

Large Language Models (LLMs) in Human-Computer Interaction: Using LLM-Generated Personas to Model *Everything* from Minority Views to Entire Ecosystems

Danial Amin *¹, Joni Salminen ², Bernard J. Jansen ³, Ilkka Kaate ⁴, and Waleed Akhtar ⁵

¹University of Vaasa, Vaasa, Finland

²University of Vaasa, Vaasa, Finland

³Qatar Computing Research Institute, Hamad Bin Khalifa University, Doha, Qatar

⁴University of Turku, Turku, Finland

⁵University of Vaasa, Vaasa, Finland

Abstract

Personas are representative of real groups and are used to enhance empathy among decision-makers. Personas have been used for commercial and social good use. However, persona generation has certain challenges when representing minority views and, on a larger scale, when modeling complex interactions in an ecosystem comprising multiple parties. To address these challenges, this chapter extends the use of LLMs in persona generation to two different directions. First, LLM-generated personas are used to represent marginalized communities by providing the example of the Global South. Second, personas are expanded from the end-user perspective to all key parties in the ecosystem. This view involves the potential to generate personas for not only human entities but also for non-human entities. By modeling the ecosystem as a “playground,” personas provide an opportunity for the parties to interact with other ecosystem parties for enhanced perspective-taking and empathy propagation. When the concept of personas is extended beyond the human user, it perpetuates empathy, and it reduces self-referential bias from the minority view to the scale of all the parties included in the entire ecosystem.

1 Introduction

1.1 Personas at a Glance

Personas, conventionally a fictional but realistic human character representing an actual user segment (Salminen, Wenyun Guan, Jung, & Jansen, 2022; Nielsen, 2019), are an essential technique for user-centered design (UCD) and human-computer interaction (HCI). Since their introduction (Cooper, 1999), personas have been enhancing the design process by allowing key stakeholders (designers, product developers, decision-makers) to empathize with users and contextualize information in a grounded form (Bødker, Christiansen, Nyvang, & Zander, 2012; Grudin & Pruitt, 2002). Personas have been applied in marketing and social science (Guan, Salminen, Nielsen, Jung, & Jansen, 2021; Salminen, Wenyun Guan, et al., 2022) and implemented in various industries, including software development, healthcare, higher education, robotics, cybersecurity, games, and recommendation systems (Salminen, Wenyun Guan, et al., 2022; Anvari, Richards, Hitchens, & Tran, 2019; Nielsen, Hansen, Stage, & Billestrup, 2015; J. Goodman-Deane et al., 2018).

In addition to the commercial use of persona, which most persona applications target, there has been an increase in the usage of *personas for social good* (PFSG). PFSG refers to the application of personas toward beneficial social goals, such as sustainability, social justice, and quality of life (Jansen, Jung, Salminen, An, & Kwak, 2018; Guan, Salminen, Jung, & Jansen, 2023). These advancements in persona application are driven by the general broader trends in the HCI landscape, which is paying more attention to applying UCD to societal purposes, such as those embodied in the United Nations (UN) sustainability development goals (SDGs)—sustainable HCI (sHCI) being a leading example (Hansson, Cerratto Pargman, & Pargman, 2021). Simultaneously, personas are increasingly being applied beyond the scope of product development, extending to awareness, engagement, communication, and development projects and solutions in a broader range of human activity (Guan et al., 2023; Wilson, De, Forbes, & Sachy, 2020).

*correspondence: danielam@uwasa.fi

Personas are widely used in HCI and UCD for increasing empathy (Salminen, Santos, Jung, & Jansen, 2023; Nielsen, 2019; Cooper, 1999) and relatability (Jansen, Salminen, Jung, & Guan, 2021a), which in turn improve the design and decision-making process. A correctly formulated persona can provide a deeper understanding of the end user (Salminen, Jung, Chowdhury, Sengün, & Jansen, 2020). While the term end-user (user) is used here as an example to explain, personas could be expanded to *any group of people* and, more broadly, *any group of parties in an ecosystem*, which we will discuss in Section 4. Furthermore, personas can also convey the needs of the target group, which helps designers empathize with the needs and expectations of a real user to develop more contextualized applications (and, more broadly, solutions) (Jansen et al., 2021a; Grudin, 2006). In almost any decision-making process, personas help decision-makers make impactful strategic decisions by helping them change their perspective (Salminen, Wenyun Guan, et al., 2022; Guan et al., 2023). Personas can mitigate the *confirmatory* and *self-referential* biases by “stepping beyond” their own experiences and taking the perspective of others (potential users, affectees and other stakeholders) represented by personas (Nielsen, 2002; Bødker et al., 2012). Similarly, personas also help different stakeholders in a project to communicate with each other more concretely as they present a true representation of user needs, (Salminen, Wenyun Guan, et al., 2022; Jensen, Elverum, & Steinert, 2017). According to the theory of personas (Grudin, 2006), a high quality persona, which generally includes attributes such as demographics, behaviors, pain points, and goals, can improve the likelihood of making informed design choices that resonate with users (Sengün, Salminen, Jung, Aldous, & Jansen, 2024).

Over the years, personas have evolved into various types and forms (Salminen, Jung, & Jansen, 2022). Although persona was considered a quantitative method in its inception paper (Cooper, 1999), the early years of persona generation generally applied qualitative methods. These methods involved subject matter experts (SMEs) often collecting data through ethnographic studies, surveys, or focus groups (Jansen, Salminen, Jung, & Guan, 2021b). There has been a shift in persona generation from qualitative to quantitative methods (Jansen, Salminen, & Jung, 2020). The creation of personas using quantitative methods primarily includes (1) data-driven persona creation (using algorithmic methods based on numerical and textual data (Jansen et al., 2020)), (2) automatic persona generation (continuous updating of personas on the latest available data (S.-g. Jung, Salminen, Kwak, An, & Jansen, 2018; Jansen, Jung, & Salminen, 2019)), and (3) Generative AI (GenAI) persona generation (using Large Language Models (LLMs) (Shin, Hedderich, Rey, Lucero, & Oulasvirta, 2024) and diffusion models (Zhou et al., 2024)). The personas generated by using GenAI technologies are called GenAI personas. Among GenAI personas, the current work focuses on *LLM-generated personas* which are partially or fully generated using LLMs (Shin et al., 2024). Despite these advancements, marginalized communities, based on either their race, gender, religion, or demographics in the global populace distribution, are often ignored or misrepresented in data-driven persona creation (Salminen, Jung, & Jansen, 2021). This misrepresentation is mainly due to a lack of representation in the data, challenges with aggregation, and the inherent algorithmic biases in the data-driven persona generation (Salminen et al., 2021; Salminen, Froneman, Jung, Chowdhury, & Jansen, 2020). This chapter discusses the applicability of LLM-generated personas for PFSG, ranging from representing minority views on one end to modeling the complete ecosystem on the other.

1.2 HCI and Generative AI Landscape

While GenAI technology is no longer novice, the release of ChatGPT by OpenAI (OpenAI, 2022) has created a butterfly effect (Nah, Zheng, Cai, Siau, & Chen, 2023), in which LLMs have shown potential in nearly all aspects of human activity, from acting as a learning companion (Salminen, Jung, et al., 2024) to solving sustainability challenges (Vinueza et al., 2020). However, these advanced LLM-based systems are prone to challenges, for example, inherent bias, lack of diversity and inclusivity, and non-transparent or opaque functional mechanisms (Nah et al., 2023; Cachat-Rosset & Klarsfeld, 2023; Farahani & Ghasemi, 2024; Roche, 2023). Studies have attempted to address these challenges (Farahani & Ghasemi, 2024; Zhuo, Huang, Chen, & Xing, 2023), e.g., by developing ethical guidelines and frameworks (Roche, 2023; Cachat-Rosset & Klarsfeld, 2023; Nah et al., 2023). However, the challenge of inclusive design (J. A.-L. Goodman-Deane, Bradley, Waller, & Clarkson, 2021) and fairness in LLMs (Anthis et al., 2024) remains persistent.

The impact of GenAI, in general, and LLMs, in particular, on HCI is increasingly prominent as HCI practitioners and researchers reshape how users interact with systems. HCI researchers are exploring how LLMs can enhance user experiences by addressing concerns about usability, transparency, and ethical implications (Nah et al., 2023). LLMs’ ability to personalize interactions and automate tasks presents an opportunity for HCI practitioners (Schuller et al., 2024; Salminen, Liu, et al., 2024) to explore LLMs and develop interactive and engaging interactions (Choi, Kang, Choi, Lee, & Kim, 2025; L. Sun et al., 2025; S.-G. Jung, Salminen, Aldous, & Jansen, 2025).

Applying LLMs in persona creation has become a topic of interest within the HCI community (Cho, Jon, Jin, Jung, & Oh, 2024; Shin et al., 2024; Schuller et al., 2024). Specifically, LLMs can help streamline persona development by processing large datasets to identify user patterns (Salminen, Liu, et al., 2024) and create coherent and cohesive text for persona generation (Shin et al., 2024). However, the use of LLM-generated personas has also increased the risks related to bias and inclusivity, as training data or model parameters may not accurately reflect the diversity of the target user base (J. A.-L. Goodman-Deane et al., 2021; Cachat-Rosset & Klarsfeld, 2023; Amin, Salminen, Jansen, Shin, & Kim, 2025).

The HCI community’s relationship to LLM and its use in practice is a balancing act between risk and opportunity. In

one body of research, HCI scholars are extremely critical about replacing authentic user research with *fabricated replicas or surrogates* (i.e., “synthetic users”) In contrast, another body of research suggests that LLMs have benefits in various persona generation tasks, ranging from data analysis to write-up (Shin et al., 2024; Salminen, Liu, et al., 2024; De Paoli, 2023). These perspectives indicate that different studies have been carried out for assessing LLMs in HCI in general and persona generation in particular, which are done primarily case by case (Shin et al., 2024; Schuller et al., 2024; Nah et al., 2023). This represents the currently significant research gap in the existing body of knowledge.

To this end, the motivational question behind our work is as follows: *How to use LLMs in HCI for persona creation?* To answer part of this question, we suggest one prominent use case for LLMs in HCI: *data-driven persona generation*. More particularly, we suggest that using LLMs could address some of the shortcomings of previous technologies in data-driven persona generation, namely (a) lack of attention to minority views (Salminen et al., 2021) and (b) lack of attention to modeling dynamic scenarios in an ecosystem setting¹. We propose two approaches to addressing these challenges through LLM-generated personas. Consequently, this chapter addresses two vital research questions (RQs):

- **RQ1:** *How to ensure that marginalized communities’ voices are represented in LLM-generated persona processes?*
- **RQ2:** *How can LLM-generated personas be deployed to model entire ecosystem?*

We address these RQs through conceptual examination, providing illustrative examples of our suggested approaches. The following section presents the literature background of this work. The following two sections dive into our two suggested approaches: (1) representing minority viewpoints using LLM-generated personas in the context of the marginalized population in the Global South and (2) modeling entire ecosystems (industrial, societal, and natural) using LLM-generated personas. We conclude by discussing design principles, key takeaways, and directions for future research.

In a nutshell, this book chapter makes notable conceptual contributions to using LLMs in HCI (and beyond). Essentially, we propose new targets for LLM-based persona generation, including minority perspectives and “voices that would not otherwise be heard” such as those of marginalized communities in the Global South and non-human parties in ecosystems. We also propose new and innovative evaluation techniques that have not been previously deployed for personas, stemming from the fact that personas have a strong tradition in HCI and business disciplines. Our contribution draws attention to representing ecosystem parties, including non-humans, using personas and creating interactive “playgrounds” where decision-makers can engage with these personas, thereby obtaining a more holistic perspective of different parties (actors and subjects) in the ecosystem. Consistent with the theory of personas (Grudin, 2006), this approach could perpetuate empathy and mitigate self-centered bias when decision-makers take actions that affect the ecosystem, whether that ecosystem is industrial, societal, or ecological in nature.

2 Literature Background

2.1 Personas for Social Good: Opportunities and Risks

Personas are generally used in commercial use cases (Salminen, Wenyun Guan, et al., 2022) (i.e., developing targeted personas to develop and align a product or service to market needs). While personas are effective for commercial purposes, personas *also* have the potential to contribute to social good (Guan et al., 2023). For example, in policymaking, the persona of the target group could be used to better align policy actions (Department of the Prime Minister and Cabinet (DPMC), 2023). There is an increasing trend to combine business needs with social good. To this end, PFSG helps decision-makers empathize with parties who benefit or are affected by the policy, leading to actions that are more focused on user empowerment and improving community well-being.

Persona science emphasizes the alignment of the needs of the targeted user groups with the persona, ensuring that personas are not only representative tools but are actionable to tackle real-world issues within a broad societal frame (Guan et al., 2023). Furthermore, incorporating additional information, such as narrative information, including social attitudes and cultural backgrounds, with persona profiles gives a richer understanding of user contexts, which in turn facilitates designs aimed at social change (Salminen, Wenyun Guan, et al., 2022). Additionally, personas can be particularly effective in designing platforms that improve civic engagement, encouraging active participation in governance and community activities (Guan et al., 2023). Lastly, the strategic use of diverse personas can also enhance cross-cultural communication, promoting inclusivity and dialogue among different cultural groups, which is essential in addressing global challenges such as inequality (Salminen, Wenyun Guan, et al., 2022). In general, the use of PFSG helps to understand various user needs and helps to create impactful designs that align with broader social objectives (Guan et al., 2023).

Building upon existing applications of PFSG, there is significant potential in integrating persona with the study of human-nature interactions (HNI) in addition to HCI. In this context, HNI research explores how people engage with and

¹By ecosystem, we refer to a community or collection of inter-dependent parties (actors and subjects) which interact with each other for a specific purpose. These parties may or may not be humans.

relate to their natural environment, encompassing aspects such as environmental stewardship, sustainability practices, and the psychological benefits of nature (Capaldi, Passmore, Nisbet, & Zelenski, 2014; Kim, Park, & Lee, 2015). Considerations from sustainability studies can help develop personas that reflect the social and economic dimensions of user groups and their interactions with the natural world (O.-J. Lee & Jung, 2019; Johnson, Martinez, & Liu, 2020). Similarly, personas can help represent the needs of all the stakeholders in HNI, including both the human and non-human participants (e.g., plants, trees, animals, birds, materials). (Yanlic & Coskun, 2024).

Integrating HCI with ecological systems requires a fundamental shift away from human-centered design toward an ecosystem-aware approach that considers the complex inter-dependencies between digital technologies, human activities, and environmental sustainability (Knowles, Bates, & Håkansson, 2018). As sustainability becomes increasingly central to HCI research, there is a growing recognition that the field must move beyond incremental improvements in energy efficiency to address systemic challenges at the intersection of computing, society and ecology (Bremer, Knowles, & Friday, 2022). Drawing from theories of group cognition and sustainable HCI, we can envision tools and systems that make visible the nested relationships between individual behaviors, collective practices, and environmental impacts (Borge & Xia, 2023). This requires developing new interaction paradigms that foreground ecological considerations alongside usability, fostering what has been termed “cyber-sustainability” (Preist, Schien, & Blevis, 2016).

Although personification (use of human-like characteristics for non-human parties) of the ecosystem could be challenging, it is essential to consider that experts in ecological landscape (Vergani & Di Liberto, 2024) have used personification to establish personalities of different non-human parties (MacKinlay & Shaw, 2023). Furthermore, through personification, humans empathize with non-human parties more strongly, leading to an overall increase in the improvement of interaction (Cherry et al., 2022). For instance, a persona representing community leaders in the context of sustainability could include attributes related to their interaction with the environment and non-human parties, environmental advocacy, and sustainable resource management. This would ideally encourage policy makers to design initiatives that support community development and ecological sustainability (Smith, Nguyen, & Brown, 2021).

Furthermore, integrating HNI into persona development can help identify and address barriers to sustainable practices, such as people’s lack of access to green spaces or inadequate environmental education (Johnson et al., 2020; Wang, Zhao, & Chen, 2019). This conceptual linkage not only enriches the depth and relevance of PFSG projects, but also ensures that solutions are aligned with the ecological realities and aspirations of the target populations (human and non-human) alike (Smith et al., 2021). Consequently, expanding PFSG to include HNI represents a promising avenue to create more comprehensive and effective personas that drive meaningful social and environmental change (Capaldi et al., 2014; Kim et al., 2015; O.-J. Lee & Jung, 2019; Johnson et al., 2020; Smith et al., 2021).

2.2 LLM-Generated Personas: Opportunities and Risks

LLM-generated personas use the natural text generation qualities of LLM to create human-interpretable coherent textual profiles (Schuller et al., 2024). This combination allows for a more immersive UX for personas, as users can interact with personas that closely mimic actual human characteristics and behaviors. This has enabled persona generation partially supported by LLMs (Shin et al., 2024) or fully automated (Schuller et al., 2024). The specific workflows in which personas are generated while keeping SMEs in the loop have showcased quality and depth of information (Salminen, Liu, et al., 2024; Shin et al., 2024). This introduces the specific new avenues that LLMs have opened. LLMs demonstrate the ability to generate coherent persona narratives in minutes, compared to the traditional persona creation process that could take days and hours. When provided with clear prompts (instructions), these models can create detailed representations, including background stories, pain points, and behavioral patterns with internal consistency (Sattele & Carlos Ortiz, 2024). LLMs are also good at maintaining internal narrative coherence and overall quality (Salminen, Liu, et al., 2024).

However, these opportunities are counterbalanced by specific risks: First, LLMs consistently sanitize reality, as evidenced in both the Iztapalapa water crisis case (Sattele & Carlos Ortiz, 2024) where serious issues like water truck hijackings were understated, and in addition personas where harsh realities were softened (Schuller et al., 2024). Second, the models exhibit systematic biases—from demographic skewing toward younger age groups to strong US-centricity (85.6% of generated personas being American without any prompt specification). Third, the hallucination problem manifests itself in the generation of plausible but factually incorrect details, such as personas with contradictory medical conditions or financially improbable scenarios (Salminen, Liu, et al., 2024).

3 Suggested Approach 1: Modeling Minority Viewpoints in a Data-Driven Personas

3.1 Potential Impact of Using LLMs to Model Marginalized Viewpoints

LLMs, with their ability to generate multiple personas in parallel and contribute to real-time changes in the persona based on contextualization, have the potential to significantly impact the fields of persona generation, especially for minority communities. As LLMs can generate multiple personas without additional cost, the persona set (a collection of personas) can be expanded to include all possible minorities. Similarly, as LLMs can generate cohesive text in real-time, the generated personas could be used interactively. Thus, research on LLM-generated personas has the potential to significantly impact the field of persona development, personas for social good, and policy-making for marginalized communities. Developing more accurate and culturally sensitive LLM-generated personas could contribute to a better understanding of marginalized and socially challenged communities. Research in LLM-generated personas can thus lead to more inclusive and effective decision-making processes as policy makers. access a closer-to-truth representation of such communities.

3.2 Example Context

We illustrate the challenges of data-driven personas and the potential use case of LLMs to represent minority views by considering the case of representing marginalized communities using the Global South as a context. The Global South region, which includes Latin America, Asia, Oceania, and Africa, is the most populous region in the world, accounting for 88% of the world's population (Kishore Mahabani, 2024). However, despite its large population, the Global South faces severe challenges when modeling minorities, especially using any data-driven approach. These challenges in representing marginalized communities in the Global South include a lack of targeted population data, inaccurate data, lack of cultural contextualization, and algorithmic bias. Due to its population, demographics, challenges in minority population, and age distribution (World Economics, 2024), the Global South appears to be a prominent (yet underrepresented) target population for LLM-generated personas. Such minority personas serve as crucial tools for understanding the complex intersections of traditional values, technological adoption, and educational aspirations in marginalized communities. To better illustrate this, we can consider the example of Indigenous students in higher education institutions in Peru, as illustrated in Figure 1.

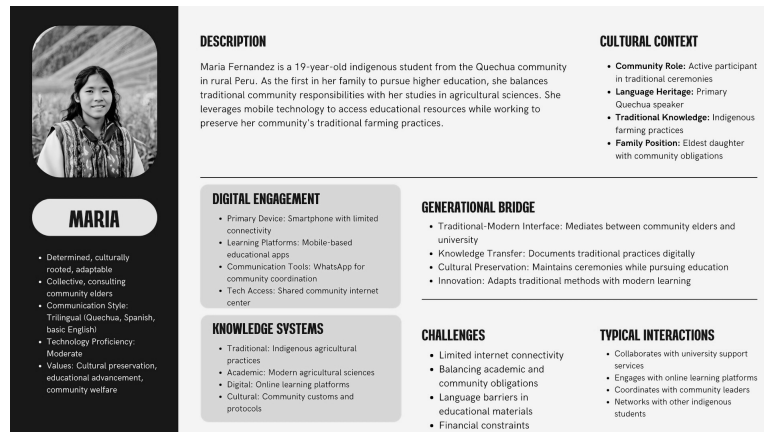


Figure 1. A representative minority persona for a rural student.

3.3 Addressing the Representation of Minority Viewpoints in LLM-Generated Personas

The effective representation of marginalized communities by LLM-generated personas is focused on three dimensions: (1) understanding the paradigms of LLM-generated personas, (2) manifestations of different strategies, and (3) technologies to improve the LLM-generated personas. These dimensions are driven by the positive impact on PSFG, contributing to an increase in transparency in representation. The overall space is presented in Figure 2[b].

The research aims to identify different improvements and enhancements to the foundational LLMs for LLM-generated personas and assess their impact in the PSFG context for modeling the marginalized community in the Global South. To address LLM-generated personas in a minority-friendly manner, we propose structured research that would follow the steps of real-data collection, persona generation, and evaluation of the personas through quantitative (statistical) and qualitative methods.

The proposed methodological structure is presented in Figure 2[a].

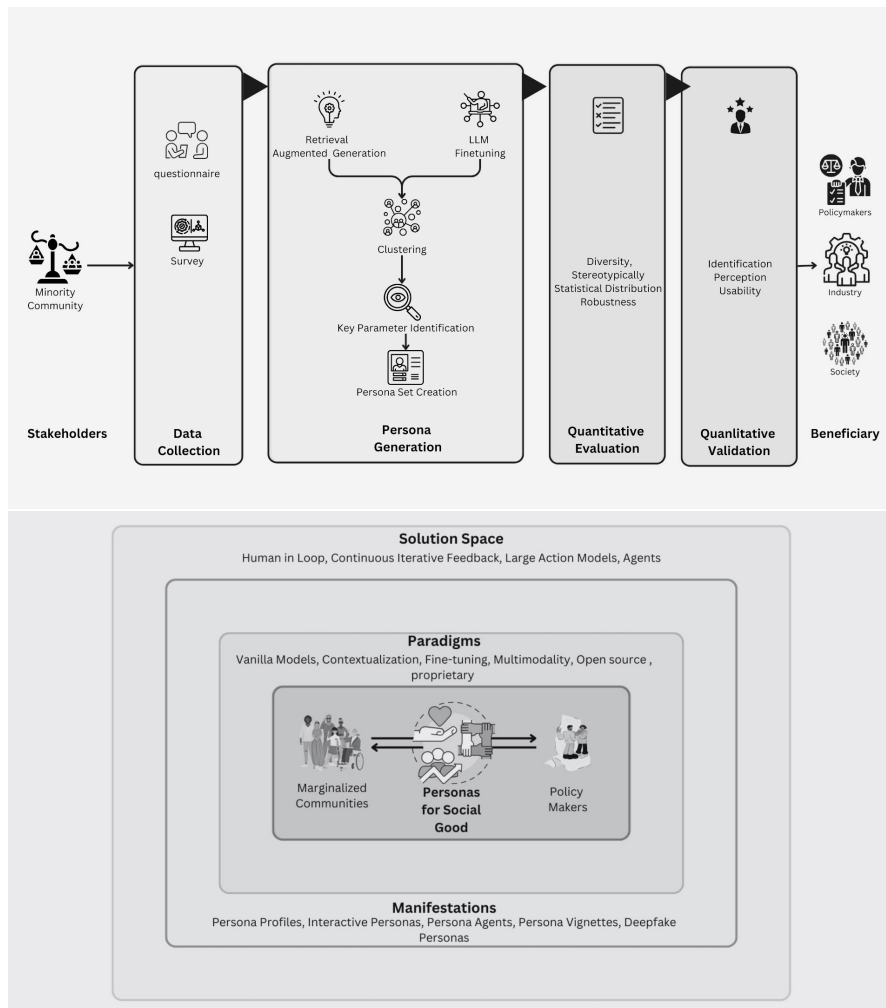


Figure 2. Comprehensive framework for Personas for Social Good (PFSG). (Top) The end-to-end methodology for generating and validating personas, showing the flow from stakeholder input to beneficiary impact. (Bottom) The conceptual framework showing the layered approach from solution space to core implementation, highlighting the connection between marginalized communities and policy makers.

In our methodology for minority-friendly LLM-generated personas, the survey data will be collected from the community through a questionnaire. They will be cross-referenced with simulated survey data to identify the efficacy of data simulation to enhance the diversity of the datasets. This data will then be passed on to a pipeline using LLMs and enhanced techniques (1) retrieval augmented generation (RAG) (i.e., textual generation supported by a larger context from a knowledge base) and (2) fine-tuned LLMs (i.e., a model that is trained over specific data to enhance its robustness) to develop persona sets. These persona sets will then be collectively assessed for quantitative metrics highlighting diversity, stereotypically (making assumptions about prejudice), distribution, and robustness. Similarly, qualitative metrics such as identification, perception, and usability by SMEs will also be measured. Through this process, the appropriate paradigms of persona enhancement for marginalized communities will be identified and used to create true representative personas. These personas can then be applied in policy-making workshops with actual policymakers to identify their effectiveness and correlate to the user’s use case to address policy-making needs.

The ethical considerations for applying LLM-generated personas for modeling minority viewpoints are extensive and critical, given its focus on LLM-generated personas for marginalized communities in the Global South. These include but are not limited to (1) obtaining genuine informed consent from participants and ensuring robust data privacy and protection measures that comply with both local and international regulations, (2) implementing rigorous strategies to identify, mitigate, and transparently report on biases in data collection, persona generation, and result interpretation, and (3) establishing transparency in the process for LLM-generated personas including clear communication of the limitations and potential biases to all stakeholders, especially key decision-makers. The approach should also (1) consider and safeguard against potential misuse of the developed personas, (2) assess long-term impacts on policy-making and perceptions of marginalized communities, (3) ensure meaningful involvement of community members throughout the research process, and (4) establish clear protocols for benefit-sharing with participating communities.

4 Suggested Approach 2: Modeling *Entire Ecosystems* as Data-Driven Personas

4.1 Why Does Modeling Ecosystems as Personas Make Sense?

As defined in the preceding section, an ecosystem encompasses a collection of parties. These parties can include *actors* who actively participate in the activities of the ecosystem, and *subjects*, who are indirectly involved in or affected by the activities of others in the ecosystem (Brussard, Reed, & Tracy, 1998). We will refer to them as *parties* hereafter. As a collection of multiple parties, ecosystems are prone to a series of complex interactions with other parties within and between ecosystems (Brussard et al., 1998; Green & Sadedin, 2005; Gross, Toombs, Wain, & Walorski, 2011).

This ecosystem modeling is essential for understanding and addressing different challenges in a broad spectrum of domains ranging from environmental science, industry, and social systems, as they all form an ecosystem in one way or another (Brussard et al., 1998; Holling, 2001; Geary et al., 2020). For example, in ecology, modeling the natural ecosystem is essential for understanding the interactions between different biotic factors (living components) and abiotic factors (non-living parties in the ecosystem) and understanding the impact of a change in the ecosystem (Keystone & others, 2021). Similarly, for the societal ecosystem, understanding the different perspectives of different members of the society is crucial for establishing and creating an action plan (Piussi & Farrell, 2000). For the industrial ecosystem, modeling the different actors and understanding their position on the challenge of supply chain or risk management is crucial (Carpenter, Kitchell, & Hodgson, 1998).

Even though the science of modeling ecosystems is not new (Geary et al., 2020), representing ecosystem parties as personas appears to be novel that, to our knowledge, has not been attempted before. Several methods and techniques exist for modeling ecosystems in different domains such as ecology, management sciences, HCI, and HNI (Acs, Stam, Audretsch, & O'Connor, 2017; Evans, 2003; Holling, 2001), among others. First, these different modeling methods are often time-consuming and require SMEs to understand and model the ecosystem. Second, these ecosystem models are static in nature and thus do not offer dynamic handling of the interactions. Third, while these interactions are formulated, they are formulated from an outsider's perspective. Our approach of using LLM-generated personas can address these shortcomings by offering a direct representation of the needs of different stakeholders, empathizing, and enabling interactive representations.

Personas inherently bridge the gap between the decision-makers and the members of the ecosystem by providing them with an empathetic representation of different parties. By representing different parties as personas in this ecosystem model, one can interact, empathize, and relate to their perspective and pain points with a reduction in self-referential biases. *LLM-generated personas help reduce the challenge of outsider's perspective in ecosystem modeling.* While personas could potentially solve the challenges of externality (third person) in ecosystem modeling, they do not solve the challenges related to complexity of time and expertise when considered in their traditional form (classical qualitative or mixed method personas) (Chapman & Milham, 2006). This challenge faced by conventional personas related to time, effort, and resource hunger is solved by LLM-generated personas. LLM-generated personas are scalable, indicating that little or no effort is required to generate either one persona or a persona set consisting of hundreds of them. This, in turn, stresses that persona sets that involve all the different parties in an ecosystem could be generated without significant effort. Furthermore, to improve the contextualization of LLM-generated personas, techniques such as RAG² and fine-tuning³ can help to create more contextualized personas in a grounded form.

Technically, LLMs can process large amounts of unstructured data and generate coherent, contextually relevant text (T. B. Brown et al., 2020), which makes LLMs suitable for creating detailed personas representing various stakeholders within an ecosystem. This data is dependent on different ecosystems. For example, in the industrial ecosystem, this data could include information on key customers, the performance of companies, and policies for regulators. For a societal ecosystem, the data can be the civic rights of the residents, the resident's population demographics, and civic engagement surveys. Lastly, for natural ecosystems, this data would include ecological reports by the SMEs, personality traits of different nonhuman parties of the ecosystem, and data about the population growth over time.

The concept of personas can be extended to represent *all parties within an ecosystem*, not just end-users and not just humans. By creating personas for every stakeholder group, including suppliers, regulators, competitors, and even environmental entities, we can try to capture the full spectrum of perspectives, constraints, and interactions that shape the ecosystem. This comprehensive approach allows for a more holistic understanding of the system, facilitating the identification of potential conflicts, synergies, and emergent behaviors that may be overlooked when focusing solely on end-users (or people, in general).

Ecosystem models require simulation of complex interactions, representing different stakeholders as dynamic agents (Z. Sun, Sun, & Strang, 2016). LLM-generated personas could be incorporated into ecosystem modeling to represent different stakeholders. This enables exploring how changes in one part of the system can ripple through and affect other components, a concept known as emergent behavior (Holland, 1992). Additionally, LLM-generated personas can

²For example, using the relevant information about a country's culture to enrich the persona of leadership.

³For example, the model is re-trained for the specific industry.

enhance predictive capabilities by enabling scenario analysis. Scenario analysis defines and implements different strategies and interventions in a virtual environment before implementation (Meierhofer et al., 2021). Moreover, modeling the complete ecosystem can enable clear communication and interactions between the different stakeholders, facilitating effective communication and perpetuating empathy across the ecosystem parties (Dietz, Ostrom, & Stern, 2003). LLM-generated personas, in general, could be used to model these interactions.

Leveraging LLMs in ecosystem modeling offers significant potential advantages, including increased realism, improved adaptability, facilitated stakeholder engagement, and informed policy-making. For instance, in urban planning, integrating LLM-generated personas representing residents, businesses, and city officials can help design infrastructure projects that balance economic development with community well-being and environmental sustainability (Batty, 2018).

4.2 Persona Ecosystem Modeling Framework

In order to extend the concept of persona development from end users to modeling complete ecosystems, we present a four-stage **Persona Ecosystem Modeling Framework (PEMF)**. These four stages are (1) **Stage01: Key Stakeholder Mapping and Selection**, (2) **Stage02: Data Collection and Persona Generation**, (3) **Stage03: Persona Validation and Selection**, and (4) **Stage04: Persona Ecosystem Playground (PEP)**.

Stage01: Key Stakeholder Mapping and Selection. The first stage of the process is **mapping and selecting stakeholders** within the ecosystem. This stage involves mapping out the entire network of parties (whether actors or participants). These stakeholders generally include *primary stakeholders*, who are directly involved or affected, and *secondary stakeholders*, who have indirect influences. For example, in modeling the renewable energy ecosystem, stakeholders might include renewable energy companies, traditional fossil fuel companies, government regulators, environmental non-governmental organizations (NGOs), consumers, financial institutions, and technology providers (Kunhikrishnan & Jose, 2021). After establishing the overall stakeholder map of the ecosystem, it is important to select the relevant stakeholders to be included in the ecosystem model. This selection is made on the basis of the nature of the problem, as well as the ecosystem.

Stage02: Data Collection and Persona Generation. This stage involves two steps, primarily as *qualitative and quantitative data collection* and *persona generation*.

As LLMs are used for persona generation, data sources are required for two different domains. First, qualitative data is required for the LLM contextualization. This data could include (1) industry reports that provide market trends and financial data, (2) academic literature that offers theoretical frameworks and empirical studies, (3) policy documents detailing regulations and governmental strategies, (4) social media and news articles reflecting public opinions and emerging issues, and (5) SME interviews or surveys providing insights from professionals within the ecosystem. This data could be used to contextualize the LLM either with RAG or fine-tuning for the given ecosystem.

Moreover, quantitative data is also collected, which could include (1) population metrics such as demographic information about the population/sample space of each stakeholder, (2) behavior and personality metrics, including data on goals, motivations, interactions, and preferred mode of communication, and (3) economic and engagement metrics indicating consumption and social media metrics. This quantitative data is used for persona development. Considering the previous example, qualitative data sets would help contextualize the LLM with industry-specific knowledge and help create a common context. The understanding of consumers' attitudes towards renewable energy adoption is modeled through the quantitative data on their environmental concerns, economic considerations, and social influences (A. Lee, Zukauskaite, & Barvidaitė, 2017). This data supports the creation of representative LLM-generated personas.

Once data is collected, the next step is *persona creation*. Personas are created following a persona generation process where LLMs are used to enrich the data, while an algorithmic data-driven approach enhances the persona generation workflow. Personas are generated using quantitative data, which involves (1) attribute selection, (2) reduction or clustering of dimensionality, and (3) enrichment (Nielsen, 2013; Salminen et al., 2018). The first two actions in this process are carried out by the SME with the help of algorithmic methods or directly with algorithmic methods, while enrichment is carried out by LLMs, which are contextualized on qualitative datasets (Shin et al., 2024).

The personas encapsulate demographic information and specific attributes such as goals, challenges, behaviors, and typical interactions with other stakeholders. The LLM processes the data to produce coherent, contextually relevant narratives that accurately represent each stakeholder. For example, a persona for an "Eco-Conscious Consumer" might emphasize their commitment to reducing their carbon footprint, their willingness to pay a premium for sustainable energy options, and their influence on peers through advocacy and social media engagement (Li, Shi, Guo, & Zhao, 2020). Through generating personas for all stakeholders, not just end-users, we extend the traditional use of personas and enable a more holistic model of the ecosystem (Grudin & Pruitt, 2006).

Stage03: Persona Validation and Selection. The third stage in the process is **persona validation and selection**, which involves validating the persona sets, representing each party of the ecosystem on three dimensions. The *first dimension* deals

with the diversity of the persona set. This metric of diversity is measured to ensure that the persona set selected for the specific party is the true representative of all the groups in the population of the given party. The *second dimension* includes validation of personas against HCI scales like the Persona Perception Scale (PPS) (Salminen, Santos, et al., 2020) to assess the persona on measures such as clarity, empathy, credibility, completeness, consistency, likability, and similarity. The *third dimension* of validation includes human-in-loop involvement, where an SME or other representative of the stakeholder party validates the persona to be a representative of the population in question. This validation also helps the persona ecosystem modelers select the relevant personas representative of each group, based on the criterion decided as a threshold for the given personas.

Stage04: Persona Ecosystem Playground (PEP). The last and final stage of the PEMF process is the **Persona Ecosystem Playground (PEP)**. A PEP is an interactive sandbox environment in which the selected personas representing different parties in the ecosystem are deployed so that they can interact with each other. In PEP, each persona representative of the party acts as an agent: an automated representative of the party of the ecosystem. This agent acts as a representation of real and grounded problems, challenges, behaviors, and characteristics of the party of interest.

PEP can support both *human-to-persona interactions (HPI)* and *persona-to-persona interactions (PPI)*. *HPI* are interactions in which users can engage with personas through dialogues and scenario-based activities, whereas *PPI* are the interactions where personas interact with each other according to predefined behavioral rules and decision-making processes. PEP is implemented using LLM-agent-based modeling platforms, such as LangChain⁴ or Lang-graph⁵, which are capable of modeling complex systems and collections of LLM agents (in our case as LLM generated personas). These interactions also help capture emergent behaviors resulting from interactions between various agents (Wilensky & Rand, 2015). For instance, in the renewable energy ecosystem model, PEP can be used to interact with the persona in the ecosystem about a policy change proposed by the personas of the government regulator and to understand its effects on investment decisions by financial institution personas and adoption rates among consumer personas. The aim is to allow users to take the perspective of different ecosystem parties.

This methodology is summarized as indicated in figure 3.

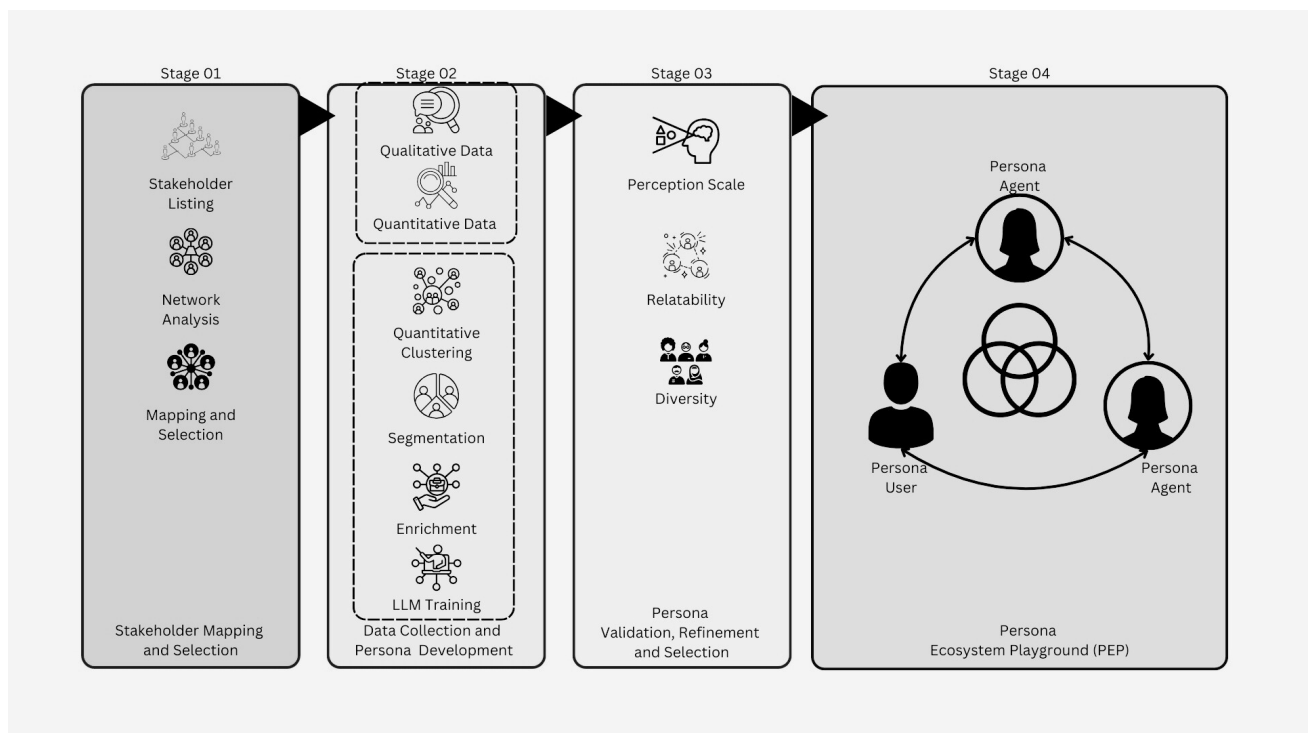


Figure 3. Theoretical framework to indicate the creation of a persona-based ecosystem.

4.3 Application of PEMF in various Ecosystems

To illustrate the framework's usability in different dimensions, we will apply the PEMF framework to model three different ecosystems: (1) the industrial ecosystem by modeling the automotive industry, (2) the societal ecosystem through

⁴<https://www.langchain.com/>

⁵<https://langchain-ai.github.io/langgraph/>

modeling an urban ecosystem, and (3) the natural ecosystem through modeling a forest. These ecosystems are considered examples and could be applied to other ecosystems as well.

4.3.1 Modeling Industry Ecosystems as Personas

The application of PEMF has the potential to be applied in various industries (see Table 1). In the *healthcare sector*, this approach can simulate interactions among patients, healthcare providers, pharmaceutical companies, insurance firms, and regulatory agencies, thus improving patient care pathways and policy development (Ferrucci, 2012). The *agricultural industry* can benefit by modeling relationships between farmers, distributors, retailers, consumers, and environmental entities to improve supply chain efficiency and sustainability practices (Rose et al., 2016). In the *financial services sector*, creating personas for banks, investors, regulators, fintech startups, and customers can help to understand market dynamics and manage systemic risks (Philippon, 2016). The *automotive industry* is another area where this methodology can be applied to model the complex interactions between manufacturers, suppliers, dealers, customers, policymakers, and environmental groups (Wells & Nieuwenhuis, 2010). To illustrate the usability of PEMF in industrial ecosystems, the automotive industry is modeled as an example. This ecosystem modeling is carried out to understand the perspective of different parties on the penetration of electric vehicles (EVs) in the market.

Context Due to the UN SDGs (United Nations, 2015) and the shift toward merging products and services so that they provide commercial and societal benefits, the automotive industry is undergoing a significant transformation driven by technological advancements, environmental concerns, and changing consumer preferences (NEF, 2020) to focus on green technology. One such green technology in the automotive ecosystem is electronic vehicles, and we are modeling the automotive ecosystem to understand the perspective of different stakeholders on penetration in the market.

Stage01: Stakeholder Mapping and Selection The first step involves systematically identifying all relevant stakeholder groups within the automotive ecosystem. These include **primary stakeholders (parties)** like (1) *traditional automobile manufacturers* (traditional internal combustion engine (ICE) vehicle and EV manufacturers), (2) *suppliers* (companies providing parts and components, including batteries, semiconductors, and raw materials to all the manufacturers (Schmidt, Hawkes, Gambhir, & Staffell, 2017)), (3) *dealers and retailers* (entities responsible for the sale and distribution of vehicles to consumers), (4) *consumers* (individual and fleet buyers with varying preferences and needs), and (5) *government regulators* (agencies setting safety standards, emissions regulations, and providing incentives for EV adoption (Wang et al., 2019)). Some other **secondary stakeholders** could include (1) *environmental NGOs* (organizations advocating for sustainable practices and reduced emissions), (2) *technology firms* (companies developing autonomous driving technologies, connectivity solutions, and mobility services (Litman, 2020)), (3) *energy providers* (utility companies and charging infrastructure providers supporting EV adoption), and (4) *financial institutions* (banks and investors financing automotive ventures and consumer purchases).

Stage02: Data Collection and Persona Generation According to PEMF, in the second stage, quantitative and qualitative data are collected. The **qualitative** data sources include (1) *industry reports* indicating market trends, sales figures, technological advancements (Company, 2016), (2) *academic literature* including research on consumer behavior, supply chain management, and environmental impact (Graham-Rowe et al., 2012), (3) *policy documents* outlining government regulations, incentives, and strategic roadmaps (Commission, 2019), (4) *social media and news articles* representing public opinion, emerging trends, and stakeholder communications (Yang & Lee, 2018), and (5) *SME interviews and surveys* that present insights from industry professionals, analysts, and consumer focus groups (Chandra, Gulati, & Kandlikar, 2010).

In addition, **quantitative** data is also collected which includes (1) *population statistics* representing age, gender, income levels, education, and geographic distribution for consumers; company size, revenue, number of employees, and market share for manufacturers and suppliers (Company, 2016), (2) *behavioral metrics* indicating purchase frequency, brand loyalty, vehicle usage patterns for different vehicle types among consumers; procurement volumes, order frequencies, and supply chain reliability metrics for suppliers (Wells & Nieuwenhuis, 2010); engagement in different sustainability programs (Yang & Lee, 2018) for all the stakeholders in the ecosystem (3) *economic indicators* such as revenue, profit margins, investment levels, and R&D expenditure for automobile manufacturers, technology firms, and financial institutions (Company, 2016), (4) *regulatory metrics* including compliance rates, number of regulatory filings, fines, and adherence to safety and emissions standards for government regulators and manufacturers (Wang et al., 2019), and (5) *operational metrics* like production volumes, inventory levels, supply chain efficiency, and logistics performance indicators for manufacturers and suppliers (Wells & Nieuwenhuis, 2010).

The qualitative data is used to contextualize the LLMs while the quantitative data is used for persona generation. For example, in the case of a traditional ICE automobile manufacturer, the company size, revenue, and number of employees will be used to establish the demographic distribution of the company, while its behaviors, motivation, and goals are gauged from its sales, engagement in sustainability initiatives, positioning and growth projections. For instance, understanding

consumer attitudes toward EVs requires data on environmental awareness, cost considerations, range anxiety, and charging infrastructure availability (Moons & Pelsmacker, 2012).

Using the collected data, we develop LLM-generated personas for each of the stakeholders. The personas capture demographics, goals, motivations, challenges, behaviors, and typical interactions. Example personas include:

1. *Traditional ICE automaker* is focused on ICE-based vehicles only while keeping the market share and is concerned about retooling costs, maintaining market competitiveness, and managing workforce reskilling.
2. *EV manufacturer* is working for innovation and production of EVs only and prioritizes sustainability, technological advancements, and expanding market share in the growing EV segment.
3. *Supplier* is someone who manufactures and provides materials to both EV and ICE manufacturers and is focused on maintaining supply chain reliability, managing production efficiencies, and fostering strong relationships with both traditional and EV manufacturers.
4. *Dealer and retailer* are responsible for the sale and distribution of vehicles to consumers and are actively involved in customer service, inventory management, and adapting sales strategies to accommodate the increasing demand for EVs and connected vehicles.
5. *Eco-conscious consumer* is a consumer who is aware of their impact on the environment and is making conscious decision making to minimize the impact. They are willing to adopt EVs despite higher upfront costs, influenced by environmental benefits, government incentives, and social responsibility.
6. *Government regulator* is a government body representative who is focused on increasing ways to support and enhance EV production through green subsidies.

Stage03: Persona Validation and Selection The generated personas are evaluated by (1) cross-referencing with the baseline data for diversity estimation, (2) assessed and evaluated on the PPS (Salminen, Santos, Jung, Chowdhury, & Jansen, 2019) for understanding the usability of these personas and (3) reviewed by the SMEs to be considered usable, and (4) reviewed by the stakeholders to understand their reliability.

Stage04: Persona Ecosystem Playground After validation, the personas of each stakeholder are integrated into an interactive simulation environment as chatbot/interactive personas using a LLM framework (e.g., LangChain- and LangGraph-based interfaces). For example, the simulation can model the effects of increased government incentives for EVs by observing how these incentives influence consumer adoption rates, manufacturer strategies, and supplier dynamics (He, Zhan, & Hu, 2017). Deploying personas using LangChain and LangGraph enables the creation of a responsive and adaptable ecosystem model that can be used to test and visualize the potential impacts of different policy and market interventions.

4.3.2 Modeling Societal Ecosystems

Similar to modeling an industrial ecosystem, the same principles can be expanded to societal ecosystems. Societal ecosystems include a diverse array of environments, where each ecosystem is composed of different parties, including actors (citizens, residents, legislators, and regulators), and subjects (children, pets, and other non-active participants of the ecosystems) (see Table 2). For instance, in *urban ecosystems*, personas might represent different socioeconomic groups, local businesses, municipal governments, and environmental organizations focused on sustainability (Jacobs, 1961). In *rural ecosystems*, personas could include farmers practicing sustainable agriculture, community leaders promoting renewable energy, and cooperatives supporting environmental conservation (L. R. Brown, 2008). *Energy ecosystems* might involve personas representing consumers, renewable energy providers, policymakers, and environmental activists (Scheer, 2004). In the case of a social ecosystem, we will apply the PEMF to an urban ecosystem, where a new awareness campaign is being launched to increase recycling.

Context An urban ecosystem is selected for a pilot program to launch an awareness campaign through local online and offline awareness campaign to increase the recycling adoption in the society is being launched. To better understand the different stakeholders perspective, the ecosystem of said society is modeled using PEMF.

Stage01: Stakeholder Mapping and Selection The initial step involves identifying parties in the urban ecosystem that are directly or indirectly affected/or affecting the said campaign. Some key parties include: (1) *eco-conscious residents* are individuals and families committed to recycling practices, (2) *green businesses* are enterprises that recycle frequently, (3) *government agencies* including municipal departments responsible for environmental policies, sustainable urban planning,

Ecosystem	Key Components	Characteristics and Examples
Technology	Hardware Manufacturers Software Developers Cloud Service Providers App Stores	Interconnected platforms, extensive developer communities, devices and services integration. Examples: Apple, Google, Microsoft, Amazon
Automotive	Vehicle Manufacturers Parts Suppliers EV Charging Networks Autonomous Technology	Collaborative R&D for electric and autonomous vehicles, partnerships with tech companies, integration with smart cities. Examples: Tesla, Toyota, General Motors, Ford
Healthcare	Hospitals Pharmaceutical Companies Insurance Providers Health Tech Startups	Data-driven care, AI diagnostics, digital health records, focus on personalized medicine. Examples: UnitedHealth Group, Pfizer, Johnson & Johnson, Cerner
Financial Services	Banks Fintech Companies Payment Processors Cryptocurrency Platforms	Digital transformation, blockchain integration, bank-fintech partnerships, focus on cybersecurity. Examples: JPMorgan Chase, PayPal, Visa, Square
Retail	E-commerce Platforms Logistics Providers Payment Gateways Suppliers	Omni-channel retail, AI-powered personalization, robust supply chain networks. Examples: Walmart, Alibaba, Amazon, Shopify
Energy	Traditional Energy Providers Renewable Energy Companies Smart Grid Providers Government Agencies	Renewable transition, smart grid integration, advancements in energy storage, sustainability efforts. Examples: ExxonMobil, Tesla Energy, Siemens, BP
Entertainment and Media	Content Creators Streaming Platforms Social Media Advertising Networks	Digital content distribution, data-driven recommendations, integration with user-generated content. Examples: Disney, Netflix, Spotify, YouTube

Table 1. Examples of Industry Ecosystems.

and resource management for recycling (UN-Habitat, 2009), (4) *environmental NGOs* are the non-profit organizations advocating for enhanced recycling initiatives and encouraging community through engagement (Putnam, 2000), (5) *recycling infrastructure* refers to elements like waste collection, disposal and management facilities (Beatley, 2011), (6) *volunteers* are members of the community who actively engage and support the recycling cause and (7) *media houses* that actively contributing to the awareness campaign.

Stage02: Data Collection and Persona Generation For this purpose, qualitative data sources include studies on sustainable behaviors, community participation in environmental initiatives (Stern, 2000), and interviews with SMEs, including recycling experts, waste management organization members, and environmentalists. Quantitative data sources include (1) demographic statistics of the population, including age, sex, household income, marital status, and education (United Nations, 2018), (2) behavioral data such as the adoption of recycling habits, reception to sustainability practices, consumption and waste management routines, (3) operational indicators such as the number of waste collectors, waste collection and management pipeline and awareness campaign metrics, and (4) infrastructure metrics such as the number of green buildings, availability of public transit, and renewable energy usage (Glaeser & Gyourko, 2010).

Based on the data collected, the personas are generated for different parties to the :

1. *Eco-conscious resident* is a resident who is conscious of their impact on the environment and actively participates in

recycling initiatives through sustainable lifestyle choices, participation in community environmental programs, and advocacy for green policies.

2. *Green business* is a business or local shop focused on implementing and adopting recycling processes across its supply chain.
3. *Government agency* is a regulatory body that is driven to create a positive impact by promoting recycling across the societal ecosystem.
4. *Environmental NGO* represents the actions taken by non-governmental organizations to promote recycling initiatives in society.
5. *General public* who represents the general public of the ecosystem that will be directly impacted by the campaign.

Representative personas for these stakeholders are presented in Figure 4.

Stage03: Persona Validation and Selection Similar to the previous case, the personas are validated through four steps (1) cross-reference with baseline data, (2) measurement of diversity, (3) assessing decision-makers' perceptions of the personas using scales like the PPS (Salminen, Santos, et al., 2020), (4) validation of the personas by SMEs and establishing the reliability of the personas by representative members. In this case, with addition of the participants from the community in the design process would reduce the self-referential bias.

Stage04: Persona Ecosystem Playground Validated personas are integrated into an interactive simulation environment, allowing for interactions based on predefined behavioral rules related to sustainability. This supports scenario exploration, such as modeling the impact of implementing awareness campaigns for recycling, improving the energy efficiency consciousness on urban energy consumption, or assessing how the expansion of public transit affects carbon emissions and social equity (Newman & Kenworthy, 1999).

4.3.3 Modeling Natural Ecosystems as Personas

Like industrial and societal ecosystems, natural ecosystems can also be modeled by adopting PEMF. However, as the natural ecosystem comprises both human and non-human parties, therefore additional considerations of non-human persona (representation of a non-human (living or non-living thing) by a persona) should be considered. Natural ecosystems comprise diverse environments, each characterized by unique species compositions and environmental factors (see Table 3). For instance, in *grassland ecosystems*, personas represent various herbivores such as bison and pronghorn, their predators like lions and coyotes, and the grasses that form the ecosystem's foundation. In *desert ecosystems*, personas include specially adapted plants like cacti and succulents, nocturnal rodents such as kangaroo rats, reptiles like Gila monsters, and drought-tolerant microbes. *Tundra ecosystems* might be modeled through personas representing Arctic mosses and lichens, herbivores like caribou, carnivores such as polar bears, and permafrost-dependent soil microorganisms. *Freshwater ecosystems* would involve personas for various fish species like trout, amphibians such as frogs, aquatic plants like cattails, and microorganisms responsible for nutrient cycling. *Marine ecosystems* would encompass diverse species, including coral polyps, plankton, fish species, and marine mammals like dolphins and whales. *Mountain ecosystems* might feature personas for alpine plants like edelweiss, mountain ungulates such as mountain goats, predatory birds like eagles, and snow microbes. Lastly, *polar ecosystems* would include personas representing polar bears, emperor penguins, specialized algae, and ice-dwelling microbes. Representing these ecosystems could make LLM-generated personas an instrument for ecological research and conservation efforts. To implement the PEM framework in natural ecosystems, forest ecosystem is modeled as an example.

Context Among the land-based natural ecosystems, forests are considered as one of the most biodiverse and ecologically significant ecosystems, playing a crucial role in carbon sequestration, climate regulation, and providing habitat for numerous species (Carpenter et al., 1998). More specifically, we will focus on a sub-ecosystem within the forest ecosystem that involves and deals with food-based interaction among different parties of the ecosystem. To further ground the example and make it manageable, we will model the sub-ecosystem with the context of observing the impact of climate change on food abundance for different members of the ecosystem.

Stage01: Stakeholder Mapping and Selection. The foundational stage in the PEMF is stakeholder mapping and selection, which in the case of natural ecosystems, would involve the selection of species and environmental factors that define the ecosystem. These elements are categorized into: (1) *producers* which are dominant tree species such as oaks, pines, and maples that form the canopy and act as primary producers by converting solar energy into chemical energy through

Ecosystem	Key Actors and Components	Characteristics and Examples
Sustainable Urban	Eco-conscious Residents Green Businesses Government Agencies Environmental NGOs Sustainable Infrastructure	Focus on sustainable living, green economy, environmental policies, and sustainable infrastructure. Examples: Urban gardeners, renewable energy companies, city environmental departments, public transit systems
Rural Sustainability	Organic Farmers Community Cooperatives Renewable Energy Projects Conservation Groups	Emphasis on sustainable agriculture, resource conservation, and community-based environmental initiatives. Examples: Organic farms, wind energy cooperatives, local conservation trusts
Energy Transition	Consumers Renewable Energy Providers Policy Makers Activists	Transition from fossil fuels to renewable energy sources, policy development, and public acceptance. Examples: Solar panel users, wind farm operators, energy regulators, environmental activists
Circular Economy	Manufacturers Recycling Firms Consumers Policy Makers	Focus on resource efficiency, waste reduction, and sustainable production and consumption. Examples: Companies using recycled materials, zero-waste stores, environmental legislation
Educational	Students Teachers Administrators Policy Makers	Knowledge exchange, sustainability education, and curriculum development focused on environmental awareness. Examples: Environmental science students, eco-friendly school programs, education ministries promoting sustainability
Healthcare	Patients Providers Public Health Officials Regulators	Focus on public health, access to healthcare, environmental health issues, and policy regulation. Examples: Community health clinics, hospitals reducing carbon footprint, health departments addressing pollution-related diseases
Digital	Online Users Content Creators Platform Administrators Cybersecurity Experts	Virtual interactions, information exchange on sustainability topics, digital activism, and online governance. Examples: Environmental bloggers, sustainable technology developers, social media campaigns for climate action

Table 2. Examples of Societal Ecosystems Focused on Sustainability and Their Key Components.

photosynthesis, (2) *understory plant* generally include shrubs, ferns, and herbaceous plants like blueberries and wildflowers that inhabit the forest floor, contributing to biodiversity and providing habitat and food sources for various fauna, (3) *consumers* are herbivores such as white-tailed deer and insects like caterpillars; carnivores including wolves and owls and omnivores like raccoons and bears that interact within the food web,(4) *decomposers* are parties such as fungi, bacteria, and detritivores including earthworms that break down dead organic matter, recycling nutrients back into the soil, and (5) *abiotic factors* including climate variables (temperature, precipitation), soil composition (pH, nutrient content), water availability, and geological features (topography, elevation) influencing species survival and interactions.

Stage02: Data Collection and Persona Generation. As all the personas generated in this case are non-human personas, therefore the quantitative data collected for persona generation would be different in this case. The **qualitative data sources** include (1) *ecological studies* such as detailed research on species behavior, habitat preferences, reproductive strategies, and interspecies relationships (Carpenter et al., 1998), (2) *field observations* that represent direct observations of species interactions, migration patterns, feeding behaviors, and responses to environmental stimuli, and (3) *SME interviews* that provide insights from ecologists, conservationists, and wildlife experts regarding species roles, threats, and conservation needs especially with regards food imbalance. Similarly, for persona generation, the **quantitative data sources** would include, in addition to the normal *population metrics, representative personality traits* including the quantitative measures of species' behavioral and physiological characteristics that influence their roles within the ecosystem. These representative personality traits could include: (a) *activity levels* (metrics such as daily movement zones/ranges and durations, eating/consumption frequency, and periods of rest), (b) *herd and community parameters* (data on group size, social hierarchy, and interaction frequency within species populations), (c) *breeding and reproductive rates* (information on breeding cycles, clutch sizes, offspring survival rates, and age of sexual maturity), (d) *territorial range* (measurements of territory sizes, overlapping ranges among individuals or groups, and migration patterns), (e) *diet preferences* (quantitative data on food intake types, quantities, and foraging behaviors), and (f) *adaptability metrics* (indicators such as cortisol levels, resilience to environmental stressors, and recovery times after disturbances). This data allows the creation of persona components such as behavior, goals, motivations, key traits, and values for these non-human personas.

Based on the data collected, the following non-human personas are created for different key stakeholders identified in the first stage. Some of these personas include:

1. *Producers* represents dominant tree species such as oak, pine, and maple, which show consistent growth rates, photosynthetic efficiency, territorial strategies
2. *Understory plants* are also plants, including shrubs, ferns, and herbaceous plants like blueberries and wildflowers which showcase growth patterns, have lower sunlight requirements, and soil nutrient uptake
3. *Consumers* includes herbivores like white-tailed deer and insects such as caterpillars; carnivores such as wolves and owls; and omnivores including raccoons and bears. These all focus on strong feeding habits, territorial behaviors, reproductive cycles, and dominance-driven personality,
4. *Decomposers* are parties like fungi (*Agaricus bisporus*), bacteria (*Bacillus subtilis*), and detritivores such as earthworms which show traits like symbiotic relationships and recycling behaviors driven by soil health improvement.
5. *Abiotic factors* that represent non-living environmental elements such as climate variables (temperature, precipitation), soil composition (pH, nutrient levels), water availability, and geological features (topography, elevation).

On the basis of the persona data collected for each stakeholder group, personas are created. Representative personas of these different stakeholders are presented in Figure 4.

Stage03: Persona Validation and Selection. Similar to previous validation approaches in industrial and societal ecosystem models, personas are validated through (1) cross-validation with the underlying population characteristics, (2) assessed on the PPS scale (Salminen et al., 2019) and are evaluated by SMEs to verify their accuracy and relevance. To ensure the accuracy and representativeness of the generated personas, a validation process is employed, which includes *cross-referencing* persona attributes against empirical data and established ecological studies to verify their accuracy and relevance, *SME (ecologists and environmental scientists)* conduct comprehensive reviews of the personas, assessing their authenticity, ecological validity, and alignment with real-world species behaviors and interactions, and *secondary stakeholder (conservation organizations, field experts, and ecological stakeholders)* provide feedback to enhance the accuracy of the persona to real and actual behaviors and traits.

Based on the collected feedback, necessary adjustments are made by refining the input data or modifying the parameters of the LLMs used, thereby addressing any identified discrepancies or biases (Sheng, Joe, Alambo, & Solaiman, 2021). This iterative validation process enhances the credibility and utility of the personas in subsequent modeling and simulation activities.

Stage04: Persona Ecosystem Playground. Once validated, the personas are integrated into an interactive simulation environment where these non-human personas can communicate with each other as well as the persona users—a human—who use these personas for making different key decisions. This PEP environment allows personas to interact based on predefined behavioral rules and ecological processes, supporting both inter-species and human-to-persona interactions for scenario exploration. For instance, the simulation can model the impact of climate change on species distribution and interactions, observing how altered temperatures and precipitation patterns influence ecosystem balance (He et al., 2017). Additionally, the platform can simulate the effects of conservation interventions, invasive species introductions, or habitat fragmentation, providing valuable insights into potential ecosystem responses and resilience.

Ecosystem	Key Species and Components	Characteristics and Examples
Forest	Dominant Tree Species Understory Plants Apex Predators Soil Microorganisms	Complex canopy structures, layered vegetation, top-down trophic interactions, and nutrient cycling facilitated by decomposers. Examples: Oak trees (<i>Quercus robur</i>), ferns, wolves (<i>Canis lupus</i>), fungi
Grassland	Grasses Herbivores Predators Soil Nutrients	Open canopy with dominant grasses, herbivore-driven grazing patterns, predator-prey dynamics, and efficient nutrient recycling. Examples: Bison (<i>Bison bison</i>), lions (<i>Panthera leo</i>), prairie dogs, nitrogen-fixing bacteria
Desert	Cacti and Succulents Desert Rodents Reptiles Drought-Tolerant Microbes	Sparse vegetation adapted to arid conditions, nocturnal and burrowing animals, extreme temperature adaptations, and specialized water-conserving mechanisms. Examples: Saguaro cactus (<i>Carnegiea gigantea</i>), kangaroo rat (<i>Dipodomys spp.</i>), Gila monsters, xerophilic bacteria
Tundra	Mosses and Lichens Herbivores Carnivores Permafrost Soil	Low temperatures, short growing seasons, limited vegetation types, specialized adaptations for cold, permafrost-dependent soil structure. Examples: Arctic moss (<i>Calliergon giganteum</i>), caribou (<i>Rangifer tarandus</i>), polar bears (<i>Ursus maritimus</i>), cold-tolerant fungi
Freshwater	Fish Amphibians Aquatic Plants Microorganisms	Diverse aquatic habitats, essential roles in water purification, complex food webs, and high biodiversity. Examples: Trout (<i>Oncorhynchus mykiss</i>), frogs (<i>Rana spp.</i>), cattails (<i>Typha spp.</i>), nitrifying bacteria
Marine	Coral Marine Mammals Plankton Seagrasses	Saltwater ecosystems with high biodiversity, symbiotic relationships, critical roles in carbon cycling, and complex trophic structures. Examples: Coral polyps (<i>Acropora spp.</i>), dolphins (<i>Delphinus delphis</i>), copepods, eelgrass (<i>Zostera marina</i>)
Mountain	Alpine Plants Mountain Ungulates Predatory Birds Snow Microbes	Varied microclimates, altitude-dependent species distributions, specialized adaptations to steep terrains, and seasonal migrations. Examples: Edelweiss (<i>Leontopodium alpinum</i>), mountain goats (<i>Oreamnos americanus</i>), eagles (<i>Aquila chrysaetos</i>), psychrophilic bacteria
Polar	Polar Bears Penguins Algae Ice-Dwelling Microbes	Extreme cold environments, ice-dependent habitats, unique reproductive strategies, and sensitivity to climate changes. Examples: Polar bears (<i>Ursus maritimus</i>), emperor penguins (<i>Aptenodytes forsteri</i>), ice algae, psychrotolerant bacteria

Table 3. Examples of Natural Ecosystems and Their Key Components.

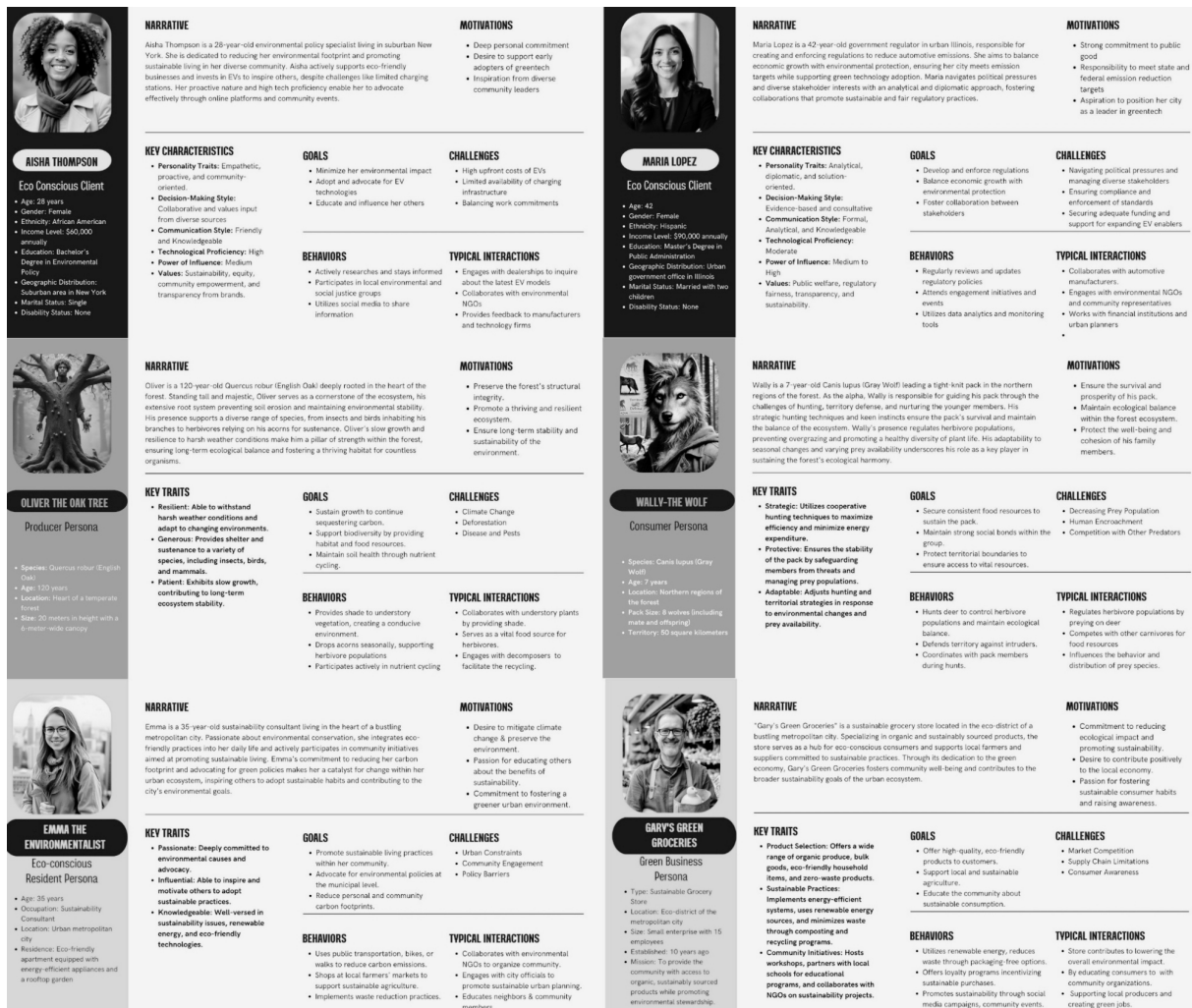


Figure 4. Representative Personas for two of the stakeholders in different ecosystems.

4.4 Forms of Interaction

In these PEPs, various forms of interactions occur. These interactions include (1) one-to-one interactions between personas, (2) one-to-many interactions between personas, and (3) human-to-persona interactions.

The primary form of interaction is the **persona-to-persona interaction**, where personas representing different parties within the ecosystem engage based on predefined rules and interactions leading to specific decision-making processes. These interactions can be categorized into *one-to-one* and *one-to-many* or *many-to-one* interactions.

In *one-to-one* interactions, two personas directly engage with each other. This form allows for detailed modeling of relationships such as negotiations, partnerships, or conflicts between individual parties. For example, in the industrial ecosystem of the automotive industry, modeling a negotiation between an *EV manufacturer persona* and a *battery supplier persona* can reveal how supply agreements impact production and innovation.

In *one-to-many* interactions, a single persona interacts with multiple personas, while in *many-to-one* interactions, multiple personas interact with a single persona. This form of interaction is crucial for modeling scenarios where parties have widespread influence or are influenced by collective behaviors. For example, a *government regulator* (one) advocating for electric vehicles can influence several *traditional automotive manufacturers* (many) to strategize and plan for the production of electric vehicles. In contrast, multiple *suppliers* (many) competing for contracts with a single *EV manufacturer* (one) can have a greater influence on market dynamics.

These interactions help us understand (1) *the propagation of influence through the ecosystem*, (2) the formation of collective behaviors and perspective formulation, especially for personas belonging to different stakeholder groups.

Another significant form is the **persona-to-human interaction**, which allows persona users and decision makers to engage directly with personas within the simulation. This interactivity enables persona users to explore "what-if" scenarios by making decisions, posing questions, altering parameters, and observing how personas respond. The benefits of personas-to-human interactions include (1) experiential learning (learning of different perspectives through engagement),

(2) enhanced comprehension of system complexities (understanding the causal and non-causal interactions), and (3) the integration of human expertise (to drive the direction) into the simulation. For instance, in a simulation of sustainable urban development, a user acting as a city planner could interact with various personas such as the *Eco-conscious Resident Persona*, the *Green Business Persona*, and the *Government Agency Persona*. The user could propose a new policy to implement city-wide renewable energy initiatives and observe how each persona responds: (1) The *Eco-conscious Resident Persona* may express support, highlighting the environmental benefits and willingness to participate, (2) the *Green Business Persona* might evaluate the economic implications, considering the costs of transitioning to renewable energy sources and potential market advantages and (3) the *Government Agency Persona* could discuss regulatory hurdles, budget constraints, and the need for stakeholder engagement.

Similarly, a user acting as a policy analyst might interact with the *EV Manufacturer Persona* and the *Government Agency Persona* to explore the impact of introducing a new subsidy for EVs. By engaging with these agents, the user can delve into the economic, environmental, and logistical implications of such a policy.

The user initiates a conversation with the *Government Agency Persona*:

Human User

I'm considering proposing a \$5,000 consumer subsidy for each electric vehicle purchased. How feasible is this policy from a governmental perspective?

Government Agency Persona

Implementing a \$5,000 subsidy per vehicle could significantly accelerate EV adoption, aligning with our emission reduction targets. However, it would require reallocating funds or increasing taxes to cover the projected cost, which could impact other public services.

Human User

What if we phase out subsidies for fossil fuels to offset the cost?

Government Agency Persona

Redirecting funds from fossil fuel subsidies is a possibility, but it may face political resistance from stakeholders in those industries. We would need to conduct a thorough impact assessment and engage in stakeholder consultations to evaluate this approach.

Next, the user consults the *EV Manufacturer Persona*:

Human User

If this subsidy were approved, how would it affect your production plans?

EV Manufacturer persona

A significant subsidy would likely boost demand for our vehicles substantially. We would need to scale up production capacity, which involves investing in manufacturing facilities and securing additional components, particularly batteries.

Human User

Are there any challenges that you anticipate in scaling up production quickly?

EV Manufacturer persona

Yes, ramping up production rapidly poses risks. Sourcing sufficient quantities of battery materials like lithium and cobalt is a concern due to limited global supply and ethical sourcing issues. We would also need to ensure our supply chain can handle increased demand without compromising quality or sustainability standards.

5 Discussion

This chapter presents a different perspective on the use of LLM-generated personas to increase their domain from a minority viewpoint to a majority viewpoint in ecosystem models. Addressing **RQ1**, we present a methodology to enrich and enhance LLM-generated personas through RAG and fine-tuned models to create persona sets. These persona sets are generated using the primary data and are evaluated to ensure their validity. Regarding **RQ2**, we present a framework (PEMF) to model ecosystems using personas. The two types of personas are compared in Table 4.

Aspect	Minority Viewpoint Personas	Ecosystem Personas
Focus	Single perspective from marginalized communities	Multiple stakeholders within complete ecosystems
Primary Purpose	Inform inclusive policy-making decisions	Model system-wide interactions and relationships
Stakeholders	Individual human perspectives from underrepresented groups	Multiple entities (human and non-human) across ecosystem
Data Sources	Community surveys, cultural studies, demographic data	Domain reports, interaction data, behavioral metrics
Generation Method	LLMs with cultural contextualization and sensitivity	LLMs with domain-specific RAG and fine-tuning
Validation	Community verification and cultural sensitivity checks	Cross-validation with baseline data and PPS assessment
Key Example	Maria Fernandez: Indigenous student balancing traditional values with modern education	Automotive ecosystem: Manufacturers, suppliers, consumers, and regulators interacting in EV transition

Table 4. Comparison of Persona Types in LLM-Generated Personas

For this, we create a four-stage framework, including (1) stakeholder mapping and segmentation, (2) data collection and persona generation, (3) persona validation and selection, and (4) persona ecosystem playground creation.

The validation of LLM-generated personas presents a methodological challenge that while SMEs provide domain expertise, they may carry their own biases, potentially perpetuating the very issues these personas aim to address. For *minority viewpoint personas*, establishing ground truth requires direct validation from community members, supported by quantitative metrics derived from demographic and behavioral data. This dual approach helps mitigate individual biases while ensuring authentic representation. The complexity of validation increases in the *personas of the ecosystem* due to the distinction between known and emerging behaviors. Known behaviors, such as documented regulatory interactions or market responses, can be validated against historical data. However, emergent behaviors in complex multi-stakeholder scenarios lack historical precedent for validation. Here, validation must focus on the logical consistency of interactions and the underlying assumptions driving these emergent patterns, rather than a direct comparison with historical data. This limitation should be explicitly acknowledged when using ecosystem personas for predictive modeling.

5.1 Design Principles

LLM-generated persona systems involve distinct design considerations. We outline three primary considerations:

Realism and Validity: *The persona generated, whether for minority representation or majority representation, has to be realistic and valid.* Realism refers to the true representation of the parties and capturing the ecosystem knowledge base, while valid indicates that the personas are up-to-date and correspond to the current user state. For nature ecosystems, realism is based on ecological data and biological behaviors, while for industry ecosystems, it involves accurate representations of market dynamics, organizational roles, and economic principles. Both systems benefit from realistic models to simulate authentic interactions, whether these involve species within an ecosystem or companies within an industry. Mere realism is not adequate but the personas need to be valid, as in representative of the true entity they aim to represent.

Adaptability and Responsiveness: *The personas should be adaptable to different scenarios and responsive to internal and external changes.* In nature ecosystems, adaptability captures species' responses to environmental changes, like predator-prey dynamics. In industry ecosystems, adaptability reflects how businesses respond to market shifts, competition, or regulatory changes. These scenario parameters could be provided by the administrator of the LLM-generated persona

system. Additionally, feedback loops could be built to provide information on real-time events (e.g., obtained through press releases) that would then be used as scenarios to initiate interaction sessions between the actors. Also, both ecosystem types benefit from flexible scenario exploration. Users can experiment with different climate conditions or species in nature ecosystems or with various business strategies and regulatory environments in industry ecosystems. Overall, initiation plays a key role in the direction in which the interaction takes place, as it provides the context and purpose for interaction. In one extreme, there are preset scenarios to choose from. In the other extreme, users may freely set initial conditions.

Scalability and Complexity Management: *The personas developed, whether using PEMF or for minority visualization, should be scalable and be able to enhance or reduce complexity as or when required.* Nature ecosystems can involve intricate webs of species interactions, just as industry ecosystems can involve complex networks of business relationships. Scalable interfaces that manage complexity without overwhelming users are essential for both, enabling users to zoom in on individual personas or zoom out to view the entire ecosystem. For example, the LLM-generated persona system could introduce each persona briefly at the beginning of an interaction session.

Certainly, this list of principles is neither definitive nor complete. However, we do believe these principles to be among the key considerations for designing LLM-generated persona systems.

5.2 Future Research Directions

Here, we identify and propose research directions (RDs) for future work on LLM-generated personas for social good.

First, while there has been research addressing the problems of the marginalized communities in the development phase through inclusive personas (J. Goodman-Deane et al., 2018; Marsden & Haag, 2016), there has been no focus on the usage of personas for the reduction of inequality and betterment of marginalized communities (Salminen, Wenyun Guan, et al., 2022). To this end, we propose:

- **RD1:** *How can LLM-generated personas accurately reflect the socio-economic and cultural realities of marginalized communities?*
- **RD2:** *How can stereotypical and biased personas be minimized in LLM-generated personas?*

Second, while personas have been used in some of the use cases for social good, they have been primarily driven by commercial applications (Salminen, Wenyun Guan, et al., 2022). Due to this, there is a scarcity of research in the PFSG domain (Guan et al., 2023; Salminen, Wenyun Guan, et al., 2022) as most of the research is focused on the commercial (software design, marketing, and other) aspects. PFSG has a strong impact in a broad spectrum of areas, including (1) *healthcare* where it could be implemented to improve well-being and access to services for vulnerable populations, (2) in *education* to design inclusive educational tools, (3) *sustainability* where it is deployed to promote sustainable practices among varying user demographics, (4) *social justice* for creating narratives around users' political views and social attitudes, and in (5) *community engagement* to enhance social cohesion and civic participation. (Guan et al., 2023; Salminen, Wenyun Guan, et al., 2022). One such area is policy-making, where the involvement of all stakeholders is essential for creating policies that can be adopted holistically by the community (Anthony, 2024). So, we propose **RD3:** *How can LLM-generated personas be utilized to improve the formulation of targeted social policies?*

Third, while major governmental organizations have considered personas as a driver for policy-making (Andrews, 2013; Department of the Prime Minister and Cabinet (DPMC), 2023), little research has been focused on identifying the key challenges of the personas for policy-making. This is further complicated for the special case of marginalized and under-represented communities (e.g., *minority races, rural population*), who lack proper representation in the policy-making process. Moreover, using LLMs to develop personas further adds to the complications as these tools are not only prone to algorithmic bias but are also susceptible to possible hallucinations (the challenge for LLMs to generate coherent and comprehensible but factually and contextually incorrect output). To better study and understand the ethical and social challenges of using LLM-generated personas as a tool in policy-making, especially for marginalized and socially challenged communities, we propose the following RDs:

- **RD4:** *What ethical challenges arise from deploying LLM-generated personas in policy-making for socially challenged communities?*
- **RD5:** *What actionable ethical guidelines can be developed to mitigate these challenges?*

5.3 Key Takeaways

In this work, we have illustrated, through concrete examples, the potential of LLMs to address the persona-generation task in HCI, ranging from the micro-level representation of marginalized, fringe, or minority perspectives to

modeling entire ecosystems. The fundamental principle in these endeavors is **basing the personas' information on primary data**. Otherwise, there is *a risk of the LLMs perpetuating stereotypes and biases* that relate to whole ecosystems and individual ecosystem stakeholder groups. **Simulations based on LLM-generated personas can only be valid when they rely on primary data**. They might appear useful even without this linkage, which is problematic: there is a perilous easy route of using LLMs to generate personas without basing them on primary data. The fluency and apparent realism of the outcomes can easily fool decision-makers into thinking that such personas are valid (because they *look* like valid!), while in fact, they are not. Therefore, the research-based data-driven approach we proposed in this work is recommended in lieu of using non-contextual prompts with vanilla LLMs.

We believe that our approach to LLM-generated persona systems has educational value and accessibility value. Modeling ecosystems through LLM-generated personas is suitable for a range of educational purposes, from understanding biodiversity to exploring business strategy. The conversational user interface makes the LLM-generated persona system suitable for novices and experts alike, and the interactive nature of the system supports learning and engagement in both contexts. LLM-generated personas can also support the development of ethical and sustainable behaviors, as they can help users consider the consequences of their actions. In nature ecosystems, this could involve conservation efforts, while in industry ecosystems, it could involve corporate social responsibility or sustainability. Users' interactions can mirror real-world impacts and considerations, similar to the dynamics of gameplay. Ideally, observing the persona-to-persona interaction and participating in human-to-persona interaction encourage critical thinking and a deeper understanding of systemic interactions.

6 Conclusion

This research proposes ways to address significant gaps in the development and application of personas, particularly concerning ethical and social considerations for marginalized communities and the lack of representation of ecosystems comprising multiple parties. Through investigating and refining methodologies aimed at producing more inclusive and representative personas, we proposed ways to reduce biases and improve the functionality of AI systems in tackling real-world challenges. LLM-generated personas can contribute meaningfully to the fields of HCI and UCD, establishing new frameworks and guidelines that can be applied in policy-making and social initiatives. This work aspires to create a more equitable digital environment where AI systems reflect and serve the diverse needs of global user communities and ecosystems in need.

References

- Acs, Z. J., Stam, E., Audretsch, D. B., & O'Connor, A. (2017, June). The lineages of the entrepreneurial ecosystem approach. *Small Business Economics*, 49(1), 1–10. Retrieved 2024-08-27, from <http://link.springer.com/10.1007/s11187-017-9864-8> doi: 10.1007/s11187-017-9864-8
- Amin, D., Salminen, J., Jansen, B., Shin, J., & Kim, D. H. (2025). Generative AI Personas Considered Harmful? Examining the Risks of Algorithmic User Representations in HCI Design. *International Journal of Human-Computer Studies*.
- Andrews, B. (2013, August). *Using personas to make better policy*. Retrieved 2024-08-19, from <https://openpolicy.blog.gov.uk/2013/08/08/using-personas-to-help-improve-policy-making/>
- Anthis, J., Lum, K., Ekstrand, M., Feller, A., D'Amour, A., & Tan, C. (2024, May). *The Impossibility of Fair LLMs*. arXiv. Retrieved 2024-08-22, from <http://arxiv.org/abs/2406.03198> (arXiv:2406.03198 [cs, stat] version: 1) doi: 10.48550/arXiv.2406.03198
- Anthony, B. (2024, March). The Role of Community Engagement in Urban Innovation Towards the Co-Creation of Smart Sustainable Cities. *Journal of the Knowledge Economy*, 15(1), 1592–1624. Retrieved 2024-08-26, from <https://doi.org/10.1007/s13132-023-01176-1> doi: 10.1007/s13132-023-01176-1
- Anvari, F., Richards, D., Hitchens, M., & Tran, H. M. T. (2019, May). Teaching User Centered Conceptual Design Using Cross-Cultural Personas and Peer Reviews for a Large Cohort of Students. In *2019 IEEE/ACM 41st International Conference on Software Engineering: Software Engineering Education and Training (ICSE-SEET)* (pp. 62–73). doi: 10.1109/ICSE-SEET.2019.00015
- Batty, M. (2018). *Inventing future cities*. MIT Press.
- Beatley, T. (2011). *Green Cities of Europe: Global Lessons on Green Urbanism*. Island Press.
- Borge, M., & Xia, Y. (2023). Beyond the individual: The regulation and negotiation of socioemotional practices across a learning ecosystem. *Journal of the Learning Sciences*, 32(3), 325–375. doi: 10.1080/10508406.2022.2157725
- Bremer, C., Knowles, B., & Friday, A. (2022). Have we taken on too much?: A critical review of the sustainable HCI landscape. *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems*, 1–11.
- Brown, L. R. (2008). *Plan B 3.0: Mobilizing to Save Civilization*. W.W. Norton & Company.

- Brown, T. B., Mann, B., Ryder, N., Subbiah, M., Kaplan, J., Dhariwal, P., ... Amodei, D. (2020, July). *Language Models are Few-Shot Learners*. arXiv. Retrieved 2024-10-12, from <http://arxiv.org/abs/2005.14165>
- Brussard, P. F., Reed, J. M., & Tracy, C. R. (1998). Ecosystem management: what is it really? *Landscape and Urban Planning*, 40(1-3), 9–20.
- Bødker, S., Christiansen, E., Nyvang, T., & Zander, P.-O. (2012). Personas, people and participation: challenges from the trenches of local government. In *Proceedings of the 12th Participatory Design Conference on Research Papers: Volume 1 - PDC '12* (p. 91). ACM Press. Retrieved 2020-03-31, from <http://dl.acm.org/citation.cfm?doi=2347635.2347649> doi: 10.1145/2347635.2347649
- Cachat-Rosset, G., & Klarsfeld, A. (2023). Diversity, Equity, and Inclusion in Artificial Intelligence: An Evaluation of Guidelines. *Applied Artificial Intelligence*. Retrieved from <https://doi.org/10.1080/08839514.2023.2176618>
- Capaldi, S., Passmore, H. A., Nisbet, E. K., & Zelenski, J. M. (2014). The Connection Between Nature and Wellbeing: A Systematic Review of the Literature. *Journal of Environmental Psychology*, 40, 409–418.
- Carpenter, S. R., Kitchell, J. F., & Hodgson, J. G. (1998). *Ecosystem management: Principles for a sustainable future*. Island Press.
- Chandra, A., Gulati, N., & Kandlikar, M. (2010). Green drivers or free riders? An analysis of tax rebates for hybrid vehicles. *Journal of Environmental Economics and Management*, 60(2), 78–93.
- Chapman, C., & Milham, R. P. (2006, October). The Personas' New Clothes: Methodological and Practical Arguments against a Popular Method. In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting* (Vol. 50, pp. 634–636). Retrieved from <http://journals.sagepub.com/doi/abs/10.1177/154193120605000503> doi: 10.1177/154193120605000503
- Cherry, C., Thomas, G., Groves, C., Roberts, E., Shirani, F., Henwood, K., & Pidgeon, N. (2022). A personas-based approach to deliberating local decarbonisation scenarios: Findings and methodological insights. *Energy Research & Social Science*, 87, 102455.
- Cho, S. H., Jon, S., Jin, Y., Jung, J., & Oh, C. (2024). Understanding the Dynamics in Creating Domain-Specific AI Design Guidelines: A Case Study of a Leading Digital Finance Company in South Korea. In *Extended Abstracts of the 2024 CHI Conference on Human Factors in Computing Systems*. New York, NY, USA: Association for Computing Machinery. Retrieved from <https://doi.org/10.1145/3613905.3650759> doi: 10.1145/3613905.3650759
- Choi, Y., Kang, E. J., Choi, S., Lee, M. K., & Kim, J. (2025). Proxona: Supporting Creators' Sensemaking and Ideation with LLM-Powered Audience Personas. In *Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems*. New York, NY, USA: Association for Computing Machinery. Retrieved from <https://doi-org.proxy.uwasa.fi/10.1145/3706598.3714034> doi: 10.1145/3706598.3714034
- Commission, E. (2019). *Clean Mobility: European Union*.
- Company, M. . (2016). *Automotive revolution—perspective towards 2030: How the convergence of disruptive technology-driven trends could transform the auto industry*.
- Cooper, A. (1999). *The Inmates Are Running the Asylum: Why High Tech Products Drive Us Crazy and How to Restore the Sanity* (1edition ed.). Indianapolis, IN: Sams - Pearson Education.
- De Paoli, S. (2023). Writing user personas with Large Language Models: Testing phase 6 of a Thematic Analysis of semi-structured interviews. *arXiv preprint arXiv:2305.18099*.
- Department of the Prime Minister and Cabinet (DPMC). (2023, June). *Personas*. Retrieved 2024-08-19, from <https://www.dPMC.govt.nz/our-programmes/policy-project/policy-methods-toolbox/design-thinking/personas>
- Dietz, T., Ostrom, E., & Stern, P. C. (2003). The struggle to govern the commons. *Science*, 302(5652), 1907–1912.
- Evans, M. D. (2003). Biodiversity and ecosystem function: current knowledge and future directions. *Ecological Complexity*, 1(1), 3–10.
- Farahani, M. S., & Ghasemi, G. (2024). Artificial Intelligence and Inequality: Challenges and Opportunities. *Qeios*.
- Ferrucci, D. (2012). Artificial intelligence for healthcare: opportunities and challenges. *Journal of the American Medical Informatics Association*, 19(5), 764–771.
- Geary, W. L., Bode, M., Doherty, T. S., Fulton, E. A., Nimmo, D. G., Tulloch, A. I., ... Ritchie, E. G. (2020). A guide to ecosystem models and their environmental applications. *Nature Ecology & Evolution*, 4(11), 1459–1471.
- Glaeser, E. L., & Gyourko, J. (2010). Housing supply and housing bubbles. *Journal of Urban Economics*, 67(2), 198–213.
- Goodman-Deane, J., Waller, S., Demin, D., González-de Heredia, A., Bradley, M., & Clarkson, J. P. (2018, June). Evaluating Inclusivity using Quantitative Personas. In *In the Proceedings of Design Research Society Conference 2018*. Retrieved 2019-06-22, from <https://www.dropbox.com/sh/cbj04ez206dexrd/AADKH19uwDXvpwndnSWEAk1a?dl=0&preview=Goodman-Deane+Waller+Demin+Gonz%C3%Allez-de-Heredia+Bradley+Clarkson+400.pdf> doi: 10.21606/drs.2018.400

- Goodman-Deane, J. A.-L., Bradley, M., Waller, S., & Clarkson, P. J. (2021, August). Developing personas to help designers to understand digital exclusion. *Proceedings of the Design Society, 1*, 1203–1212. Retrieved 2023-07-17, from <https://www.cambridge.org/core/journals/proceedings-of-the-design-society/article/developing-personas-to-help-designers-to-understand-digital-exclusion/06B867BC99A504C2D1DE38903820C6BD> doi: 10.1017/pds.2021.120
- Graham-Rowe, E., Gardner, B., Abraham, C., Skippon, S., Dittmar, H., Hutchins, R., & Stannard, J. (2012). Mainstream consumers driving plug-in battery-electric and plug-in hybrid electric cars: A qualitative analysis of responses and evaluations. *Transportation Research Part A: Policy and Practice, 46*(1), 140–153.
- Green, D. G., & Sadedin, S. (2005). Interactions matter—complexity in landscapes and ecosystems. *Ecological Complexity, 2*(2), 117–130.
- Gross, S., Toombs, A., Wain, J., & Walorski, K. (2011). Foodmunity: designing community interactions over food. In *Proceedings of the 2011 annual conference extended abstracts on Human factors in computing systems - CHI EA '11* (p. 1019). ACM Press. Retrieved 2020-03-29, from <http://portal.acm.org/citation.cfm?doid=1979742.1979504> doi: 10.1145/1979742.1979504
- Grudin, J. (2006). Why Personas Work: The Psychological Evidence. In J. Pruitt & T. Adlin (Eds.), *The Persona Lifecycle* (pp. 642–663). Elsevier. Retrieved 2020-06-23, from <https://linkinghub.elsevier.com/retrieve/pii/B9780125662512500137> doi: 10.1016/B978-012566251-2/50013-7
- Grudin, J., & Pruitt, J. (2002). Personas, Participatory Design and Product Development: An Infrastructure for Engagement. In *Proceedings of Participation and Design Conference (PDC2002)* (p. 8).
- Grudin, J., & Pruitt, J. (2006). Personas, participatory design and product development: An infrastructure for engagement. In *Proceedings of the Participatory Design Conference* (Vol. 11, pp. 144–161).
- Guan, K. W., Salminen, J., Jung, S.-G., & Jansen, B. J. (2023, September). Leveraging Personas for Social Impact: A Review of Their Applications to Social Good in Design. *International Journal of Human–Computer Interaction, 1–16*. Retrieved 2024-07-25, from <https://www.tandfonline.com/doi/full/10.1080/10447318.2023.2247568> doi: 10.1080/10447318.2023.2247568
- Guan, K. W., Salminen, J., Nielsen, L., Jung, S.-G., & Jansen, B. J. (2021). Information Design for Personas in Four Professional Domains of User Experience Design, Healthcare, Market Research, and Social Media Strategy. In *Proceedings of the 54th Hawaii International Conference on System Sciences (HICSS'21)* (p. 10). Retrieved from <http://hdl.handle.net/10125/71157> doi: 10.24251/HICSS.2021.540
- Hansson, L. E. J., Cerratto Pargman, T., & Pargman, D. S. (2021, May). A Decade of Sustainable HCI: Connecting SHCI to the Sustainable Development Goals. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems* (pp. 1–19). Yokohama Japan: ACM. Retrieved 2024-08-16, from <https://dl.acm.org/doi/10.1145/3411764.3445069> doi: 10.1145/3411764.3445069
- He, X., Zhan, X., & Hu, Y. (2017). The impact of policy incentives on electric vehicle adoption in China. *Transportation Research Part A: Policy and Practice, 103*, 188–200.
- Holland, J. H. (1992). Complex adaptive systems. *Daedalus, 121*(1), 17–30.
- Holling, C. S. (2001). Understanding the complexity of economic, ecological, and social systems. *Ecosystems, 4*(5), 390–405.
- Jacobs, J. (1961). *The Death and Life of Great American Cities*. Random House.
- Jansen, B. J., Jung, S.-g., & Salminen, J. (2019). Creating Manageable Persona Sets from Large User Populations. In *Extended Abstracts of the 2019 CHI Conference on Human Factors in Computing Systems* (pp. 1–6). ACM. doi: 10.1145/3290607.3313006
- Jansen, B. J., Jung, S.-g., Salminen, J., An, J., & Kwak, H. (2018, March). Leveraging Online Social Media Data for Persona Profiling. In (Vol. 2018, p. ICTPP78). Hamad bin Khalifa University Press (HBKU Press). Retrieved 2019-06-19, from <https://www.qscience.com/content/papers/10.5339/qfarc.2018.ICTPP78> doi: 10.5339/qfarc.2018.ICTPP78
- Jansen, B. J., Salminen, J., Jung, S.-g., & Guan, K. (2021a). Evaluating Data-Driven Personas. In *Data-Driven Personas* (pp. 209–237). Cham: Springer International Publishing. Retrieved 2024-08-08, from https://link.springer.com/10.1007/978-3-031-02231-9_1 (Series Title: Synthesis Lectures on Human-Centered Informatics) doi: 10.1007/978-3-031-02231-9_1
- Jansen, B. J., Salminen, J., Jung, S.-g., & Guan, K. (2021b). Selecting the Appropriate Persona Creation Method. In *Data-Driven Personas* (pp. 239–259). Cham: Springer International Publishing. Retrieved 2024-08-08, from https://link.springer.com/10.1007/978-3-031-02231-9_10 (Series Title: Synthesis Lectures on Human-Centered Informatics) doi: 10.1007/978-3-031-02231-9_10
- Jansen, B. J., Salminen, J. O., & Jung, S.-G. (2020, March). Data-Driven Personas for Enhanced User Understanding: Combining Empathy with Rationality for Better Insights to Analytics. *Data and Information Management, 4*(1), 1–17. Retrieved 2024-08-08, from <https://www.sciencedirect.com/science/article/pii/S2543925122000560> doi: 10.2478/dim-2020-0005

- Jensen, M., Elverum, C., & Steinert, M. (2017, March). Eliciting unknown unknowns with prototypes: Introducing prototrials and prototrial-driven cultures. *Design Studies*, 49, 1–31. doi: 10.1016/j.destud.2016.12.002
- Johnson, A., Martinez, K., & Liu, Y. (2020). Barriers to Sustainable Practices: Insights from Human-Nature Interaction Studies. *Environmental Management*, 55, 789–805.
- Jung, S.-G., Salminen, J., Aldous, K. K., & Jansen, B. J. (2025, March). PersonaCraft: Leveraging language models for data-driven persona development. *International Journal of Human-Computer Studies*, 197, 103445. Retrieved 2025-05-25, from <https://linkinghub.elsevier.com/retrieve/pii/S1071581925000023> doi: 10.1016/j.ijhcs.2025.103445
- Jung, S.-g., Salminen, J., Kwak, H., An, J., & Jansen, B. J. (2018). Automatic Persona Generation (APG): A Rationale and Demonstration. In *Proceedings of the 2018 Conference on Human Information Interaction & Retrieval - CHIIR '18* (pp. 321–324). New Brunswick, NJ, USA: ACM Press. Retrieved 2024-08-08, from <http://dl.acm.org/citation.cfm?doid=3176349.3176893> doi: 10.1145/3176349.3176893
- Keystone, J. R., & others. (2021). Biodiversity enhances ecosystem resilience to climate extremes. *Nature Communications*, 12(1), 1–10.
- Kim, J., Park, S., & Lee, H. (2015). Human-Nature Interactions: Enhancing Environmental Stewardship Through Urban Green Spaces. *Urban Forestry & Urban Greening*, 14, 45–53.
- Kishore Mahabani. (2024, February). Measuring the power of the Global South. *The World Today*(Feb-March 2024). Retrieved 2024-08-22, from <https://www.chathamhouse.org/publications/the-world-today/2024-02/measuring-power-global-south>
- Knowles, B., Bates, O., & Håkansson, M. (2018). This changes sustainable HCI. *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, 1–12. doi: 10.1145/3173574.3174045
- Kunhikrishnan, T., & Jose, S. (2021). Stakeholder engagement in renewable energy transitions: Lessons from social innovation. *Energy Research & Social Science*, 80, 102211.
- Lee, A., Zukauskaitė, M., & Barvidaite, V. (2017). Consumer behavior towards green energy: Evidence from a Lithuanian household survey. *Energy Policy*, 106, 733–743.
- Lee, O.-J., & Jung, J. J. (2019, September). Integrating character networks for extracting narratives from multi-modal data. *Information Processing & Management*, 56(5), 1894–1923. Retrieved 2019-10-15, from <http://www.sciencedirect.com/science/article/pii/S0306457318304618> doi: 10.1016/j.ipm.2019.02.005
- Li, Y., Shi, Y., Guo, J., & Zhao, X. (2020). Modeling consumer behavior in the sharing economy using activity theory and agent-based modeling. *Technological Forecasting and Social Change*, 155, 119986.
- Litman, T. (2020). *Autonomous vehicle implementation predictions: Implications for transport planning* (Tech. Rep.). Victoria Transport Policy Institute.
- MacKinlay, R. D., & Shaw, R. C. (2023). A systematic review of animal personality in conservation science. *Conservation Biology*, 37(1), e13935.
- Marsden, N., & Haag, M. (2016). Evaluation of GenderMag personas based on persona attributes and persona gender. In *International Conference on Human-Computer Interaction* (pp. 122–127). Springer.
- Meierhofer, J., Schweiger, L., Lu, J., Züst, S., West, S., Stoll, O., & Kiritsis, D. (2021). Digital twin-enabled decision support services in industrial ecosystems. *Applied Sciences*, 11(23), 11418.
- Moons, I., & Pelsmacker, P. D. (2012). Emotions as determinants of electric car usage intention. *Journal of Marketing Management*, 28(3-4), 195–237.
- Nah, F. F.-H., Zheng, R., Cai, J., Siau, K., & Chen, L. (2023, July). Generative AI and ChatGPT: Applications, challenges, and AI-human collaboration. *Journal of Information Technology Case and Application Research*.
- NEF, B. (2020). *Reinventing the Wheel: Mobility's Coming Transformation*.
- Newman, P., & Kenworthy, J. (1999). *Sustainability and Cities: Overcoming Automobile Dependence*. Island Press.
- Nielsen, L. (2002). From User to Character: An Investigation into User-descriptions in Scenarios. In *Proceedings of the 4th Conference on Designing Interactive Systems: Processes, Practices, Methods, and Techniques* (pp. 99–104). ACM. Retrieved from <http://doi.acm.org/10.1145/778712.778729> doi: 10.1145/778712.778729
- Nielsen, L. (2013). *Personas - User Focused Design* (1st ed.). London, UK: Springer-Verlag.
- Nielsen, L. (2019). Persona Writing. In L. Nielsen (Ed.), *Personas - User Focused Design* (pp. 55–81). London: Springer. Retrieved 2020-06-02, from https://doi.org/10.1007/978-1-4471-7427-1_4 doi: 10.1007/978-1-4471-7427-1_4
- Nielsen, L., Hansen, K. S., Stage, J., & Billestrup, J. (2015). A Template for Design Personas: Analysis of 47 Persona Descriptions from Danish Industries and Organizations. *International Journal of Sociotechnology and Knowledge Development*, 7(1), 45–61. Retrieved 2018-03-18, from <http://dx.doi.org/10.4018/ijskd.2015010104> doi: 10.4018/ijskd.2015010104
- OpenAI. (2022). *Introducing ChatGPT* \textbar OpenAI. Retrieved 2024-10-20, from <https://openai.com/index/chatgpt/> (Type: Introducing ChatGPT \textbar OpenAI)

- Philippon, T. (2016). *The fintech opportunity* (Tech. Rep. No. w22476). National Bureau of Economic Research.
- Piussi, P., & Farrell, E. P. (2000). Interactions between society and forest ecosystems: challenges for the near future. *Forest Ecology and Management*, 132(1), 21–28.
- Preist, C., Schien, D., & Blevis, E. (2016). Understanding and mitigating the effects of device and cloud service design decisions on the environmental footprint of digital infrastructure. *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*, 1324–1337. doi: 10.1145/2858036.2858378
- Putnam, R. D. (2000). *Bowling Alone: The Collapse and Revival of American Community*. Simon and Schuster.
- Roche, C. (2023). Ethics and diversity in artificial intelligence policies, strategies and initiatives. *AI and Ethics*.
- Rose, D. C., Sutherland, W. J., Parker, C., Lobley, M., Winter, M., Morris, C., & Dicks, L. V. (2016). Decision support tools for agriculture: Towards effective design and delivery. *Agricultural Systems*, 149, 165–174.
- Salminen, J., Froneman, W., Jung, S.-g., Chowdhury, S., & Jansen, B. J. (2020, April). The Ethics of Data-Driven Personas. In *Extended Abstracts of the 2020 CHI Conference on Human Factors in Computing Systems Extended Abstracts* (pp. 1–9). Association for Computing Machinery. Retrieved 2020-04-28, from <https://doi.org/10.1145/3334480.3382790> doi: 10.1145/3334480.3382790
- Salminen, J., Jung, S.-G., Chowdhury, S., Sengün, S., & Jansen, B. J. (2020, April). Personas and Analytics: A Comparative User Study of Efficiency and Effectiveness for a User Identification Task. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (pp. 1–13). New York, NY, USA: Association for Computing Machinery. Retrieved 2024-08-08, from <https://doi.org/10.1145/3313831.3376770> doi: 10.1145/3313831.3376770
- Salminen, J., Jung, S.-G., & Jansen, B. (2022, March). Developing Persona Analytics Towards Persona Science. In *27th International Conference on Intelligent User Interfaces* (pp. 323–344). Helsinki Finland: ACM. Retrieved 2024-08-05, from <https://dl.acm.org/doi/10.1145/3490099.3511144> doi: 10.1145/3490099.3511144
- Salminen, J., Jung, S.-g., & Jansen, B. J. (2021, December). Are Data-Driven Personas Considered Harmful? : Diversifying User Understandings With More Than Algorithms. *Persona Studies*, 7(1), 48–63. Retrieved 2024-07-25, from <https://ojs.deakin.edu.au/index.php/ps/article/view/1236> (Number: 1) doi: 10.21153/psj2021vol7no1art1236
- Salminen, J., Jung, S.-g., Medina, J., Aldous, K., Azem, J., Akhtar, W., & Jansen, B. J. (2024, July). Using Cipherbot: An Exploratory Analysis of Student Interaction with an LLM-Based Educational Chatbot. In *Proceedings of the Eleventh ACM Conference on Learning @ Scale* (pp. 279–283). Atlanta GA USA: ACM. Retrieved 2024-10-25, from <https://dl.acm.org/doi/10.1145/3657604.3664690> doi: 10.1145/3657604.3664690
- Salminen, J., Liu, C., Pian, W., Chi, J., Häyhänen, E., & Jansen, B. J. (2024, May). Deus Ex Machina and Personas from Large Language Models: Investigating the Composition of AI-Generated Persona Descriptions. In *Proceedings of the CHI Conference on Human Factors in Computing Systems* (pp. 1–20). Honolulu HI USA: ACM. Retrieved 2024-07-25, from <https://dl.acm.org/doi/10.1145/3613904.3642036> doi: 10.1145/3613904.3642036
- Salminen, J., Santos, J. M., Jung, S., Chowdhury, S. A., & Jansen, B. J. (2019). Persona Perception Scale: Developing and Validating an Instrument for Human-Like Representations of Data. *International Journal of Human-Computer Studies*, 129, 1–14.
- Salminen, J., Santos, J. M., Jung, S.-g., & Jansen, B. J. (2023, December). How does an imaginary persona’s attractiveness affect designers’ perceptions and IT solutions? An experimental study on users’ remote working needs. *Information Technology & People*, 36(8), 196–225. Retrieved 2024-08-08, from <https://www.emerald.com/insight/content/doi/10.1108/ITP-09-2022-0729/full/html> doi: 10.1108/ITP-09-2022-0729
- Salminen, J., Santos, J. M., Kwak, H., An, J., Jung, S.-g., & Jansen, B. J. (2020, September). Persona Perception Scale: Development and Exploratory Validation of an Instrument for Evaluating Individuals’ Perceptions of Personas. *International Journal of Human-Computer Studies*, 141, 102437. Retrieved 2024-08-08, from <https://www.sciencedirect.com/science/article/pii/S1071581920300392> doi: 10.1016/j.ijhcs.2020.102437
- Salminen, J., Wenyun Guan, K., Jung, S.-G., & Jansen, B. (2022, April). Use Cases for Design Personas: A Systematic Review and New Frontiers. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems* (pp. 1–21). New York, NY, USA: Association for Computing Machinery. Retrieved 2024-08-08, from <https://dl.acm.org/doi/10.1145/3491102.3517589> doi: 10.1145/3491102.3517589
- Salminen, J., Şengün, S., Kwak, H., Jansen, B. J., An, J., Jung, S.-g., . . . Harrell, D. F. (2018, June). From 2,772 segments to five personas: Summarizing a diverse online audience by generating culturally adapted personas. *First Monday*, 23(6). Retrieved 2020-04-01, from <https://www.firstmonday.org/ojs/index.php/fm/article/view/8415> doi: 10.5210/fm.v23i6.8415
- Sattele, V., & Carlos Ortiz, J. (2024). Generating user personas with ai: Reflecting on its implications for design. *DRS2024:Boston*.
- Scheer, H. (2004). *The Solar Economy: Renewable Energy for a Sustainable Global Future*. Earthscan.

-
- Schmidt, O., Hawkes, A., Gambhir, A., & Staffell, I. (2017). The future cost of electrical energy storage based on experience rates. *Nature Energy*, 2(8), 17110.
- Schuller, A., Janssen, D., Blumenröther, J., Probst, T. M., Schmidt, M., & Kumar, C. (2024). Generating personas using LLMs and assessing their viability. In *Extended Abstracts of the 2024 CHI Conference on Human Factors in Computing Systems*. New York, NY, USA: Association for Computing Machinery. Retrieved from <https://doi.org/10.1145/3613905.3650860> doi: 10.1145/3613905.3650860
- Sengün, S., Salminen, J., Jung, S.-G., Aldous, K. K., & Jansen, B. J. (2024, July). “There’s Something About Noura”: Exploring Think-Aloud Reasonings for Users’ Persona Choice in a Design Task. In *Designing Interactive Systems Conference* (pp. 1234–1247). IT University of Copenhagen Denmark: ACM. Retrieved 2024-08-08, from <https://dl.acm.org/doi/10.1145/3643834.3661512> doi: 10.1145/3643834.3661512
- Sheng, E., Joe, L., Alambo, A., & Solaiman, I. (2021). A societal-aware methodology for managing bias in AI applications. *Patterns*, 2(6), 100238.
- Shin, J., Hedderich, M. A., Rey, B. J., Lucero, A., & Oulasvirta, A. (2024, July). Understanding Human-AI Workflows for Generating Personas. In *Designing Interactive Systems Conference* (pp. 757–781). IT University of Copenhagen Denmark: ACM. Retrieved 2024-07-25, from <https://dl.acm.org/doi/10.1145/3643834.3660729> doi: 10.1145/3643834.3660729
- Smith, T., Nguyen, P., & Brown, C. (2021). Enhancing Community Well-Being Through Human-Nature Interaction Personas. *Journal of Community Psychology*, 49, 123–140.
- Stern, P. C. (2000). Toward a coherent theory of environmentally significant behavior. *Journal of Social Issues*, 56(3), 407–424.
- Sun, L., Qin, T., Hu, A., Zhang, J., Lin, S., Chen, J., ... Prpa, M. (2025). Persona-L has Entered the Chat: Leveraging LLMs and Ability-based Framework for Personas of People with Complex Needs. In *Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems*. New York, NY, USA: Association for Computing Machinery. Retrieved from <https://doi-org.proxy.uwasa.fi/10.1145/3706598.3713445> doi: 10.1145/3706598.3713445
- Sun, Z., Sun, L., & Strang, K. D. (2016). Big data analytics services for enhancing business intelligence. *Journal of Computer Information Systems*, 56(2), 133–145.
- UN-Habitat. (2009). *Planning Sustainable Cities: Global Report on Human Settlements 2009*. Earthscan.
- United Nations. (2015). *Transforming Our World: The 2030 Agenda for Sustainable Development*. United Nations General Assembly.
- United Nations. (2018). *World Urbanization Prospects: The 2018 Revision*. Department of Economic and Social Affairs, Population Division.
- Vergani, F., & Di Liberto, F. (2024). Designing from the plants’ perspective. a field case study in urban forest of “la goccia”. *DRS2024:Boston*.
- Vinuesa, R., Azizpour, H., Leite, I., Balaam, M., Dignum, V., Domisch, S., ... Fuso Nerini, F. (2020, January). The role of artificial intelligence in achieving the Sustainable Development Goals. *Nature Communications*, 11(1), 233. Retrieved 2024-08-20, from <https://www.nature.com/articles/s41467-019-14108-y> (Publisher: Nature Publishing Group) doi: 10.1038/s41467-019-14108-y
- Wang, L., Zhao, M., & Chen, R. (2019). Global Perspectives on Incentive Policies for Electric Vehicle Adoption. *Sustainable Cities and Society*, 44, 597–603.
- Wells, P., & Nieuwenhuis, P. (2010). Understanding the changing automotive industry: dynamics of supply and demand. *International Journal of Automotive Technology and Management*, 10(2-3), 121–135.
- Wilensky, U., & Rand, W. (2015). *Introduction to agent-based modeling: modeling natural, social, and engineered complex systems with NetLogo*. MIT Press.
- Wilson, A., De, P. S., Forbes, P., & Sachy, M. (2020, November). Creating personas for political and social consciousness in HCI design. *Persona Studies*, 4(2), 25–46. Retrieved 2024-08-19, from <https://search.informit.org/doi/abs/10.3316/informit.032482973719629> (Publisher: Deakin University - School of Communication and Creative Arts) doi: 10.3316/informit.032482973719629
- World Economics. (2024, August). *Global South* [Economic Data]. Retrieved 2024-08-22, from <https://www.worlddeconomics.com/Regions/Global-South/default.aspx>
- Yang, S., & Lee, H. (2018). Identifying electric vehicle drivers’ characteristics and their intention to adopt electric vehicles. *Transportation Research Part D: Transport and Environment*, 57, 116–127.
- Yanlic, B. S., & Coskun, A. (2024). Understanding the needs of nonhuman stakeholders in design process: An overview of and reflection on methods. *arXiv preprint arXiv:2407.14750*.
- Zhou, L., Fang, Y., Ding, S., Cheng, Y., Yan, B., Zhu, W., ... Song, S. (2024). Vivid-persona: customizable persona tool with interactive and immersive experiences. *Journal of Engineering Design*, 0(0), 1–22. Retrieved 2024-10-22, from <https://doi.org/10.1080/09544828.2024.2383543> (Publisher: Taylor & Francis _eprint: <https://doi.org/10.1080/09544828.2024.2383543>) doi: 10.1080/09544828.2024.2383543

Zhuo, T. Y., Huang, Y., Chen, C., & Xing, Z. (2023, May). *Red teaming ChatGPT via Jailbreaking: Bias, Robustness, Reliability and Toxicity*. arXiv. Retrieved 2024-08-20, from <http://arxiv.org/abs/2301.12867> (arXiv:2301.12867 [cs]) doi: 10.48550/arXiv.2301.12867