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Matching Synthetic Populations with Personas: A Test Application for Urban Mobility

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Abstract

Design is increasingly influenced by digitalisation yet differs largely across domains. We present synergies between the works of UX designers and data scientists. We can utilise personas to represent users and their behaviours, or synthetic populations to represent agent groups. Despite sharing characteristics, their synergies have not been explored so far. We propose a workflow and test it in the urban mobility context to link a synthetic population of Paris with a set of contextual personas. This builds the basis for an integrated approach for designing urban mobility across fields.

Keywords: user-centred design, data-driven design, inclusive design, persona, synthetic population

1. Introduction

Design engineering activities are increasingly influenced by digitalisation. The consequences for design research can be classified into three areas of interest: (1) Modification of the designer's activity, individually or in a team; (2) Transformation of the design processes through digitalisation; and (3) Development of tools for supporting data-driven design processes (Cantamessa et al., 2020). A data-driven design process impacts the role of designers and the collaboration between designers and data scientists. Lu et al. (2021) list four roles that require new skills from designers: (1) Translator, to be aware of the data science jargon to communicate with data scientists; (2) Empathiser, to be able to tell stories based on data; (3) Project leader, to ask and answer questions through data; and (4) Analyst, to decide what data to collect and how to process them. This paper contributes primarily to designers' roles as translators by aligning two traditionally distant user-centric tools and proposing a workflow that combines them to feed both processes with novel insights.

While the proposed approach remains general, the dominant application of both methods is urban mobility design. Thus, we chose examples from that domain. In the urban mobility design field, some approaches inspired by User Experience (UX) design focus on developing individual mobility experiences (Al Maghraoui et al., 2019). This is usually done in a qualitative manner. More specifically, persona models can inform designers on users' diversity by providing some archetypical fictional representations, including a name, socio-economic characteristics, and a short story (Cooper, 1999). They can help consider the 'spirit' of users in the design process. However, they are mostly qualitatively shaped or imagined and not strongly linked to an actual population.

On the other hand, data-driven methods can model the behaviour of individual agents (commuters, for example) via agent-based simulations, quantitatively ruled by a utility function at the scale of a geographical area (district, city, or region). A synthetic population (SP), representative of the target area, must be created for such methods to feed the simulation model. The SP represents the individual agents for whom there is no access to microdata but only a set of aggregated data. SP are used extensively to understand detailed individualised, optimised mobility services today (for instance, sharing and on-demand services). However, they are neither used as inputs to inform the design process of new developments nor adapted to possible future changes within the population, such as changing qualitative components, changing practices or behaviours. We argue that the merged approach between SP and persona-based methods can contribute to this while simultaneously feeding into the persona development. Therefore, the described process shall lead to an improved consideration of qualitative changes in SP-fed approaches and a more context-specific and future-trend responsive design in simulating, for example, urban mobility solutions.

The motivation of the paper is to present cross-fertilised knowledge between UX designers and data scientists working with simulation to contribute to both sides. The assumption is that SP act as the link between the primarily quantitative, data-driven simulation and system optimisation on the one side and more qualitative and user-centred approaches on the other. The research questions are: **'What are synergies between synthetic populations (SP) and persona-based approaches, and how can they strengthen and complement each other?'**

To answer to these questions, this paper is organised in four sections following the introduction. The next chapter provides a short literature review and background description of persona-based models as well as SP. The third chapter presents a proposed workflow between the two models. Subsequently, the approach is tested in the case of building the user-centred foundation for urban mobility design in Paris. Lastly, we discuss the findings so far and outline future research, in particular (1) how to expand the approach to integrate qualitative trends and/or scenarios from the personas and their distribution into the SP model, as well as (2) how to build on the underlying replicable, open-source SP generation to standardise the persona generation and matching process.

2. An overview of personas and synthetic populations

This section briefly presents core characteristics of persona models and typical types of development, as well as synthetic populations and their role in, for example, multi-agent simulations. The latter pays particular attention to its application in mobility and transport and its connected data sources and characteristics due to its dominance in this field. The section is completed by a short description of works related to this paper's ambition.

2.1. Personas

When designing current and future services or designs, it is necessary to consider the diversity of usages and lifestyles. Designers can use personas to consider individual differences. Frequently implemented in user-centred design, a persona model is a fictitious character representing a homogeneous class of users (Cooper, 1999). Etymologically, persona originates from the Latin word 'personare', meaning 'speaking through' (Bornet et Brangier, 2013). In ancient Greek theatre, the persona was a masking prop worn by comedians to embody their character fully.

Bornet and Brangier (2013) specify that personas help represent users in a prospective mode and embed three main characteristics: (1) a user model; (2) a communication tool; (3) a decision aid and prospective tool. A persona is traditionally defined by a name, a photo and a narrative section describing specific attitudes and behavioural traits (Adlin and Pruitt, 2010). The narrative part gives life to the persona (Cooper, 1999; Grudin and Pruitt, 2002).

Persona generation can follow three main approaches (Salminen et al., 2020). First, we can complement fictional elements with qualitative data from interviews. Goodman-Deane et al. (2021) report the creation of twelve personas to study digital exclusion, using a quantitative questionnaire with 328 participants conducted in public space and ten interviews followed by cluster analysis. Second, we can build personas upon fictional elements (Vallet et al., 2020). Third, given the rise of big data in design, the most recent approach relies on massive data or quantitative surveys, leading to 'data-driven' or statistically representative personas (see persona generator by Stevenson and Mattson, 2019).

Having a set of personas creates a joint base for discussion between designers and their clients (Grudin and Pruitt, 2002). Using personas for manufactured products and services design is common. It appears in design approaches for mobility services, for example, to feed the emotional design of autonomous shuttles (Kong, Cornet, and Frenkler, 2018) or the design of a dynamic ride-sharing

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service (Gargiulo et al., 2015). While personas represent a real or imaginary population, synthetic populations reflect an actual population. We introduce the latter in the following section.

2.2. Synthetic populations

The literature describes synthetic populations as digital representations of the real population (Ramadan and Sisiopiku, 2020; Hermes and Poulsen, 2012). Rather than macroscopic descriptions such as zonal population densities, synthetic populations represent reality in terms of individual persons, often grouped into households. On the personal and household level, sociodemographic attributes are available for the individuals ('agents'). There is a broad range of literature on generating such synthetic populations. Some approaches based on statistical fitting algorithms (Durán-Heras et al., 2018; Yameogo et al., 2021) aim at generating individuals such that specific attributes like age or income classes are distributed according to given reference distributions, often on a zonal level, to preserve spatial heterogeneity. Other approaches make use of disaggregated but sparse data sets such as household travel surveys, for instance, by describing them using Bayesian networks (Sun and Erath, 2015) or Hidden Markov Models (Saadi et al., 2016). The latter allows sampling persons such that population-level characteristics are maintained. Recently, efforts have been put into methods for fusing multiple sources of information based on machine learning and deep generative modelling (Borysov et al., 2019; Saadi et al., 2018).

Synthetic populations are frequently used in modelling the mobility patterns of the population. This allows, for instance, the simulation of novel mobility services (Hörl et al., 2021) by integrating them in the daily schedules of the synthetic persons, estimating externalities from greenhouse gases and noise emissions (Le Bescond et al., 2021), or assessing energy use policies (Panos and Margelou, 2019) based on the activities performed by the population. To perform such analyses, not only a synthetic population but synthetic travel demand is needed, which arises when also synthesising the daily mobility patterns. Various methods have been proposed, some of which are well-established, such as activity-based modelling (Rasouli and Timmermans, 2014). While those tend to depend strongly on context-specific statistical models with significant needs in calibration, novel tools look increasingly into more data-focused approaches and machine learning, for instance, using Bayesian networks (Joubert and de Waal, 2020). While following closely observed data patterns, the latter gives modellers vast freedom to modify the person's behaviour and test hypotheses on travel and consumption patterns. At the same time, methods for using large-scale mobility trace data from GPS or phone records are explored (Anda et al., 2021).

2.3. Existing approaches combining big data and personas

Recent studies report more quantitatively informed personas through surveys (Schäfer et al., 2019; Goodman-Deane et al., 2021) or big data (Stevenson and Mattson, 2019). On the other hand, on the synthetic population side, attempts are made to enrich traveller agents by persona model attributes by using semantic technology (Nguyen et al., 2021). This semantic structure bears the potential to reuse the agents in different scenarios, which is otherwise a complicated task (Nguyen et al., 2021). While existing approaches provide valuable insights on various processes, such as using a large quantity of data to build a persona set, they neither fully consider the bi-directional communication between both parts nor adapt to future situations. Thus, despite the common attributes of personas and synthetic populations, their practical connection remains a challenge.

3. Linking persona models and synthetic population

This section describes the research method, focusing on the process of combining the two approaches, their respective application in more detail, and finally, the proposed combined approach.

3.1. Approach

This work is a multidisciplinary collaboration between the authors: two (user-centred) designers and a multi-agent simulation data scientist. We looked at different SP generation and persona development components, exploring the mismatches and connection points. Figure 1 acknowledges that (1) both

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data-based personas and SP can originate from aggregated data (surveys, census data…); and (2) Relying on an SP could be an alternative path to generate personas, as these models can share some features (e.g., socio-professional category, age, sex, living area).

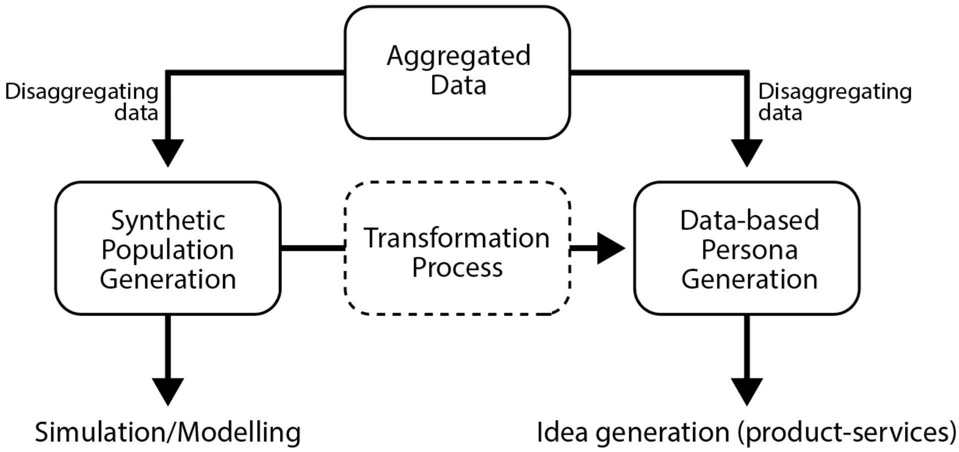

Figure 1. Initial model for linking synthetic population and personas

Building on this, a combined method framework has been developed (Figure 2). It shows the input data and SP development on the left side, resulting in n households and nested individuals with their socio-economic profiles, activity profiles, mobility-specific resources, and constraints. These households are clustered (exemplary described in 4.1) and fed into the persona development. With qualitative input (in this case from the authors) and a set of base personas created for a prospective study (Elioth, 2017), several personas are attributed to the different clusters, with varying numbers depending on the overall occurrence of clusters within in the SP, as well as the probability of the 'model fit' of the attributes of the personas to the respective clusters.

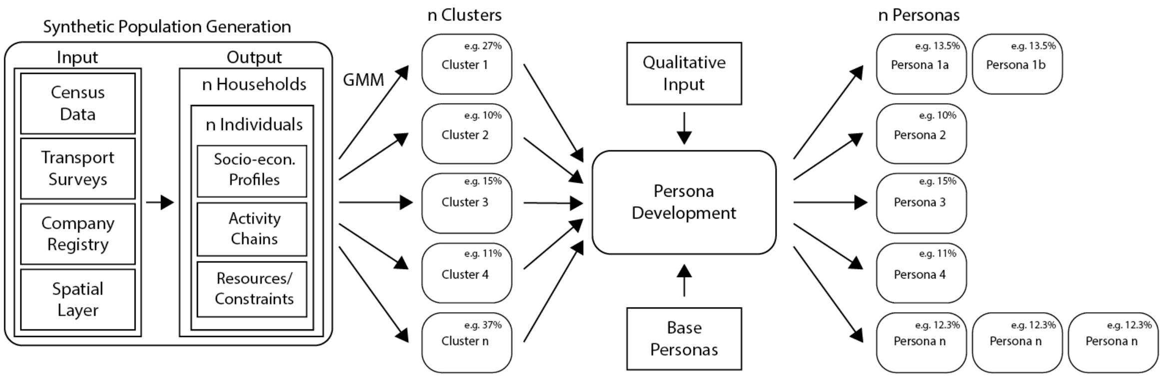

Figure 2. Process description from SP (left) to clusters (centre) to personas (right)

4. The example of supporting urban mobility design

SP are already used in different fields, primarily in energy consumption or mobility and transport simulation. New areas which require a detailed understanding of varying profiles are explored. We chose the case of urban mobility due to the dominant co-occurrence of both approaches to exemplary apply the concept behind the proposed workflow.

In the first step, the goal is to link SP and personas through clustering. Building on this, we can use SP to inform a data-driven approach for persona development. Finally, the SP can be adapted based on qualitative attributes of the personas. The described example below focusses on the first step as the core ambition of this paper.

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The development of the original SP is seen as the universal starting point. From this, clusters of socio-economic characteristics are formed and, after that, attributed to Paris' spatial features (arrondissements, meaning administrative sub-divisions). These clusters are attributed qualitatively by two of the authors to a set of pre-existing, local personas. The preparatory processes are described in more below, followed by a more detailed description of the clustering and assignment processes.

Synthetic population generation: Hörl and Balac (2021) proposed a method that generates a synthetic travel demand data set for Paris based on publicly available and open data. The pipeline starts with detailed census data, which is used to generate an SP of households and individuals, including sociodemographic attributes and their place of residence. Afterwards, a statistical matching method is used to attach daily activity chains to those individuals, either based on an openly available national household travel survey or a proprietary regional one if available to the user. The procedure is the first of its kind that is entirely repeatable by any researcher, as the process itself is published as open source. Therefore, the research based on the resulting synthetic travel demand is reproducible, and verification is possible. To date, the travel demand data has been used to estimate the impact of an Automated Mobility on Demand (AmoD) service within the city boundaries of Paris (Hörl et al., 2019).

Selecting an existing set of personas: We selected an existing set of personas because the focus lies on matching personas with a synthetic population. It is based on the quality of the development process and adequacy of provided information to allow the matching with the SP. Nine existing households (13 individual personas) are in a study on the transition of lifestyles towards 2050, including mobility habits (Elioth, 2017). The personas were extracted and synthesised in Table 1. The development of personas from the SP is possible as well and will be tested at a later stage.

4.1. Clustering synthetic populations for Paris

For a first proof-of-concept, we generated and analysed synthetic travel demand for Paris. We estimated a Gaussian Mixture Model (GMM) using the scikit-learn package in Python for the analysis. Next, we chose the clustering attributes sex, age, and socio-professional category. The latter is a standard statistical classification of individuals applied by the French statistical office (INSEE, 2021) with eight levels, including independent business owners, employees, workers, retired and unemployed persons. The GMM is a two-level approach with a predefined number of clusters. We chose eight clusters for this example. Each cluster is represented as a multivariate normal distribution over the individuals' attribute values, with a distinct per-cluster weight. An interesting property of the GMM model is that individuals have fractional class memberships, i.e., one agent may belong to 20% to the first class and 80% to the second class. To visualise the resulting clusters, we show the three attributes and their attributes and the mean of the corresponding normal distribution. For instance, cluster 5 has a mean in 'Age' of 67 (Figure 3, indicated by the horizontal red line), while cluster 6 has a value of 52 (not shown). Cluster 5 captures retired people, while cluster 4 refers to children. Furthermore, we visualise the variability along one attribute dimension in relative terms using the vertical line.

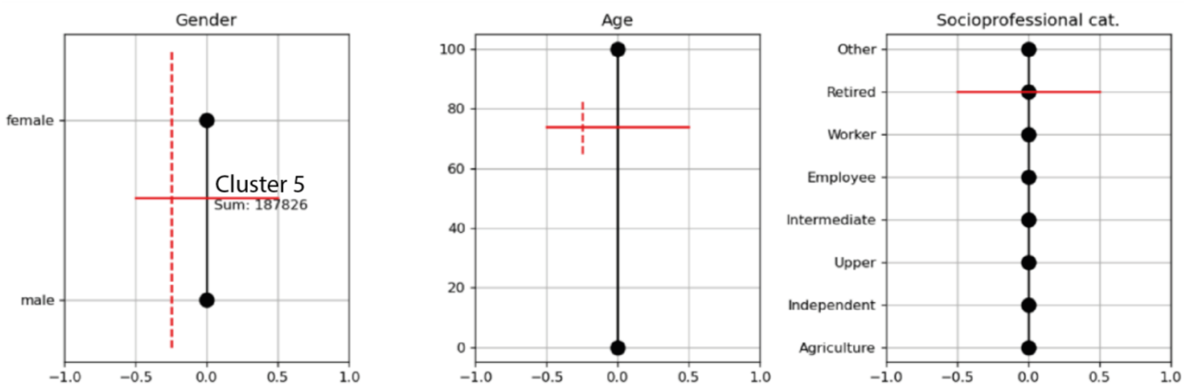

Figure 3. Representation of attributes for cluster 5 'Retired people'

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Figure 4 (right) shows the overall number of memberships to each cluster across the population. For a more detailed analysis, Figure 4 (left) shows the arrondissements in Paris and the weight of each cluster among the persons in each cluster. Finally, Figure 5 shows a spatial analysis of the clusters, clearly indicating that some have higher relevance in some arrondissements while being less or not represented in others.

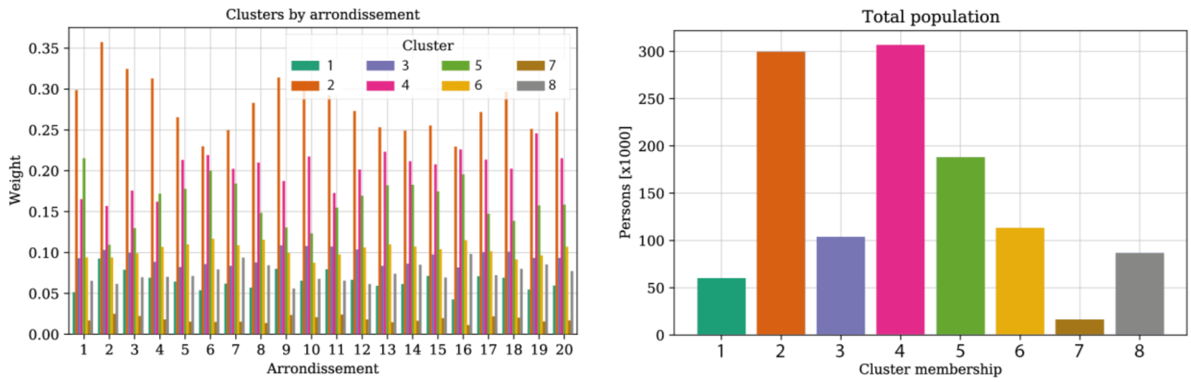

Figure 4. Cluster by arrondissement (left), population by cluster (right)

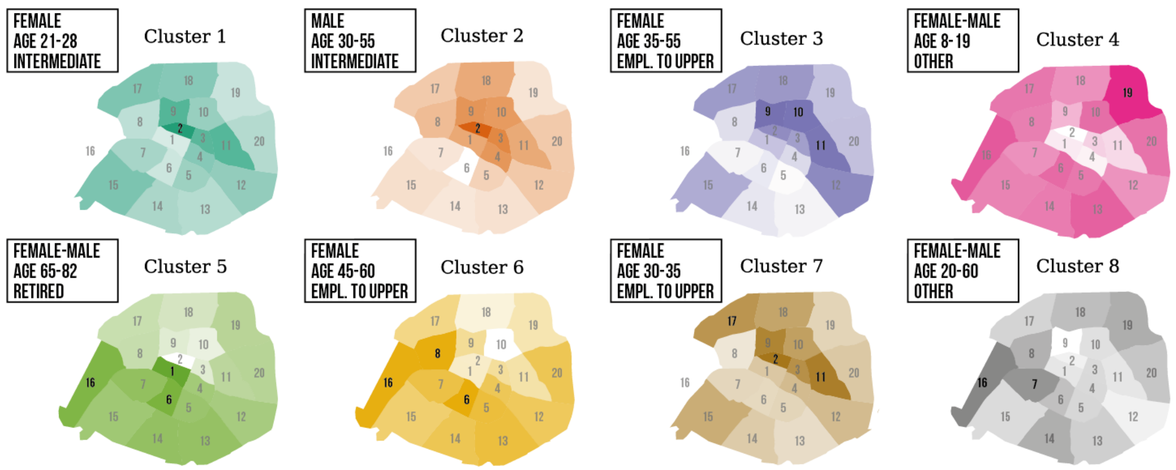

Figure 5. Cluster distribution per arrondissement (darker = higher occurrence)

4.2. Matching personas with clusters

We matched the above-described set of personas for Paris (Elioth, 2017; for the closest year to the present) with the clusters to check and explore the correspondence. This process allows creating a geographical mapping of personas and complementing their description. Table 1 shows the personas (partially grouped in households), their pre-existing characteristics and attributed probable cluster. For instance, for the persona 'Stéphanie', the matching between sex, position and age was primarily compared to clusters definition, showing compatibility with cluster 3: age span [35-55], socio-professional category [employee-upper]. Secondly, the compatibility check for cluster 3 showed that the 13th arrondissement was not a probable living area. Provided a slight change in Stéphanie's age from 41 to 46, cluster 6 is more suitable for all attributes, thus the choice for this persona. Alternatively, we could consider Stéphanie representative for cluster 3 if she lived in the 11th or 12th arrondissement. We repeated the same approach for all personas, with minor adjustments as described above in a few cases.

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Table 1. Persona development for Île-de-France (personas from Elioth, 2017)

PERSONAS	STÉPHANIE	MONIQUE	JACQUES	LEILA	JULIEN	ERIC	NADIA	OLGA	CAMILLE	EMILIE	MANUEL	THIERRY	ADNAN
AGE	41	65	68	28	32	53	53	77	22	34	39	50	22
POSITION	Care assistant	Retired		IT project manager		Journalist	Asset manager	Retired	Student	Teacher	Civil servant	Job seeker	Syrian refugee
CHILDREN	1	0		0		2		0	0	1		0	0
STATUS	Modest	High		Average		Very high		Average	Modest	Average		Modest	Very modest
APP. SIZE	44 sqm	90 sqm		45 sqm		256 sqm		60 sqm	16 sqm	56 sqm		36 sqm	15 sqm
ARRONDIS.	13th	4th		9th		7th		16th	19th	2th		14th	18th
HOUSING	S	-		R		-		-	SH	-		S	H-T
SHORT TRIPS	Car	Car		Petrol scooter		Car	Taxi	Bike	Public transport	Public transport (PT)		Walk/PT	Walk
LONG TRIPS	Train	Car	Plane	Train	Plane	Car	Plane	Plane	Carsharing /train	Car	Plane	Car pooling	HiH Carsharing
NUTRITION	Carnivore	Omnivore		Carnivore		Carnivore		Carnivore	Flexiterian	Flexiterian		Carnivore	Omnivore
CLUSTER	C6	C5		C1	C2	C8	C6	C5	C1/C8	C7	C2	C8	C8

SH: Social housing; R: Rent; S: Shared; H: Hostel; T: Tent; PT: Public transport; HiH: Hitchhiking

This approach allows matching personas with clusters (multiple with varying probability) and matching clusters with arrondissements with varying distributions (Figure 6). Note that in the defined clusters, extreme personas with very high income (Eric, Nadia) or modest male personas (Adnan and Thierry) cannot easily fit. However, considering this social contrast can be seen as important for studying the transition of lifestyles in Paris. Cluster 4 was not populated as the personas did not include children.

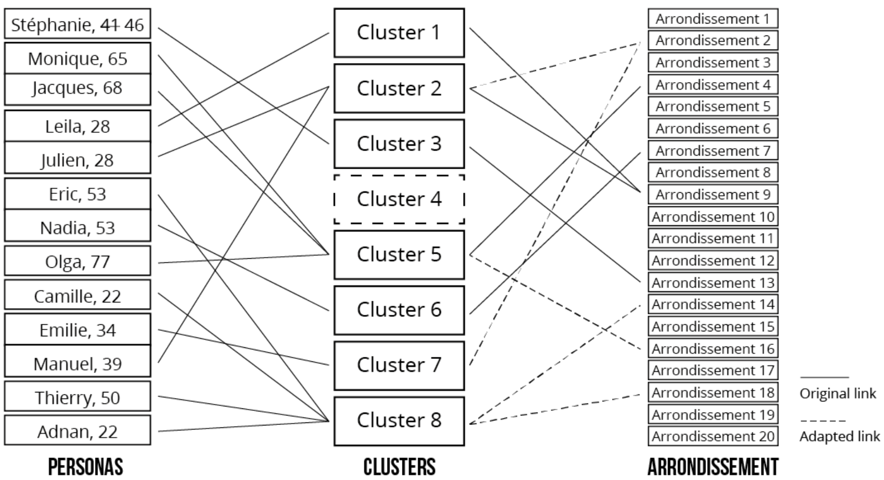

Figure 6. Matching of personas, clusters, and arrondissements

5. Discussion

Compared to the work by Goodman-Deane et al. (2021), the proposition can reduce the effort of persona development as it avoids an additional large-scale primary data collection. Further, the workflow shares characteristics with the computational persona generator introduced by Stevenson and Mattson (2019). Similarly, we intend to create a set of representative personas for product and service design starting while de-aggregating national-level data collected by public or private organisations. In Stevenson and Mattson's (2019) work, the authors generate a large population of statistically representative personas followed by filtering and creating a reduced number of realistic individual personas. In comparison, we start by generating a complete synthetic population of agents and replace filtering with clustering, our personas being centroids of the population clusters. The current paper proposes a workflow that allows navigating between product and service development

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for a set of personas on one side and simulation of individual behaviours of the same personas on the other side.

We chose to work with an existing set of personas in this example due to their existence and suitable characteristics. Two further directions are possible. Either we compile or build a set of base personas that can be adapted and chosen according to specific contexts. Alternatively, we can add the persona-development process as another in-between step, building on the quantitative input from the SP. The focus remains on the former, while we must consider the latter in geographical or topical contexts that lack well-developed personas. The persona-based analysis of clusters as proposed above can be used, for example, to generate new populations for areas of a city or take socio-economic changes and societal trends into consideration. To do so, we can redefine cluster probabilities for a specific neighbourhood to design the expected mix of populations in a to-be-developed area. Using the GMM, it is possible to sample households and personas from the baseline population. Those new personas can be used in various fields, such as transport and mobility simulations or energy assessment models. For the moment, different limitations remain.

On the clustering side, the adequate approach for clustering and the number of clusters requires further attention, experimentation, and validation. Nevertheless, a significant number of works in the field strengthen the generation of SP and their clustering towards being robust and reproducible. On the side of personas, we build on existing works of standardised and validated persona development processes, which – while remaining always more subjective than the SP, ensure a solid approach within inherent limitations. Lastly, the above work describes a static situation. In the following steps, different components shall be adapted to explore different constellations and potentials of the approach. These can be, for example, the adaptation of cluster distribution or characteristics, the changing attribution of clusters to arrondissements, or the qualitative adaptation of personas (and/or their groups) with a subsequent adaptation of clusters and SP on that basis.

6. Conclusion and future work

This paper aimed to elaborate on synergies between synthetic populations (SP) and persona-based approaches and how these can contribute to, for example, designing people-centred urban mobility. After clarifying the attributes of both models, we proposed a framework to move from an SP to intermediate clusters and finally to a set of personas associated via the clusters. Through this process, persona development can be nourished by following a data-driven approach. Further, it can be supplemented by an SP's spatial information and activity chains. Activity chains are another layer of information in SP that contain detailed information on geo-referenced stations throughout the day and associated departure/arrival times and/or stay durations. In the case of SP, the qualitative data can, on the one hand, contribute to the quality of the SP itself while further allowing the modelling, simulations, and adaptation of SP. Bringing the two approaches together may allow the integration of primarily qualitative trends in the future SP development processes to inform changing personas and, thus, changing distributions of clusters, which informs the simulations part. In this paper, the focus is on the initial analysis and concepts. The following steps are the direct generation of personas based on an SP and the reverse adaptation of SP based on personas. In summary, this paper contributes to data-driven design by proposing a collaboration ground between UX designers and data scientists developing simulation models.

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