>
- Gosling, J. P. (2018). *SHELF: The Sheffield Elicitation Framework* (pp. 61–93).
https://doi.org/10.1007/978-3-319-65052-4_4
- Huang, X., Tian, M., Tan, W., Sun, Y., Pan, X., Tang, H., & Ding, Z. (2022). Joint Charging Infrastructure and Autonomous Fleet Planning Considering Distributed Renewable Resources. *IEEE Transactions on Industry Applications*, 58(6), 6920–6930.
<https://doi.org/10.1109/TIA.2022.3202878>
- Javed, A. R., Shahzad, F., Rehman, S. ur, Zikria, Y. Bin, Razzak, I., Jalil, Z., & Xu, G. (2022). Future smart cities: requirements, emerging technologies, applications, challenges, and future aspects. *Cities*, 129, 103794. <https://doi.org/10.1016/j.cities.2022.103794>
- Kezar, A., & Maxey, D. (2016). The Delphi technique: an untapped approach of participatory research. *International Journal of Social Research Methodology*, 19(2), 143–160.
<https://doi.org/10.1080/13645579.2014.936737>
- Kold-Taylor, L., & de Guerre, D. W. (2020). From Cars to Bicycles: an Ecosystem View of Montreal Traffic as a Wicked Problem. *Systemic Practice and Action Research*, 33(1), 55–75.
<https://doi.org/10.1007/s11213-019-09514-8>
- Lesteven, G., & Godillon, S. (2020). Fuelling the controversy on Uber’s arrival: A comparative media analysis of Paris and Montreal. *Cities*, 106, 102864.
<https://doi.org/10.1016/j.cities.2020.102864>
- Li, P., Castelo, N., Katona, Z., & Sarvary, M. (2024). Frontiers: Determining the Validity of Large Language Models for Automated Perceptual Analysis. *Marketing Science*, 43(2), 254–266.
<https://doi.org/10.1287/mksc.2023.0454>

- Melander, L. (2018). Scenario development in transport studies: Methodological considerations and reflections on delphi studies. *Futures*, 96, 68–78. <https://doi.org/10.1016/j.futures.2017.11.007>
- Merfeld, K., Wilhelms, M.-P., Henkel, S., & Kreutzer, K. (2019). Carsharing with shared autonomous vehicles: Uncovering drivers, barriers and future developments – A four-stage Delphi study. *Technological Forecasting and Social Change*, 144, 66–81. <https://doi.org/10.1016/j.techfore.2019.03.012>
- Miao, H., Jia, H., Li, J., & Qiu, T. Z. (2019). Autonomous connected electric vehicle (ACEV)-based car-sharing system modeling and optimal planning: A unified two-stage multi-objective optimization methodology. *Energy*, 169, 797–818. <https://doi.org/10.1016/j.energy.2018.12.066>
- Mildenberger, M., Howe, P., Lachapelle, E., Stokes, L., Marlon, J., & Gravelle, T. (2016). The Distribution of Climate Change Public Opinion in Canada. *PLOS ONE*, 11(8), e0159774. <https://doi.org/10.1371/journal.pone.0159774>
- Nabizadeh Rafsanjani, H., & Nabizadeh, A. H. (2023). Towards human-centered artificial intelligence (AI) in architecture, engineering, and construction (AEC) industry. *Computers in Human Behavior Reports*, 11, 100319. <https://doi.org/10.1016/j.chbr.2023.100319>
- Nalmpantis, D., Roukouni, A., Genitsaris, E., Stamelou, A., & Naniopoulos, A. (2019). Evaluation of innovative ideas for Public Transport proposed by citizens using Multi-Criteria Decision Analysis (MCDA). *European Transport Research Review*, 11(1), 22. <https://doi.org/10.1186/s12544-019-0356-6>
- Park, J. S., O'Brien, J., Cai, C. J., Morris, M. R., Liang, P., & Bernstein, M. S. (2023). Generative Agents: Interactive Simulacra of Human Behavior. *Proceedings of the 36th Annual ACM Symposium on User Interface Software and Technology*, 1–22. <https://doi.org/10.1145/3586183.3606763>
- Pelletier, S., Jabali, O., Mendoza, J. E., & Laporte, G. (2019). The electric bus fleet transition problem. *Transportation Research Part C: Emerging Technologies*, 109, 174–193. <https://doi.org/10.1016/j.trc.2019.10.012>
- Schmalz, U., Spinler, S., & Ringbeck, J. (2021). Lessons Learned from a Two-Round Delphi-based Scenario Study. *MethodsX*, 8, 101179. <https://doi.org/10.1016/j.mex.2020.101179>
- Schröder, P., Vergragt, P., Brown, H. S., Dendler, L., Gorenflo, N., Matus, K., Quist, J., Rupprecht, C. D. D., Tukker, A., & Wennersten, R. (2019). Advancing sustainable consumption and production in cities - A transdisciplinary research and stakeholder engagement framework to address consumption-based emissions and impacts. *Journal of Cleaner Production*, 213, 114–125. <https://doi.org/10.1016/j.jclepro.2018.12.050>
- Shanahan, M., McDonnell, K., & Reynolds, L. (2023). Role play with large language models. *Nature*, 623(7987), 493–498. <https://doi.org/10.1038/s41586-023-06647-8>
- Sheppard, C. J. R., Bauer, G. S., Gerke, B. F., Greenblatt, J. B., Jenn, A. T., & Gopal, A. R. (2019). Joint Optimization Scheme for the Planning and Operations of Shared Autonomous Electric Vehicle Fleets Serving Mobility on Demand. *Transportation Research Record: Journal of the Transportation Research Board*, 2673(6), 579–597. <https://doi.org/10.1177/0361198119838270>
- Tatum, K., Cekic, T., Landwehr, A., Noennig, J., Knieling, J., & Schroeter, B. (2020). *Co-creation of Local Mobility Solutions: Lessons from the Mobility Lab in Hamburg-Altona* (pp. 16–27). https://doi.org/10.1007/978-3-030-38028-1_2
- Thouez, J.-P., André, P., & Bussière, Y. (2007). Does a sustainable development concept bring a change in transport planning? The case of the implementation of three major infrastructures in

- Montreal. *Sustainable Development and Planning III*, 835–842.
<https://doi.org/10.2495/SDP070792>
- Vosooghi, R., Puchinger, J., Bischoff, J., Jankovic, M., & Vouillon, A. (2020). Shared autonomous electric vehicle service performance: Assessing the impact of charging infrastructure. *Transportation Research Part D: Transport and Environment*, 81, 102283.
<https://doi.org/10.1016/j.trd.2020.102283>
- Wang, H., Zhao, D., Meng, Q., Ong, G. P., & Lee, D.-H. (2019). A four-step method for electric-vehicle charging facility deployment in a dense city: An empirical study in Singapore. *Transportation Research Part A: Policy and Practice*, 119, 224–237.
<https://doi.org/10.1016/j.tra.2018.11.012>
- Wang, L., Ma, C., Feng, X., Zhang, Z., Yang, H., Zhang, J., Chen, Z., Tang, J., Chen, X., Lin, Y., Zhao, W. X., Wei, Z., & Wen, J. (2024). A survey on large language model based autonomous agents. *Frontiers of Computer Science*, 18(6), 186345. <https://doi.org/10.1007/s11704-024-40231-1>
- Wang, S., & Noe, R. A. (2010). Knowledge sharing: A review and directions for future research. *Human Resource Management Review*, 20(2), 115–131.
<https://doi.org/10.1016/j.hrmr.2009.10.001>
- Wang, Z., Yu, J., Li, G., Zhuge, C., & Chen, A. (2023). Time for hydrogen buses? Dynamic analysis of the Hong Kong bus market. *Transportation Research Part D: Transport and Environment*, 115, 103602. <https://doi.org/10.1016/j.trd.2022.103602>
- Yin, Y. H., Nee, A. Y. C., Ong, S. K., Zhu, J. Y., Gu, P. H., & Chen, L. J. (2015). Automating design with intelligent human–machine integration. *CIRP Annals*, 64(2), 655–677.
<https://doi.org/10.1016/j.cirp.2015.05.008>
- Yu, J., & Chen, A. (2021). Differentiating and modeling the installation and the usage of autonomous vehicle technologies: A system dynamics approach for policy impact studies. *Transportation Research Part C: Emerging Technologies*, 127. <https://doi.org/10.1016/j.trc.2021.103089>
- Yu, J. G., Hyland, M. F., & Chen, A. (2023). Improving Infrastructure and Community Resilience with Shared Autonomous Electric Vehicles (SAEV-R). *IEEE Intelligent Vehicles Symposium, Proceedings, 2023-June*. <https://doi.org/10.1109/IV55152.2023.10186785>
- Yu, J. G., & Jayakrishnan, R. (2018). A Cognitive Framework for Unifying Human and Artificial Intelligence in Transportation Systems Modeling. *IEEE Conference on Intelligent Transportation Systems, Proceedings, ITSC, 2018-Novem*.
<https://doi.org/10.1109/ITSC.2018.8569322>
- Yu, J. G., Selby, B., Vlahos, N., Yadav, V., & Lemp, J. (2021). A feature-oriented vehicle trajectory data processing scheme for data mining: A case study for Statewide truck parking behaviors. *Transportation Research Interdisciplinary Perspectives*, 11.
<https://doi.org/10.1016/j.trip.2021.100401>
- Zapolskytė, S., Trépanier, M., Burinskienė, M., & Survilė, O. (2022). Smart Urban Mobility System Evaluation Model Adaptation to Vilnius, Montreal and Weimar Cities. *Sustainability*, 14(2), 715. <https://doi.org/10.3390/su14020715>
- Zhang, C., Kim, J., Jeon, J., Xing, J., Ahn, C., Tang, P., & Cai, H. (2022). Toward Integrated Human-Machine Intelligence for Civil Engineering: An Interdisciplinary Perspective. *Computing in Civil Engineering 2021*, 279–286. <https://doi.org/10.1061/9780784483893.035>

Appendix A: Prompt and Scenario Specifications

Input and outputs in an example scenario in Section 5.

<p>System Input: You are an expert in simulating a participatory planning process for the City of Montreal's future shared automated electric mobility systems (SAEMS). Suppose the planning activity occurs in the year 2024, and the planning horizon year is 2044.</p>
<p>Input/Prompt: Create 10 stakeholder(s) as their digital avatar(s).</p>
<p>Output/Response: To develop a simulation for Montreal's future shared automated electric mobility systems (SAEMS) with an effective participatory planning process, creating diverse and representative digital avatars for stakeholders is crucial. Here are ten stakeholder avatars that could play key roles in shaping the city's mobility strategies:</p> <ol style="list-style-type: none"> 1. City Transport Planner: Jean Beaulieu <ul style="list-style-type: none"> - Avatar: Mid-40s, meticulous and forward-thinking, has glasses and a constant readiness in his eyes. - Role: Guides the regulation and integration of SAEMS into Montreal's existing urban fabric while optimizing land use and promoting green mobility. 2. Environmental Advocate: Lila Tremblay <ul style="list-style-type: none"> - Avatar: Early 30s, vibrant and passionate, with an eco-friendly badge and attire that includes recycled materials. - Role: Ensures environmental considerations, sustainability, and green technologies are at the forefront of SAEMS planning and operations. 3. Technology Developer: Arjun Patel <ul style="list-style-type: none"> - Avatar: Late 20s, tech-savvy, always with a smartwatch and tablet, displaying real-time data. - Role: Brings the latest in AI and automation technology to enhance system efficiency and safety, focusing on software and hardware innovations. 4. Community Representative: Marie-Claude Dupuis <ul style="list-style-type: none"> - Avatar: Mid-50s, a warm and approachable look, often seen in community center settings. - Role: Voices the concerns and needs of Montreal residents, ensuring the mobility solutions are accessible and beneficial to all community segments. 5. Urban Developer: Elijah Smith <ul style="list-style-type: none"> - Avatar: Early 40s, sharp dresser, has a blueprint or city map in hand. - Role: Works on integrating SAEMS within new and developing housing and commercial projects, ensuring smart growth and urban density are maintained. 6. Public Health Official: Dr. Amira Hussein <ul style="list-style-type: none"> - Avatar: Late 30s, wearing a lab coat with a health data smart screen. - Role: Advises on the health implications of SAEMS, focusing on reducing pollution, minimizing accidents, and promoting active transport options. 7. Business Owner: Carlos Gomez <ul style="list-style-type: none"> - Avatar: Mid-40s, casual yet determined, often seen in a café setting with business plans. - Role: Represents the interests of local businesses that could be affected by changes in urban mobility, ensuring economic impacts are considered. 8. Tourism Director: Sophie Labelle <ul style="list-style-type: none"> - Avatar: Late 30s, stylish, holds brochures of Montreal's attractions. - Role: Looks at how SAEMS can enhance Montreal as a destination, improving transport links and experiences for tourists. 9. Senior Citizen Representative: Annette Giroux <ul style="list-style-type: none"> - Avatar: Early 70s, kind-faced, often in public parks or social halls. - Role: Ensures that the needs and concerns of older adults, particularly regarding mobility and accessibility, are addressed. 10. Youth Advocate: Jamal Carter <ul style="list-style-type: none"> - Avatar: Early 20s, modern and dynamic, constantly interacting through social media. - Role: Represents the younger population who are tech-savvy and forward-thinking, pushing for innovative solutions and engagement through digital platforms. <p>These avatars can be used in various planning simulations, workshops, and public forums to ensure comprehensive and meaningful participation in the development of Montreal's SAEMS. Each stakeholder brings a critical perspective, helping to build a robust and inclusive mobility system that anticipates future community and environmental needs.</p>
<p>Input/Prompt: Concretely simulate the process and obtain the results from using a 3-round Delphi method to let them collaboratively identify issues, objectives, performance metrics, and decision weights for each round. Then synthesize the information to form 5 issues, 5 objectives, 10 performance metrics (0-10 for each metric), and decision weights (sum up to 1.0). Be clear which performance metric is for which objective.</p>

Output/Response:**### Delphi Method Simulation: 3-Round Process******Round 1: Identifying Issues and Objectives****

- ****Method****: Stakeholders anonymously submit perceived issues and initial objectives for the SAEMS development.
- ****Results****:
 - Identified Issues: Accessibility, Environmental Impact, Economic Effectiveness, Technological Integration, Public Acceptance
 - Proposed Objectives: Enhance Mobility Access, Minimize Environmental Footprint, Foster Economic Growth, Integrate Cutting-edge Technology, Build Public Trust

Round 2: Defining Performance Metrics and Preliminary Decision Weights

- ****Method****: Stakeholders propose performance metrics for each objective and suggest preliminary weights based on the importance they perceive.

- ****Results****:
 - ****Enhance Mobility Access****
 - ****Metrics****: Coverage ratio (0-10), User satisfaction (0-10)
 - ****Weight****: 0.25
 - ****Minimize Environmental Footprint****
 - ****Metrics****: GHG emissions reduction (0-10), Energy efficiency (0-10)
 - ****Weight****: 0.20
 - ****Foster Economic Growth****
 - ****Metrics****: Jobs created (0-10), ROI from SAEMS (0-10)
 - ****Weight****: 0.20
 - ****Integrate Cutting-edge Technology****
 - ****Metrics****: System reliability (0-10), Update frequency (0-10)
 - ****Weight****: 0.15
 - ****Build Public Trust****
 - ****Metrics****: Public approval rating (0-10), Safety record (0-10)
 - ****Weight****: 0.20

Round 3: Finalizing Decision Weights and Confirming Metrics

- ****Method****: Re-evaluation of the performance metrics and finalization of decision weights through consensus or majority.

- ****Results****:
 - ****Enhance Mobility Access****:
 - ****Metrics Unchanged****: Coverage ratio, User satisfaction
 - ****Final Weight****: 0.20
 - ****Minimize Environmental Footprint****:
 - ****Metrics Unchanged****: GHG emissions reduction, Energy efficiency
 - ****Final Weight****: 0.25
 - ****Foster Economic Growth****:
 - ****Metrics Unchanged****: Jobs created, ROI from SAEMS
 - ****Final Weight****: 0.20
 - ****Integrate Cutting-edge Technology****:
 - ****Metrics Unchanged****: System reliability, Update frequency
 - ****Final Weight****: 0.15
 - ****Build Public Trust****:
 - ****Metrics Unchanged****: Public approval rating, Safety record
 - ****Final Weight****: 0.20

Synthesized Results

- ****Key Issues (5)****: Accessibility, Environmental Impact, Economic Effectiveness, Technological Integration, Public Acceptance
- ****Key Objectives (5)****: Enhance Mobility Access, Minimize Environmental Footprint, Foster Economic Growth, Integrate Cutting-edge Technology, Build Public Trust
- ****Performance Metrics (10)****:
 - Coverage Ratio (0-10)
 - User Satisfaction (0-10)
 - GHG Emissions Reduction (0-10)
 - Energy Efficiency (0-10)
 - Jobs Created (0-10)
 - ROI from SAEMS (0-10)
 - System Reliability (0-10)
 - Update Frequency (0-10)

<ul style="list-style-type: none"> - Public Approval Rating (0-10) - Safety Record (0-10) - **Decision Weights (Summing up to 1.0)**: - Enhance Mobility Access: 0.20 - Minimize Environmental Footprint: 0.25 - Foster Economic Growth: 0.20 - Integrate Cutting-edge Technology: 0.15 - Build Public Trust: 0.20 <p>This structured approach through the Delphi method allows stakeholders to collaboratively refine and prioritize elements crucial for the success and acceptance of Montreal's SAEMS, ensuring broad consensus and a balanced consideration of different perspectives.</p>
<p>Input/Prompt: Concretely simulate a 90-min free-style brainstorming session to generate 3 mutually exclusive SAEMS alternatives with detailed specifications and the corresponding 20-year implementation plans with 4-year intervals (with a specific monetary amount for each interval) under a total budget of \$100 million CAD (Net Present Value).</p>
<p>Output/Response:</p> <p>### Free-Style Brainstorming Session: Generating SAEMS Alternatives</p> <p>**Duration**: 90 minutes</p> <p>**Participants**: 10 Stakeholder Avatars</p> <p>**Objective**: Develop three mutually exclusive alternatives for Montreal's SAEMS, including detailed specifications and 20-year implementation plans, with a total budget of \$100 million CAD (Net Present Value).</p> <p>### Alternative 1: Fully Automated Taxi Network</p> <p>#### Specifications:</p> <ul style="list-style-type: none"> - **Fleet Size**: 500 autonomous electric vehicles (AEVs) - **Service Area**: Downtown and surrounding residential areas - **Technology**: Level 5 automation, with in-vehicle connectivity and real-time monitoring - **Charging Stations**: 50 fast-charging stations across the service area <p>#### 20-Year Implementation Plan (4-Year Intervals):</p> <ul style="list-style-type: none"> - **2024-2028**: Research and procurement (\$20 million), deployment of initial 200 AEVs - **2028-2032**: Analysis and expansion; adding 150 more AEVs (\$25 million) - **2032-2036**: Establish additional charging stations; expand service area (\$30 million) - **2036-2044**: Maintenance, technology upgrades, and replacement vehicles (\$25 million) <p>### Alternative 2: Neighborhood Electric Pods (NEP) Initiative</p> <p>#### Specifications:</p> <ul style="list-style-type: none"> - **Fleet Size**: 200 smaller, pod-like AEVs - **Service Area**: Targeted at suburban communities with connectivity to major transport hubs - **Technology**: Level 4 automation with central control hub for monitoring - **Charging Infrastructure**: Solar-powered charging pods <p>#### 20-Year Implementation Plan (4-Year Intervals):</p> <ul style="list-style-type: none"> - **2024-2028**: Development and initial deployment of 100 NEPs; set up solar-powered infrastructures (\$15 million) - **2028-2032**: Evaluate effectiveness, optimize routes, and deploy an additional 50 NEPs (\$20 million) - **2032-2036**: Scale up infrastructure with more charging pods; add 50 NEPs (\$30 million) - **2036-2044**: Ongoing maintenance, system updates, and flexibility enhancements (\$35 million) <p>### Alternative 3: Integrated Public AEV System</p> <p>#### Specifications:</p> <ul style="list-style-type: none"> - **Fleet Size**: 300 AEVs - **Service Area**: Wide city coverage including key transit hubs, parks, and commercial areas - **Technology**: Level 4 automation integrated with Montreal's existing public transit system for optimized route planning - **Charging Stations**: Hybrid stations using both grid power and renewable sources <p>#### 20-Year Implementation Plan (4-Year Intervals):</p> <ul style="list-style-type: none"> - **2024-2028**: Planning and integration with current transit systems; launch 100 AEVs (\$25 million) - **2028-2032**: Extend service coverage; add 100 AEVs and additional hybrid charging stations (\$30 million) - **2032-2036**: Consolidation and optimization based on user feedback and system data; add 100 AEVs (\$25 million) - **2036-2044**: System enhancements, sustainability improvements, and tech upgrades (\$20 million) <p>### Budget Allocation Overview</p> <p>Each plan is structured to make the most efficient use of the \$100 million CAD budget over the 20 years, focusing on phased deployment and sustainability. Stakeholders would need to prioritize goals such as coverage, technological advancement, and integration with existing infrastructure. Each alternative emphasizes</p>

different facets of urban mobility, providing diverse solutions to cater to various needs and challenges in Montreal's future mobility landscape.
<p>Input/Prompt: Evaluate the alternatives using the previously identified performance metrics -- make best guess about values about the variables and probabilities collaboratively. Compare the final scores and recommend the best alternative. Evaluate the three alternatives using the previously identified performance metrics -- make best guess about values about the variables and probabilities collaboratively. Compare the final scores and recommend the best alternative.</p>
<p>Output/Response:</p> <p>### Evaluating SAEMS Alternatives Using Identified Performance Metrics</p> <p>To evaluate the alternatives, let's score each one using a scale of 0-10 for each of the previously identified performance metrics. We will calculate the weighted sum for each alternative to determine their overall scores under the specified weights.</p> <p>#### Performance Metrics and Weights:</p> <ol style="list-style-type: none"> 1. **Coverage Ratio** (Objective: Enhance Mobility Access) - Weight: 0.20 2. **User Satisfaction** (Objective: Enhance Mobility Access) - Weight: 0.20 3. **GHG Emissions Reduction** (Objective: Minimize Environmental Footprint) - Weight: 0.25 4. **Energy Efficiency** (Objective: Minimize Environmental Footprint) - Weight: 0.25 5. **Jobs Created** (Objective: Foster Economic Growth) - Weight: 0.20 6. **ROI from SAEMS** (Objective: Foster Economic Growth) - Weight: 0.20 7. **System Reliability** (Objective: Integrate Cutting-edge Technology) - Weight: 0.15 8. **Update Frequency** (Objective: Integrate Cutting-edge Technology) - Weight: 0.15 9. **Public Approval Rating** (Objective: Build Public Trust) - Weight: 0.20 10. **Safety Record** (Objective: Build Public Trust) - Weight: 0.20 <p>#### Scoring Simulation (Scale 0-10, where 10 is the best):</p> <p>##### Fully Automated Taxi Network - Alternative 1</p> <ul style="list-style-type: none"> - Coverage Ratio: 8 - User Satisfaction: 7 - GHG Emissions Reduction: 9 - Energy Efficiency: 9 - Jobs Created: 6 - ROI from SAEMS: 7 - System Reliability: 9 - Update Frequency: 8 - Public Approval Rating: 8 - Safety Record: 9 <p>##### Neighborhood Electric Pods (NEP) Initiative - Alternative 2</p> <ul style="list-style-type: none"> - Coverage Ratio: 6 - User Satisfaction: 8 - GHG Emissions Reduction: 6 - Energy Efficiency: 7 - Jobs Created: 7 - ROI from SAEMS: 6 - System Reliability: 7 - Update Frequency: 7 - Public Approval Rating: 7 - Safety Record: 8 <p>##### Integrated Public AEV System - Alternative 3</p> <ul style="list-style-type: none"> - Coverage Ratio: 9 - User Satisfaction: 9 - GHG Emissions Reduction: 8 - Energy Efficiency: 8 - Jobs Created: 8 - ROI from SAEMS: 8 - System Reliability: 8 - Update Frequency: 7 - Public Approval Rating: 9 - Safety Record: 9 <p>### Calculating Weighted Scores</p> <p>Weighted scores are calculated by multiplying each metric's score by its weight and summing these products for each alternative. Below are the totals:</p> <p>##### Alternative 1: Fully Automated Taxi Network</p>

- ****Total Score****: $\backslash ((8 \times 0.20) + (7 \times 0.20) + (9 \times 0.25) + (9 \times 0.25) + (6 \times 0.20) + (7 \times 0.20) + (9 \times 0.15) + (8 \times 0.15) + (8 \times 0.20) + (9 \times 0.20) = 8.1 \backslash)$

Alternative 2: Neighborhood Electric Pods Initiative

- ****Total Score****: $\backslash ((6 \times 0.20) + (8 \times 0.20) + (6 \times 0.25) + (7 \times 0.25) + (7 \times 0.20) + (6 \times 0.20) + (7 \times 0.15) + (7 \times 0.15) + (7 \times 0.20) + (8 \times 0.20) = 6.85 \backslash)$

Alternative 3: Integrated Public AEV System

- ****Total Score****: $\backslash ((9 \times 0.20) + (9 \times 0.20) + (8 \times 0.25) + (8 \times 0.25) + (8 \times 0.20) + (8 \times 0.20) + (8 \times 0.15) + (7 \times 0.15) + (9 \times 0.20) + (9 \times 0.20) = 8.55 \backslash)$

Conclusion and Recommendation

Based on the evaluation using the identified metrics and their weights, the ****Integrated Public AEV System (Alternative 3)**** scores the highest with a total of 8.55. Therefore, this alternative would be recommended for implementation as Montreal's SAEMS plan owing to its superior performance in enhancing mobility access, environmental considerations, economic benefits, technologic integration, and public trust.