GenAI for Sustainable Mobility Behavior Change: Building MUV's AI Driven Game Engine

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Abstract:
Achieving sustainability objectives necessitates a transformation in passenger mobility behaviour. This paper introduces a Generative AI framework developed by the MUV platform to address the enduring attitude-behaviour gap in sustainable urban mobility. Anchored in Self-Determination Theory, the system utilises behavioural, contextual, and qualitative data to create personalised competitions that enhance intrinsic motivation. The framework features a threelayer architecture and a virtual mobility trainer to support game dynamics, while federated learning and bias audits provide ethical safeguards. The framework is set to be piloted at ISPRA, with a mixed-methods evaluation planned to assess its impact on behaviour and inclusivity. This study presents a replicable model for responsible AI-driven behavioural change in alignment with the European Green Deal.

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SECTION I. Introduction

Urban mobility is integral to the European Green Deal's objective of achieving climate neutrality by 2050, given that transport contributes 23 % of the EU's greenhouse gas emissions [1]. However, despite increasing environmental awareness, a persistent attitude-behaviour gap hinders progress: 68% of Europeans recognise the urgency of climate change but prioritise convenience in their daily travel decisions [2]. This gap is exacerbated by car-centric infrastructure and gamification platforms that offer generic incentives (e.g., “Cycle 50 km this month”), which fail to consider individual preferences, abilities, or socioeconomic constraints [3].

Mobility Urban Values (MUV), a platform that promotes sustainable travel through behaviour change [4], exemplifies this challenge. Although its individual challenges and team tournaments initially succeed in engaging participants [5], user involvement diminishes as individuals become disengaged from repetitive and non-personalized competitions [6]. This decline in participation highlights the limitations of extrinsic rewards, such as points and badges, and underscores the necessity for interventions that foster intrinsic motivationspecifically, autonomy, competence, and relatedness-as articulated by Self-Determination Theory (SDT) [4].

Generative AI (GenAI) represents a significant paradigm shift. By integrating behavioural data through federated learning, contextual urban signals, and user feedback, open-source LLMs generate personalised game dynamics whilst preserving privacy through distributed processing on user devices. For instance, a parent might be presented with challenges that incorporate school runs (“Walk your child to school 3x this week”), whereas a commuter might receive prompts aimed at cost savings (“Swap two car trips with public transit”). This personalisation level aligns with the EU Green Deal's emphasis on inclusive, citizencentric solutions [1]. However, technical and ethical barriers, including data privacy and algorithmic bias, remain key issues to address properly [7].

This paper introduces the GenAI framework developed by MUV, a system specifically designed to address existing limitations. The framework employs a three-layer data architecture that feeds fine-tuned LLMs (e.g., Llama-based models) to generate dynamic challenges, with federated learning enabling local processing whilst aggregating anonymised patterns for personalisation [7]. A virtual trainer offers realtime feedback, adjusting goals based on user progress and contextual constraints, such as providing rerouting suggestions during inclement weather. The design incorporates ethical safeguards, including bias audits and transparent user dashboards, to ensure equitable access for diverse populations [8].

The initial validation phase will involve deploying the engine within the ISPRA (the Italian Institute for Environmental Protection and Research) corporate community, a network comprising environmental researchers and policymakers, which has used MUV services since 2022. The technologically adept and sustainabilityfocused users of ISPRA present an optimal target group for assessing engagement metrics, such as challenge completion rates and behavioural changes, such as a reduction in car trips [10]. The findings from this phase will guide iterative enhancements before broader implementation across European Union cities, in alignment with the European Green Deal Investment Plan's €1 trillion sustainability funding objective [1].

This study contributes to sustainable mobility research by:

1. Operationalizing SDT within a GenAI framework, demonstrating how intrinsic motivation can be systematically nurtured.

2. Proposing a privacy-preserving technical architecture using open-source LLMs, balancing personalization with compliance.

3. Establishing a roadmap for ethical AI deployment in public-sector behaviour change initiatives.

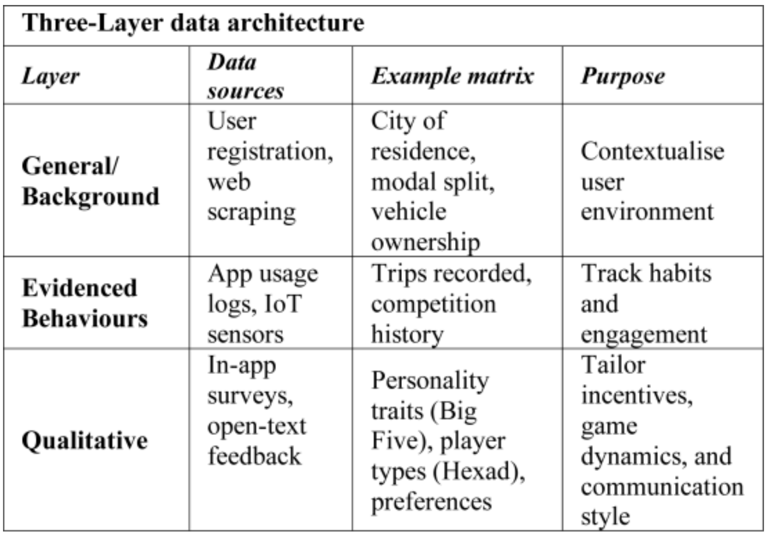
The remainder of this paper details the GenAI framework (Section 2), its technical and ethical implementation (Section 3), the upcoming ISPRA trial (Section 4), and implications for policy and scalability (Section 5).

SECTION II.
AI Engine for Adaptive Game Dynamics

This chapter elucidates the architecture and mechanics of MUV's generative AI framework, which reconceptualises gamification as a dynamic and adaptive system. The framework customises challenges by incorporating behavioural theory, multi-source data, and scalable cloud infrastructure to foster intrinsic motivation while addressing ethical risks.

A. Data-Driven Personalisation Architecture

The GenAI framework is structured around three interconnected data layers, which are used to model user behaviour and urban contexts (Table 1). These layers facilitate detailed personalisation while ensuring compliance with GDPR [2].



Three-Layer data architecture			
Layer	***Data sources***	***Example matrix***	***Purpose***
General/ Background	User registration, web scraping	City of residence, modal split, vehicle ownership	Contextualise user environment
Evidenced Behaviours	App usage logs, IoT sensors	Trips recorded, competition history	Track habits and engagement
Qualitative	In-app surveys, open-text feedback	Personality traits (Big Five), player types (Hexad), preferences	Tailor incentives, game dynamics, and communication style

Fig. 1.
Three-layer data architecture.

The General/Background layer establishes foundational profiles for users and their environments. For instance, a user in Rome is associated with the city's public transit schedules closed to her/his home/office, areas of traffic congestion, and air quality indices. Data on vehicle ownership, such as the distinction between e-bike and car ownership, informs the design of challenges, exemplified by the suggestion “Try a 5 km e-bike commute” for car owners [3]. Additionally, climate data, including seasonal rainfall patterns, further refines prompts by encouraging walking during periods of mild weather [4].

The Evidenced Behaviours layer leverages dynamic app usage data and feeds reinforcement learning (RL) algorithms that adapt to competition difficulty and associated rewards [10]. For instance: a user who cycles 20 km weekly may be presented with incremental goals, such as “Cycle 25 km, ” whereas beginners might receive more modest prompts, such as “Cycle 5 km “ [5]. Engagement metrics are employed to identify users who are disengaged, prompting AI-generated nudges, such as “Join this weekend's walking challenge to win a local reward” [6].

The Qualitative layer incorporates psychological assessments to map user personalities and gaming preferences, thereby facilitating hyper-personalised interventions [12].

1) Personality profiling

- The Big Five Inventory (BFI) is a 10 item survey administered during onboarding to evaluate individuals across five personality traits: Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism (OCEAN) [12].

- Self-Determination Theory (SDT) surveys employ concise questionnaires to assess individuals' intrinsic motivation factors, namely autonomy, competence, and relatedness, in order to enhance the framing of challenges [13].

2) Player Typology

- The Hexad player types survey, grounded in Marczewski's framework, categorises users into six distinct gaming personas [14], as delineated in Table 2.

3) Integration with NLP

- Open-text survey responses (e.g., “I love competing with friends”) are analysed using NLP to refine player typology and personality clusters [11]. Sentiment detection flags frustration (e.g., “Biking uphill is exhausting”), prompting AI to adjust challenge difficulty or suggest alternatives (e.g., e-bike rentals).

Player Type	***Motivation***	***AI Game engine possible intervention***
Philanthropist	Desire to contribute to others	Team-based CO_2 reduction challenges
Achiever	Focus on mastery and progression	Tiered goals with badges (e.g., “Gold Cyclist”)
Free Spirit	Value creativity and exploration	Open-ended challenges (e.g., “Design a green commute”)
Socializer	Driven by social interaction	Community tournaments and group rewards
Disruptor	Seek change through unconventional actions	“Hack the system” tasks (e.g., “Find a faster bike route”)
Player	Motivated by extrinsic rewards	Point-based incentives (e.g., “Earn 500 points for metro trips”)

Fig. 2.
Hexad player types

For instance, an individual exhibiting a high level of Agreeableness, as measured by the BFI, and identified as a Socializer according to the Hexad model, is likely to engage in team-oriented challenges that offer communal rewards. An example of a challenge might be, “Participate in your neighbourhood's walking league to unlock a park renovation”.

SECTION III.

Implementation

A. Organizational Data

As user information is collected, it represents the foundational input for the AI-based system to develop customised game dynamics. This user profile comprises five components: mobility, personality, lifestyle, tastes, and community closeness. The mobility component delineates the user's travel profile by analysing habits and choices, vehicles owned, CO_2 emissions saved, and behavioural changes. The personality component encompasses the player profile, performance in various competitions, and social interactions. Lifestyle is determined by the level of physical activity, household characteristics, profession, and neighbourhood of residence, while tastes are influenced by individual interests and preferences. Lastly, if the user is part of a community, it is beneficial to evaluate the similarity of their profile to that of the average member.

The profile construction follows a sequential data flow: local user profiling, federated aggregation of behavioural patterns, then server-side integration with geographical context and sponsor data to generate LLM-driven personalised challenges. Collectively, these three elements contribute to the creation of game dynamics through a three-step process, contingent upon the type of competition in question.

B. Building Tailoring Competitions

The generation of tailored competitions constitutes the ultimate outcome of MUV's AIdriven system. As previously indicated, this process encompasses not only the formulation of various competitions but also the development of supplementary activities designed to enhance the competitions' overall efficacy.

1) Language and Tone of Voice

The initial phase of this process entails establishing an appropriate language and tone to engage the user. The system selects the most suitable style based on the individual profile, thereby determining the content of the messages dispatched to initiate the competition, encourage participation throughout its duration, and ultimately convey the results. Notably, the same challenge or tournament involving multiple users can employ varied communication strategies tailored to the profiles they intend to engage. Consequently, the communications may range from informal to formal, appealing to individual competitiveness or health benefits, among other factors. It is imperative that the language employed consistently considers gender issues and accurately addresses users.

2) Frequency and Method of Communications

The determination of the timing and method for disseminating communications is intrinsically linked to the language employed and is further associated with the user profile type. Specifically, some individuals prefer push notifications, while others are more comfortable with emails. Additionally, certain users are accustomed to receiving communications in the morning, whereas others opt for evening notifications. The frequency of push notifications is also contingent upon the type of user; some desire updates whenever a significant event transpires within the competition, while others prefer a daily summary. By analysing user interactions with these notifications, feed elements, or emails, it is possible to assess their effectiveness and enhance them through automatic fine-tuning, which can modify either the content or the method of communication delivery.

3) Training Sessions, Challenges and Tournaments

Following the establishment of language and communication methods, the final step involves defining the actual game dynamics [4], incorporating all relevant constraints and characteristics. These dynamics vary depending on the type of activity to be initiated. For “training sessions”, the design consists of individual, spontaneous, short-term challenges offered daily or weekly. Customisation is linked to the objectives and their complexity and the type of reward, such as a customisable badge. Each user receives personalised training content daily and weekly, tailored specifically for them. In contrast, “challenges” or “tournaments”, which may be open to all or targeted at specific communities, present a more complex scenario due to their collective nature, targeting groups of potential participants. Therefore, it is essential to consider all user profiles and categorise them into personas, representing typical users for each category. Once this categorisation is complete, the game dynamics can be defined according to the number and type of each group. Each game dynamic launched is evaluated at the conclusion based on a series of indicators that measure its effectiveness, which informs the system to enhance this process, thereby offering increasingly successful competition.

4) Your Virtual Mobility Trainer

This approach to competitions could be further enhanced by conceptualising the establishment of a virtual trainer that becomes acquainted with users, assisting them in defining their objectives and analysing their performance. This coach would propose training sessions, challenges, and tournaments tailored to their individual development trajectory, profile, and context. With the support of artificial intelligence, a gamification engine could be developed to autonomously manage the initiation and administration of all competitions that engage MUV users. This would be achieved through an iterative mechanism that refines the game dynamics based on the outcomes of completed competitions.

SECTION IV.
Discussion

The incorporation of generative AI into urban mobility platforms such as MUV presents a promising approach to addressing the persistent attitude-behaviour gap that hinders sustainability initiatives. By grounding the framework in SelfDetermination Theory (SDT), the system facilitates a shift.

The emphasis has shifted from extrinsic rewards, which are often transient and impersonal, to fostering intrinsic motivation through autonomy, competence, and relatedness. This approach acknowledges that sustainable habits are not developed through generic prompts but through interventions that resonate with individual identities, lifestyles, and social contexts. For example, a parent motivated by family health may embrace walking challenges integrated into school routines, while a commuter driven by cost savings might prioritise carpooling incentives. However, such personalisation requires a careful balance of innovation and ethical responsibility.

A. Ethical Complexities and Mitigation Strategies

The framework's dependence on granular data-such as GPS logs, psychological profiles, and behavioural patterns-inevitably raises privacy concerns. Although federated learning decentralizes data training to safeguard user anonymity, the psychological profiling inherent in tools like the Big Five Inventory and Hexad player typology introduces more profound ethical questions. For instance, categorizing users as “Socializers” or “Achievers” risks reducing complex human behaviours to algorithmic labels, potentially reinforcing stereotypes or excluding individuals who do not conform to such classifications. To address this issue, the system incorporates transparency dashboards that enable users to view and contest their assigned profiles, thereby fostering agency over how their data influences their experience [1]. This transparency is not solely technical but also psychological, demystifying AI's role in curating challenges and building trust-a critical factor often overlooked in behaviour change technologies [2].

Algorithmic bias introduces an additional layer of complexity [11]. The artificial intelligence system's propensity to prioritize users in wellserved urban areas-where bike lanes and transit options are plentiful-may inadvertently marginalize residents in underserved neighbourhoods. Monthly bias audits address this issue by cross-referencing user personas with infrastructure data. For example, in Rome, challenges in districts with inadequate bike connectivity might emphasize walking routes or bus partnerships to ensure inclusivity [3]. However, even these measures are not without flaws. The Hexad player typology, although validated across various demographics, may not fully capture cultural nuances. A “Disruptor” in Stockholm might enjoy unconventional tasks such as hacking transit routes, whereas a user in Prague might perceive such prompts as impractical amidst his/her traffic conditions. Iterative feedback loops, wherein users rate challenges and propose alternatives, contribute to refining these cultural calibrations [4].

Psychological manipulation presents a more subtle risk. Hyper-personalised rewards, designed to exploit cognitive biases such as loss aversion or social proof, may encourage addictive engagement. The framework incorporates ethical safeguards to mitigate this: nudges are crafted to promote autonomy rather than coercion. For instance, when a user declines a challenge, they receive supportive feedback (e.g., “Maybe next time!”) instead of punitive reminders, aligning with SelfDetermination Theory's emphasis on voluntary participation [5].

B. Methodology: Testing with the ISPRA Community

The planned 6 -month trial at ISPRA's Rome office, which employs approximately 600 environmental researchers and policymakers, serves as a critical evaluation of the framework's efficacy and ethical considerations. This trial employs a mixed-methods approach, integrating A/B testing with qualitative insights to assess both behavioural changes and user perceptions.

- A/B testing: Participants are allocated into two distinct groups. Group A is exposed to AIpersonalised challenges tailored based on their BFI and Hexad profiles, whereas Group B engages with static, non-personalised tasks. The impact of the AI intervention will be quantified through metrics such as challenge completion rates and CO_2 savings. Preliminary simulations indicate that Group A may experience a 25 % increase in retention; however, this hypothesis requires validation through real-world tests.

- Qualitative depth: post-trial surveys and interviews investigate the reasons behind the success or failure of specific interventions. For instance, if participants identified as “Socializers” in Group A report higher satisfaction levels than “Achievers,” this may indicate the AI's proficiency in utilising social incentives. Conversely, dissatisfaction with repetitive challenges may highlight deficiencies in the adaptability of the RL algorithms [10].
- Iterative refinement: Biweekly data reviews enable real-time adjustments. When users identify a challenge as “too easy,” the AI system increases difficulty.

Anticipated challenges encompass sample bias, as ISPRA's environmentally conscious users may exhibit greater responsiveness to sustainability prompts than the general populace and cultural specificity. The dense urban fabric of Rome, characterised by its amalgamation of historic landmarks and traffic congestion, necessitates localised adaptations. For example, initiatives promoting walking might emphasise scenic routes that pass by the Colosseum, thereby integrating practicality with cultural appeal [9].

SECTION V.
Conclusion

The GenAI framework for MUV represents a pioneering initiative aimed at bridging the longstanding gap between environmental consciousness and sustainable practices in urban mobility. Grounded in Self-Determination Theory, this system transcends superficial incentives by fostering intrinsic motivation, thereby enabling users to embrace eco-friendly behaviours driven by a sense of autonomy, competence, and collective purpose. The incorporation of ethical safeguards, including federated learning and bias audits, ensures that this innovation upholds privacy and equity, establishing it as a paradigm for responsible AI implementation.

As urban centres globally confront the pressing need for climate action, the scalability of the framework within initiatives such as the European Green Deal presents a viable strategy for reducing emissions while enhancing civic participation. However, the true potential of this approach extends beyond merely transforming mobility; it lies in reconceptualizing how AI-driven personalization can advance sustainability across all aspects of daily life.

Platforms such as Edugo (edugo.ai) within the educational sector, where AI customises learning experiences to meet individual needs, suggest a broader applicability of these principles.

Consider the potential for extending such personalisation to lifestyle choices, wherein challenges encourage households to conserve water, reduce food waste, or optimise energy consumption while fostering a sense of community through shared objectives. For example, an AIbased system could analyse a family's electricity consumption patterns to propose customised energy-saving tasks, such as unplugging devices during idle periods or shifting laundry cycles to offpeak times. Similarly, gamified prompts could motivate neighbourhoods to engage in recycling competitions, with progress monitored via smart bins and rewards linked to local environmental initiatives. These interventions, grounded in the same adaptive algorithms and psychological insights that underpin MUV, have the potential to transform abstract sustainability goals into engaging, actionable routines.

Nevertheless, this broad vision is not without limitations. From a technological perspective, the integration of AI systems across diverse domains-such as mobility, energy, and waste management-necessitates interoperability among fragmented IoT devices and data infrastructures, a challenge further complicated by disparate regulatory standards. Ethically, the detailed profiling required for hyper-personalisation poses significant privacy concerns, particularly as systems collect sensitive data on household behaviours. Behaviourally, the abstract nature of global sustainability outcomes-such as reducing one's carbon footprint-may struggle to compete with the immediate rewards of mobility challenges, such as earning a cycling badge. Furthermore, the current framework's emphasis on mobility, while significant, fails to account for synergies between sectors.

The paper acknowledges several limitations. Although the framework's theoretical foundation in SDT is robust, its practical effectiveness remains to be validated through the ISPRA trial, which may uncover unforeseen challenges in user engagement or data accuracy. Furthermore, while the ethical safeguards are comprehensive, they have not yet been tested in culturally diverse settings. What proves effective in Rome's technologically adept ISPRA community may not succeed in regions with limited digital literacy or infrastructure.

Addressing these gaps necessitates a comprehensive approach. Interdisciplinary collaboration is crucial to integrate sustainability efforts across various domains, involving urban planners, behavioural scientists, and IoT developers to establish cohesive systems that monitor and incentivise holistic environmental impact.

Furthermore, ethical scalability requires public-sector investment in inclusive infrastructure to ensure that AI-driven tools do not become the exclusive domain of the digitally privileged.

In conclusion, by applying its principles to lifestyle domains-while diligently addressing technical, ethical, and cultural challengessustainability can be reconceptualised not as a series of sacrifices but as a collective journey enhanced by technology. The path forward is undoubtedly complex; however, through iterative refinement and inclusive design, AI can transform from a tool of efficiency into a bridge that connects individual agency with planetary well-being.

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Figures

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Keywords

Metrics