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(FRS) FUTURE RESILIENT SYSTEMS

Social Archetypes and Social Resilience – Framework and Methodology

#8

Executive Summary

Cities and their residents are faced with an increasing number of challenges and stresses, such as more extreme natural hazards, unexpected outbreaks of viruses, ageing population, more diverse social groups etc. Many of these challenges and stresses may turn into disruptions with devastating consequences to the well-being of urban communities. It is, therefore, paramount to build resilient urban societies that can anticipate, manage and recover from any known and unknown future disruption. In this working paper, we offer a conceptual framework for understanding social resilience in urban environments, modelling social resilience based on the concept of social archetypes. This framework helps to understand the social resilience performance of different social groups sharing capacities, perceptions, and contexts.

Background

The document has been created in support of the project "Social resilience archetypes and live-work trends", a collaboration project between the Singapore-ETH Centre (SEC) and the Centre for Liveable Cities.

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1 Social Archetypes as a Tool to Assess Social Resilience

1.1 The Need for Social Resilience

Social resilience has been commonly referred to as the ability or capacity of groups of individuals or a community to respond positively to and recover from a crisis [1-4]. A high level of social resilience is desirable as it reflects a strong ability of social entities to maintain stable interactions and collaborations between individuals, as well as between individuals and their respective governing institutions in times of crisis [5]. Crises may occur as a result of climate change, rapid urbanization, migration, pandemics, digitalization, economic and geopolitical transformations, etc. [6-8]. Given the numerous threats, challenges, and disruptions we may be confronted with in the next years and decades, social resilience is of utmost importance to ensure society's prosperity and well-being [9].

Key factors determining the level of social resilience are social capital, social values and mechanisms, social diversity and equity, social beliefs, and social structures [2, 10]. According to many empirical studies, social capital, encompassing social support, support networks and social cohesion seems to be the most relevant factor with respect to geological hazards, like earthquakes or disruptions like hurricanes, floods, etc [2, 3, 10]. It is shaped by the psychological, cognitive and socio-demographic attributes of individuals, as well as by social, economic, technical and institutional factors [2, 11-13].

1.2 What Are Social Archetypes?

In the past, the analysis of social resilience was essentially done through the measurement of various social resilience indicators. Yet, the diversity of lifestyles today as well as the considerable dynamics of individuals and groups under changing lifestyle trends and disruptions make it imperative to depart from static indicator measurements. The concept of social archetypes seems adequate to cope with such dynamic changes and to contribute to the understanding of the respective societal dynamics, especially when disruptions occur. Social archetypes represent clusters of individuals which are characterized by small differences related to specific attributes within a specific cluster and larger attribute differences compared to people in other clusters. Based on social archetypes, patterns in perceptions, attitudes or behaviours may be unveiled [14]. For instance, consumer archetypes would show profiles of different user behaviours with respect to a specific service or product [15]. The Appendix shows examples of the applications of existing archetypes in Singapore. Archetypes are context-dependent, and identified with respect to a specific research question [14].

Social archetypes focus on individuals' attributes like personality, value orientation, attitudes, socio-demographic traits, behaviours, social connections, experiences etc. [16-20]. Social archetypes help identify groups of individuals with strong or weak interest in other people, presence, or absence of knowledge of how to support others, individuals with altruistic or egocentric values etc. Hence, social archetypes enable the identification of groups of individuals that should be targeted in similar or differential ways if interventions to cope with crises are designed [21-23].

The concept of social archetypes is similar to the concept of 'personas'. Both concepts aim to identify population subgroups sharing commonalities in attributes like socio-demographic characteristics, perceptions, attitudes, beliefs, or behaviours [21-24]. The key difference between archetypes and personas is how the information about subgroups is presented [25]. Personas are often presented with a human face, adding detailed biographical information. For example, in the presentation of a persona 'The isolated elderly', names, specific details and often photos are shared. You would see, for instance, the picture of an elderly man named Ahmad, aged 75, of Malay ethnicity, living in a 2-room public housing flat, having low mobility but aspiring to live independently [24]. Social archetypes would provide a more general portrait of a group of individuals and their core characteristics [21-23]. Vaillancourt et al. (2014), for instance, identified a patient archetype in the emergency department as a 'medical complexity' archetype [26]. This archetype was described as patients with limited physical energy, social support, and psychological intervention requirements [26].

Social archetypes and personas each have their own merits. Well-crafted personas invite empathy and form powerful narratives that might be more impactful [27]. Yet, focusing on a specific type of individual may generate biases and implicit exclusion of similar individuals [27]. Social archetypes support a more inclusive approach by avoiding personified characters and emphasize to look at groups of people with similar attributes [25].

1.3 How Social Archetypes Can Be Used to Assess Social Resilience

As mentioned above, societies are confronted with many serious threats, and disruptions. To cope with some of them, governments design and implement various interventions on national, regional and community levels. Given the aforementioned importance of social resilience for the well-being of populations, it matters to know the social resilience impacts of crises as well as of government interventions.

Often, social resilience implications of disruptions or interventions are assessed through the lens of different socio-demographic or socio-economic groups [28-30]. Yet, focusing on socio-demographic or socio-economic groups may not provide sufficient clarity on how individuals and social groups perform during disruptions. We all agree that there are some specifically vulnerable groups like older adults, poor people, disabled persons or children, but less attention is given to the relevance of lifestyle, individual habits, capabilities or preferences. These aspects, however, may be decisive for how individuals anticipate and respond to disruptions or threats. Some people, for example, who are more risk averse than others may stock food and supplies for emergencies, while other people may rather rely on the government to help them during an emergency. Understanding such patterns is not only the core research question underlying our study on social archetypes but may also fill a scientific gap.

Assessing effects for groups that stand for different lifestyles or different combinations of a variety of attributes corresponds more to the current preferences and needs of policymakers. Differences with respect to social resilience seem rather small between age groups [30] or other socio-demographic or socio-economic groups [31]. Grouping individuals based on attributes from various contexts, like capacities, perceptions and framework conditions may lay the ground for more meaningful and relevant analyses of the impacts of threats and interventions on social resilience indicators of a community or society. The social resilience of such groups or archetypes may vary amongst each other and the relative importance of archetypes with high or low social resilience may change over time as well as in the aftermath of policy interventions. The use of social archetypes to characterize populations by clusters of people with similar attributes [16-20] is hence needed to better understand how individuals anticipate, manage and respond to disruptions. Social archetypes may be leveraged to profile the resilience of population groups and identify solutions to minimize the adverse impacts of threats or interventions [32]. They also help to identify population segments that may be prioritised over other groups for support.

2 Conceptual Framework for Assessing Individuals' Social Archetypes

We hypothesize that social archetypes are determined by individuals' capacities [13, 33-38], their perceptions of risks and challenges surrounding them [2, 37, 39-47], as well as the specific contexts in which they live [13, 48-50] (see Figure 1).

Capacities can be understood as the person-related abilities of individuals to achieve specific goals, for instance in the areas of education, health, professional careers, social engagement etc. [33]. The potential for individual goal achievement essentially depends on the psychological traits of a person (for instance how optimistic a person is, how determined to achieve a goal or how perseverant while attempting to reach a goal) [34, 35, 51], a person's cognition and knowledge (how well do they know, for instance, which different strategies would be adequate and available to achieve a goal)[33], their social resources (better-embedded individuals with bigger and well-functioning social networks would have more (social) resources to rely on to achieve their goals) [33, 38, 52] and financial resources of which they dispose to achieve their goals [13, 33, 38].

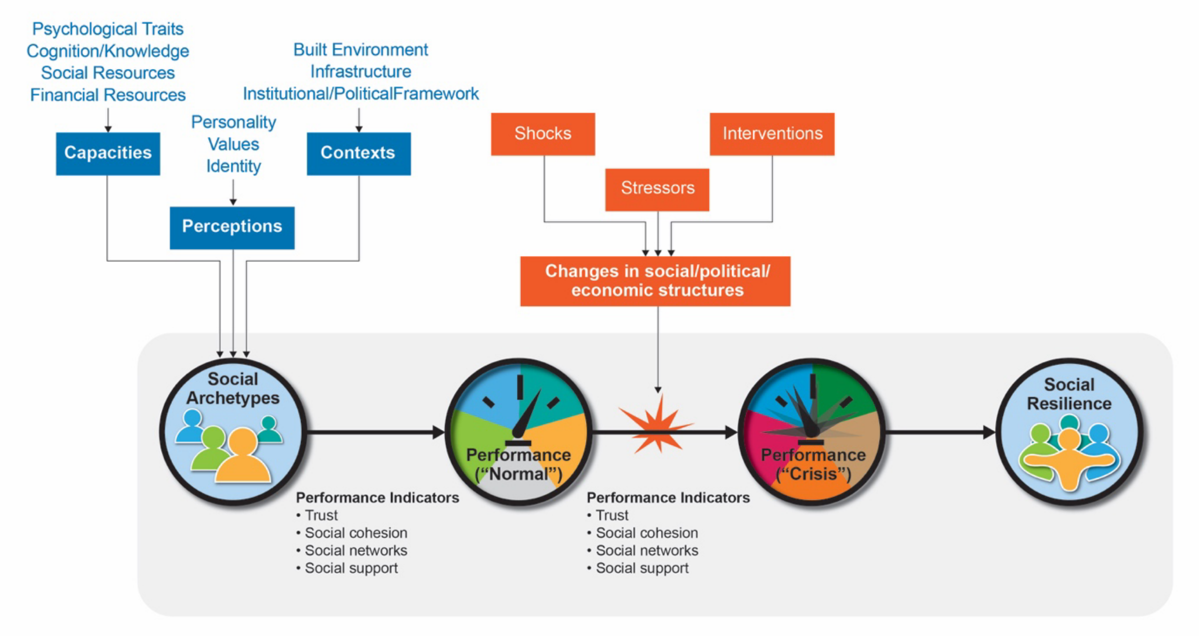

Figure 1: Conceptual Framework for Social Resilience Impact Analysis

Perceptions of risks or threats, potentially originating from multiple causes, will influence individual decision-making processes and the resulting activities of individuals [41]. We hypothesize that the perceptions are essentially modulated by an individual's personality [39, 53] (are they rather risk-prone or risk-averse person, are they rather courageous or timid, etc.), including emotional attributes (for instance, whether they are afraid of changes and new developments or rather embracing them) [39, 54], by the values to which an individual adheres (for instance are they rather conservative or rather open and innovative persons, are they generally welcoming or not for all sorts of new circumstances, or are they more in favour of collectivistic or individualistic approaches) [55, 56], and by the identity an individual sees for themselves (individuals may, for instance, see themselves as open or less open persons, as competent or not so competent in technical or social support tasks, as more or less environmentally friendly etc.) [39, 57]. Identities are often reflected in an individual's leisure activities [58].

Finally, ***contexts*** influence the type of social archetype into which an individual will fall. These contexts comprise the built environment in which individuals live (an environment, for instance, that is rather hostile and does not offer many possibilities to satisfy one's own needs or to interact with others may make your behaviours as an individual different from those living in a much more open, friendly and welcoming environment) [59-61], the physical and technical infrastructure which individuals can dispose of (like quantity and quality of educational institutions, health care institutions, public transport systems, water and electricity provision etc.) [59, 60] as well as the institutional and/or political framework (for instance possibilities for individuals to voice their opinions and concerns related to regional and national developments, trust in government and political decision-makers, national security or the enforceability of property rights) [2, 13, 38, 61]. Depending on the specific topic in which one is interested, additional context-specific features must be considered. If, for instance, social resilience impacts of changing work-live patterns are of interest, facts about current and future work-live conditions (including the duration of commutes, options to work from home, types of work arrangements, or individuals' housing conditions may be looked at [62-66].

Once social archetypes are identified based on data on the various factors mentioned above, differing performances of different social archetypes can be identified. To keep the respective analyses manageable, we suggest to keep the number of different social archetypes limited (in the range of 3-6).

If one is focusing, for instance, on the situation of older people in a society, one may focus on behaviours (performance) that are either very elder-supportive (coming essentially from individuals who dispose of abundant cognitive, social and financial resources, who perceive a marginalisation of older people as a threat or who live under conditions that encourage voluntary work and where the provision of basic public goods is not a problem), or hardly supportive (for example coming from individuals who have rather low cognitive and emotional resources, who are strongly individualistic or who do not trust the social compact of the society).

Performance in the case of social resilience requires different indicators to be looked at. In this article, which is focused on social resilience, we suggest key social resilience indicators (see Chapter 1.1) to assess the respective performance of social archetypes: social cohesion, social support, and social networks [2]. Each of these three social capital indicators is usually assessed by a set of more fine-grained sub-indicators [2, 5]. Social cohesion may comprise sub-indicators such as social bonds, mutual social trust, or place attachment, for instance [2, 10]. Social support may comprise sub-indicators such as norms of reciprocity, help exchange or volunteerism [2, 5, 10] Social networks may comprise sub-indicators such as the quantity or quality of support systems, community engagement, civic organisation or volunteerism, for instance [2, 5, 67]. To make the analysis not overly complex, we recommend focusing essentially on the above-mentioned social capital indicators and their sub-indicators [2].

If no specific threat, challenge, or intervention occurs, we will refer to the respective performance of the various social archetypes as “normal performance” (see Figure 1). If due to shocks, stressors or interventions, changes in social, political, or economic structures take place, “crisis performance” will be observed (see Figure 1). As mentioned in Chapter 1, natural disasters (like floods or smog/haze), man-made disasters (like a pandemic or a terrorist attack), and medium to long-term threats (like increasing temperatures, ageing populations, increasing geopolitical tensions or societal fragmentation) could be termed as shocks and stressors. Interventions could, for instance, be initiatives to improve the skills of a (specific part of a) population, to increase the awareness and ability of individuals to cope with climate change or an induced shift of work-live patterns through bringing workplaces and homes closer together.

Changes in social, political, or economic conditions would change performance from ‘normal’ to ‘crisis’ in two ways: on the one hand, the shares of the different social archetypes may change; on the other hand, the performance of the original social archetypes may change.

Looking specifically at the impacts of government intervention, the percentages of pro-social and ego-centric social archetypes may shift. An increase in the percentage of pro-social archetypes could be seen as an improvement of the community’s or society’s social resilience whereas a decrease would have to be interpreted as a deterioration of social resilience. Since social resilience matters for every community and society (see Chapter 1), government interventions should not only be analysed with respect to their direct costs or immediate effects but also with respect to their social resilience impacts. Interventions that spur a shrinking in the proportion of pro-social social archetypes should be reconsidered. Interventions may be designed in a different way so that the immediate effects and cost levels are acceptable and social resilience can be kept stable or increased in the medium to long-term range. Such an intervention would then be a preferred option from a societal perspective.

3 Methodology for Empirically Identifying Social Archetypes

3.1 Five-Step Approach

In the identification of archetypes, several steps must be taken (see Figure 2). Consideration should first be given to identifying individuals' attributes which are deemed relevant for the specific context. Secondly, empirical data for these attributes, ranging across scales and types, qualitative or quantitative attributes, should be collected. The data may stem from existing databases or customized collections of fresh data. Thirdly, there might be a need for attribute reduction (or clustering of attributes), particularly in cases where a comprehensive list of attributes contains highly correlated (and potentially redundant) attributes. Fourthly, applying the most common approach for individuals' archetype identification, i.e., cluster analysis will deliver clusters of individuals displaying similar configuration patterns across clustering attributes. Depending on the number, quality, and ease of interpretability (based on qualitative judgment) of derived clusters, steps two to four may involve an iterative process. Lastly, once "final" clusters have been identified, each cluster should be described, as well as labelled or named to assure that the key features of archetypes with distinct and unique sets of attributes can be more clearly communicated to interested stakeholders. In the following, the five steps mentioned above for the identification of social archetypes will be explained in more detail.

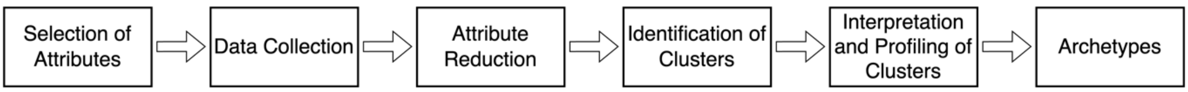

Figure 2: Five key steps in the identification of archetypes

3.2 Selection of Attributes

Identification of relevant attributes

Individuals' attributes considered relevant for a specific context or problem statement should be well justified and linked to an underlying conceptual framework like the one presented in Figure 1 [68, 69]. The use of expert opinions may enhance confidence in the relevance and importance of selected attributes [70].

Ideally, selected quantitative attributes are operationalized into variables that are measurable, observable and have a high separating power, i.e., tend to be neither similar nor constant across the population of individuals considered [71]. Also, qualitative attributes can be used to define archetypes. They may include, for instance, qualitatively assessed characteristics such as the types of needs or behavioural traits of individuals [26].

In general, attributes selected for grouping individuals are never “right” or “wrong”, but some may be better suited for the purposes of a specific analysis than others. Selected attributes should tend to not rely exclusively on dynamic attributes that change quickly over time but consider the inclusion of attributes which are likely to remain static at least for a given period of time. Depending on the archetypes of interest, a combination of dynamic (or changing) and static (or unchanging) attributes may inform the situational or inherent characteristics of individuals respectively. While more dynamic attributes allow for flexibility and adaptation of archetypes over time, the inclusion of static attributes can additionally provide a stable foundation for archetype identification. Such a stable foundation may be useful for analyses of interventional effects, for instance, which often require time to show effects.
Selected attributes may be classified as attributes for clustering (e.g., variables that will be used to identify clusters of individuals) and secondary attributes that are “optional”. They may be used to either enhance the description of identified archetypes [72] or for exploratory analyses to assess potential links between identified clusters with specific predictors or outcomes.

Deductive versus inductive selection of attributes

Typically, in the first run, the identification of relevant attributes will result in a rather long list. Yet, the longer the list, the more complex the data collection and subsequent cluster identification will be. Hence, a fine balance has to be found between being comprehensive on the one hand and workable on the other hand.

One way to find the balance would be to aim at a targeted list of attributes, i.e., to restrict the number of attributes a priori, based on the underlying theoretical framework. This approach may be called “deductive”. For instance, Paveglio et al. (2015) studied adaptive capacity archetypes based on seven main theoretical categories of an existing conceptual adaptive capacity framework (e.g., seven variables which measure the levels of trust in government, financial resources and personal abilities to reduce risks etc.) [32]. In a similar way, Nunez et al. identified archetypes that differed across two main attributes (e.g., two variables which measure the degree of interaction with change, or technology, respectively) [73]. Often, studies have identified groups of individuals using a limited number of pre-defined variables [74-79].

On the other hand, one could start with a more comprehensive list of attributes. This may be recommendable if the specific archetype identification is more exploratory, with a focus rather on theory building than on theory testing [70]. This approach may be called “inductive”. Typically, when starting with a comprehensive list of attributes, an additional attribute reduction step could be considered to omit or condense attributes which, for instance, hardly contribute to illuminating the heterogeneity between groups of individuals (see Chapter 3.4) [74-76, 79].

The targeted or deductive attributes selection approach is parsimonious and yields clusters which may reflect the most relevant and important attributes from a stereotypical stakeholders' perspective. However, potentially relevant attributes may be overlooked. As a priori, the cluster-building relevance of specific attributes is not known, using a large number of potentially relevant attributes has been suggested to maximize the likelihood of discovering meaningful differences [70]. Yet, the related reduction processes require significant resources. Hence, the availability of resources (time and financial resources) seems to be a key criterion for choosing a deductive or an inductive approach. The more limited the resources are, the more recommendable the targeted or deductive way of attribute identification.

3.3 Data Collection

Scales of attributes

Attributes typically vary considerably across scales and types [19, 22, 74-77, 80, 81]. Generally, they may be collected at either the individual level, the aggregated level (i.e., individual data averaged by geographic area, by year or by subgroups etc), or both [74, 75, 77]. Aggregated level attributes (e.g., neighbourhood or community level information such as infrastructural features) may be linked to individuals. This could, for instance, be the case if different individuals are from the same community or geographic area. The respective features can then be seen as proxies for individual-level attributes [75, 76].

Based on individual-level attributes, patterns across different groups have a better resolution and may provide insights for more refined policy interventions [74]. If based on attributes at aggregated levels, patterns will be useful at a broader level, e.g., for interventions targeting the neighbourhood or household scale. Aggregated-level attributes may be more readily available from existing databases [74]. Thus, depending on the underlying goal of the respective archetypes' identification as well as on the available resources (again time and financial resources) decisions about the attributes' scales have to be made. The more fine-grained the interventions are aimed at and the more resources are available, the more the collection of individual-level data seems recommendable.

Fields of attributes

In the identification of individuals' clusters, attributes often relate to personal characteristics. Depending on the respective research question, personal attributes cover a range of fields, like beliefs, emotions, attitudes, needs, behaviours, psychographics, socio-demographics, and socio-economic, or household-related variables [74-77, 80]. Clustering attributes may also relate to features of the external environment like, for instance, community amenities.

Hughes et al., for instance, studied a comprehensive set of attributes related to climate change, the natural environment, and energy use. They looked at building characteristics (such as the age and floor area of the buildings) and also referred to personal attitudes (e.g., current environmentally friendly beliefs, future beliefs of resource limitations) and behavioural characteristics (e.g., energy use patterns, energy-saving actions) [74].

National Agencies in Singapore have studied archetypes based on individuals' perceptions, their behaviours, and socio-demographic information. For instance, the National Youth Council of Singapore studied local youths' perceptions of the current and future world. They relied on young people's perceptions (values and aspirations), behaviours and demographics (see Appendix) [22]. Data for similar fields was collected in studies from the Civil Service College of Singapore (on the challenges of employing seniors to guide the re-design of workplace practices and jobs) or from the Housing Development Board (on the needs and aspirations of residents to guide neighbourhood designs for improving quality of life) [19].

Sources of data

Data sources for individuals' attributes are multiple. Data may be obtained from existing datasets [19, 22, 74, 81], through the customized collection of fresh data [75-77, 80], or from both sources. Existing sources of information could refer to national surveys (e.g. population census, household surveys) or databases (e.g., national household expenditure data, energy use based on standardized household electricity meters, ambient interventions, or infrastructural features) [75, 76, 79, 82]. Such sources may be publicly available or require permission for access.

Customized fresh surveys may be administered through web-based surveys (using survey platforms such as Qualtrics Survey Software or via unique email links), face-to-face surveys, and/or postal surveys [76, 77]. When choosing the respective administration method, the advantages and disadvantages of online versus traditional survey methods have to be considered [83]. Traditional survey methods that involve face-to-face interviews are more adaptable and may enable researchers to better reach specific population segments (e.g., elderly that may lack digital access or literacy), but are often more resource intensive (in terms of costs and time) [84]. Online surveys, on the other hand, may not always obtain samples that are representative of the entire population, but are less resource intensive (completed with a lower cost and in a shorter time) compared to traditional surveys [84]. Qualitative interviews may be considered to complement insights from quantitative surveys [75]. This option, however, is rather resource-intensive and hence only recommendable in case of abundant resources (time and financial resources).

Overall, the scales, fields and sources of data must be carefully chosen when planning a study on archetype identification, bearing in mind the research question of interest and the available resources.

3.4 Attribute Reduction

Motivation for attribute reduction

As previously mentioned, in the case of comprehensive lists of attributes, an additional attribute reduction step should be considered to reduce the number of clustering attributes to only the most important and non-redundant ones [85]. This step is not mandatory, but recommendable given the prevailing resource limitations. In the case of a targeted attribute selection process (i.e., a deductive approach), such attribute reduction measures are typically not needed since the number of attributes considered is rather low.

In a comprehensive list of attributes, some attributes may be more suitable to undergo an attribute reduction procedure than others. Attribute reduction will be specifically appropriate if attributes cover similar dimensions or themes [74]. Having many correlated variables describing a common attribute would over-emphasize the importance of these attributes and deteriorate the statistical quality of the results [70]. Such multicollinearity may be addressed manually, through correlation analyses, to identify highly correlated variables (e.g., $r>0.9$). Another option would be to rely on factor analyses [74].

Factor analyses for identification of highly correlated attributes

The principal component analysis (PCA) is the most common method to address multicollinearity by applying a factor analysis approach [74, 79]. PCA is a variable reduction technique which condenses a large number of potentially correlated variables into a set of uncorrelated principal components without the loss of main information [86]. The resulting principal components (each may be based on a subset of variables) explain the patterns of correlations among a set of variables. The correlation patterns determine the number of principal components that best fit a given dataset or list of attributes. A manageable number of principal components [79] or a refined set of the most important variables can then serve as input for identifying individuals' clusters or archetypes.

A study on consumer archetypes, for instance, assessed a comprehensive list of 29 attitudinal and behavioural variables [74]. They all referred to respondents' beliefs and actions with respect to climate change and energy conservation. When subjected to a PCA [86], the number of attributes could be reduced to three uncorrelated principal components that accounted for most of the variance of the measured attributes. These three key principal components were then used as input for the subsequent clustering of consumers [74].

Potential limitations of attribute reduction based on PCA are that the derived main principal components may be difficult to interpret. It may also occur that attributes which were previously, for instance, based on experts' opinions, deemed important with respect to the research context do not end up loading well onto any of the derived main principal components. In such cases, one may consider the option of either re-thinking the previous attributes' list or retaining the original attributes.

To determine the number of principal components that best fit the data, Catell's scree test is typically leveraged. The scree plot shows graphically the interdependence between eigenvalues (a statistic of the amount of variance explained by a component) in descending order and an increasing number of principal components. The appropriate number of principal components may then, for instance, correspond to the start position of the 'Elbow' (i.e., where a significant drop off in eigenvalues, as indicated by an inflexion point, can be observed as the number of principal components increases) [74, 87]. Eigenvalues >1 indicate that a component accounts for more variance than the original variables. The benchmark "1" for eigenvalues is often used as a cut-off for retaining principal components, while components with low eigenvalues are dropped [70]. The cumulative percentage of explained variance may also be plotted for a visualization of the incremental gain with each additional component. The statistical validity of the derived principal components may be confirmed with measures of sampling adequacy (i.e., Kaiser-Meyer-Olkin measure) or highly significant Bartlett test of sphericity [74, 88, 89]. The resultant uncorrelated principal component scores can then be used as input for clustering individuals, i.e., for identifying the respective archetypes[90].

Each of the final principal components should contain a minimum of two, preferably at least three attributes that highly correlate with it. Attributes with loadings larger than 0.40 [91] may be appropriate to be retained. On the other hand, variables that do not explain the heterogeneity across factors (e.g., load ambiguously or highly on several principal components), or do not load well on any of the principal components should be considered for omission [79]. However, such omissions could result in the loss of potentially important information and should hence be considered carefully.

PCA is well suited for continuous data. Yet, extensions of the concept of PCA for mixed data (continuous and categorical variables) may be considered. For instance, the factor analysis of mixed data (FAMD), an extension of PCA that incorporates a multiple correspondence analysis (for handling categorical variables), could be considered for handling mixed data [92]. Similar to PCA, statistical outputs from FAMD such as the scree plots, eigenvalues and percentage of explained variances (as described above) may be used to identify the number of derived principal components that best fit the data [92].

Attribute reduction appears as a useful step when the starting list of attributes is comprehensive rather than targeted, i.e. when an inductive instead of deductive process of attribute selection is chosen. However, the reduction process is time-intensive and the derived principal components may be hard to interpret compared to making use of the original attributes for the clustering or archetype-identification process.

3.5 Identification of Individuals' Archetypes

Two-stage cluster analysis

The most common methodological approach used to identify individuals' archetypes is cluster analysis [93-95]. Different methods of cluster analyses have the same underlying principle, according to which individuals' differences in attributes such as attitudes, behaviours, or socio-demographic/-economic characteristics are minimised within each cluster, and maximized between clusters [74]. Cluster analyses thus enable us to explore groups of individuals beyond pure socio-demographics/-economics and across multiple attributes.

Irrespective of a specific type of cluster analysis, prior to clustering, the detection and potential elimination of outliers should be considered [71]. A variety of statistical procedures can serve this purpose. The adequate choice depends on aspects such as data type, the distribution of data, or sample size [71].

One of the most widely used approaches in the identification of archetypes for groups of individuals is the two-stage cluster analysis [22, 74, 79, 80]. Generally, this analysis combines two of the basic types of clustering algorithms, hierarchical clustering and the non-hierarchical (partitioning) clustering algorithm [70, 90]. The two-stage clustering starts with hierarchical clustering to do some pre-clustering (identifying core clusters and cluster centres), followed by non-hierarchical clustering for refinement [71, 74, 78, 79].

Relying on a hierarchical algorithm means that data across all possible clusters are organized in a tree-like structure to establish a hierarchical organization of clusters, otherwise known as a dendrogram. Such a dendrogram (see Figure 3) allows for a visual representation of the relationships between clusters at different hierarchical levels [96]. Individual observations are first treated as separate clusters [96]. 'Similar' observations are then put into the same cluster. Similarity refers to a short distance to a cluster centre. Cluster centres represent the average observation within specific clusters. The distance between an observation and a cluster centre can be measured, for instance, by the widely applied Gower distance for mixed data [97].

Clusters that are 'similar' with respect to the clustering attributes are iteratively merged with other clusters to form larger clusters. This merging process is known as 'agglomerative' hierarchical clustering [96]. The distance between different cluster centres is typically measured by Ward's method [71, 74, 80, 90]. Cluster centres should have a large distance from each other [71, 74, 80, 90]. Figure 3, i.e., the dendrogram, shows a graphical representation of the merging process. The dendrogram can be cut at any preferred similarity level to identify the respective number of clusters, including the number of observations within these clusters.

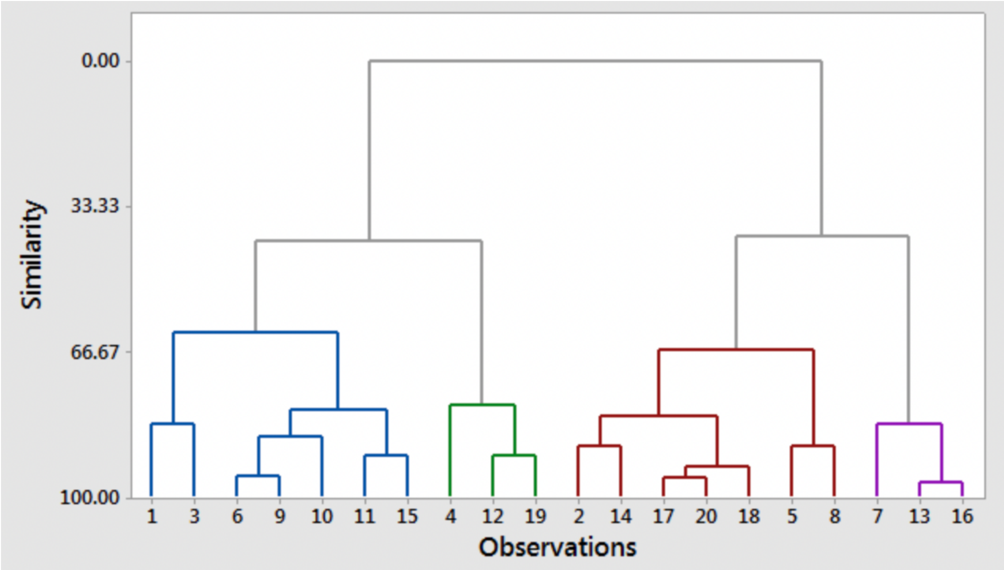

Figure 3: Dendrogram showing relationships between clusters based on agglomerative hierarchical clustering. (Source: Dendrogram Minitab Statistical Software 21)

The clusters (and cluster centres) identified based on the agglomerative hierarchical algorithm serve as a starting point for the second stage, i.e., the non-hierarchical clustering [70]. The aim of this non-hierarchical (or partitioning) clustering is to identify mutually exclusive, i.e., non-overlapping clusters. To do so, individual data points are clustered according to their respective distances to the different cluster centres. An often-used approach is the K-means clustering [98]. This approach separates observations into K distinct, non-overlapping clusters. K initially represents the number of clusters derived from the agglomerative hierarchical algorithm in the first stage. The K-means clustering algorithm optimizes the cluster solution by assigning all data points (or individuals) to the closest cluster centre of the K clusters. In this process, individuals' cluster membership may change until an optimal cluster solution is obtained.

The two-stage cluster analysis applies to continuous as well as categorical individuals' attributes [75, 99-101]. It does not require a pre-specification of the number of clusters, and it enables the testing of several cluster solutions. It enables the identification of an optimal number of clusters and allows for the detection of outliers that do not fit well into any cluster [71, 102-104]. Furthermore, the method can deliver statistically robust results if data distribution assumptions are not met, for instance, if clustering variables are not independent.

Further clustering approaches

On the side of the two-stage clustering, other clustering methods are promoted in the literature. One other approach is the two-step cluster analysis [72, 75]. This approach is similar to the two-stage cluster analysis, including the above-mentioned properties of the approach. It also consists of pre-clustering and cluster refinement in the second step, using the agglomerative hierarchical clustering algorithm mentioned above [70]. Compared with the two-stage clustering, the two-step cluster analysis has a higher computational efficiency in handling large datasets (≥1000 observations). It also has lower demands for user expertise in programming the respective clustering algorithm, so that it is accessible to a wider range of users [71, 100]. On the other hand, so far the two-step cluster analysis can be applied only with the IBM SPSS software [100], which limits the use of this approach.

An alternative clustering method is the Latent Profile Analysis (LPA) [105]. LPA treats the cluster membership as an unobserved categorical variable (latent class) and can hence handle a broad range of mixed data such as continuous and categorical attributes. Contrary to the two-stage and two-step method, LPA assigns individuals to clusters using membership probabilities [105].

The use of LPA may be preferred if there is a need to account for nuanced overlaps between clusters, heterogeneities or uncertainties in cluster assignments. The other two methods mentioned above are preferable if clear-cut cluster assignments that are more straightforward, easy to interpret and/or intuitive are desired [105].

Number of clusters

To identify the optimal number of clusters, we are in the same situation as was described for the clustering of attributes. The number may be either determined a priori based on insights from literature and/or on experts' opinions or it may be determined using statistical measures of data fit. No universal criterion to specify the appropriate number, size or complexity of archetypes is available [106]. In the following, we provide some points of consideration for the identification of the optimal cluster number.

An a priori determination of the number of clusters would be based on existing knowledge related to the topic that is researched, on stereotypes about the population under investigation or on practicality issues. If, for instance, archetypes are used to analyse the impacts of governmental interventions, a limited number like 3 to 6 archetypes might be reasonable to prevent the analysis from getting overly complex [107]. In a study by Nunez et al. aiming at defining digital archetypes, two personality axes were used (horizontal axis: degree of attitude and openness to change; vertical axis: attitude towards the use of digital technologies), so that the authors pre-defined four digital archetypes (i.e., digital, analogic, conservative and explorer) [73].

In cases where the number of clusters is not known or fixed a priori, various statistical measures may be leveraged to find an "optimal" number of clusters. As discussed in Chapter 3.2 for attributes, the "optimal" number of clusters is balancing a high degree of detailed information (i.e., many clusters) with a less complex variety of clusters (i.e., few clusters). Considerations made for clustering to identify attributes in Chapter 3.2 hold analogously for the identification of individuals' archetypes. As the number of clusters (or archetypes) increases, the within-cluster sum of squares, indicating the distance between observations and the respective cluster centre should decrease. Hereby, this sum of squares measures how 'compact' or homogenous clusters are, with smaller values indicating more compact clusters. A higher compactness suggests a higher degree of similarity between observations within a cluster. Plotting the within-cluster sum of squares (x-axis) against the range of the number of clusters (y-axis), the Elbow method (as mentioned above in Chapter 3.4) may be used to assess the optimal number of clusters [108]. If there is no distinctive elbow or if there are multiple elbows, several other statistical metrics exist to corroborate the optimal number of clusters. Examples of these metrics are the Aikaike Information Criterion (AIC), Bayesian Information Criterion (BIC) [78], or the Variance Ratio Criterion (VRC), applied to compare neighbouring clusters [109].

The identification of the optimal number of archetypes may combine a priori settings with the use of statistical metrics. For example, in the abovementioned study on consumer archetypes, the authors complemented statistical metrics and practicality in terms of sample size considerations [74]. Based on the goodness of the statistical fit, the authors identified a 7-cluster solution and a 9-cluster solution as the two best solutions. Yet, for practical reasons, the 7-cluster solution was recommended over the 9-cluster solution [74]. If, however, in an analysis of the impacts of policy interventions on different population archetypes, the needs of minority groups would be of key interest, having more clusters with smaller sample sizes might still be of interest.

Evaluation of clusters' quality

Individuals' archetypes or clusters should have two basic properties. First, they should be distinctive, i.e., identify useful and meaningful patterns across individuals. Secondly, the clusters should be consistent, i.e., they should not exhibit drastic changes in case of small perturbations in the dataset [68]. In addition to these requirements, 'good' clusters would be judged useful by the respective users [110].

The **distinctiveness** of clusters may be judged by statistical measures, indicating whether the distribution of attributes between clusters is significantly different and/or whether the number of attributes differs significantly between clusters. An ANOVA test (analysis of variance) may be performed to assess if single attributes differ between clusters. The respective test characteristic, the F-value, indicates the ratio of the variance between each cluster and the variance within each cluster [74, 100]. The higher a statistically significant F-value is, the higher the variance between clusters. Hence, a high F-value indicates distinctiveness. i.e., significant differences between the clusters with respect to a single attribute. A high F-value also suggests a high relative contribution of the respective attribute in the cluster.

In addition, a Pearson's Chi-Square test or multinomial logistic regressions may be used to compare whether clusters are distinctive in the case of categorical attributes [78, 80]. Also, the silhouette coefficient, which measures how compact each cluster is and how well-separated clusters are from each other can be used [111]. Silhouette values above 0.2 may suggest a sufficient degree of clusters' distinctiveness [75, 76, 111].

The more attributes that can be found to differ significantly across clusters, the higher the clusters' distinctiveness [74, 100]. In the case of low distinctiveness, i.e., just a few attributes differing significantly between clusters, either the underlying statistical procedures have to be revisited or – to save resources - a manual merging of "similar" clusters may be considered.

The **consistency** of clusters may be explored through a cross-validation exercise, which assesses the stability of cluster solutions if the clustering procedure is iterated based on splitting all data points used for the clustering into varying subgroups [96]. The sample of all data points may, for instance, be randomly divided into two equal parts, with one part being a "training subgroup" and the other part being a "testing subgroup" [96]. The clustering solution obtained from the "training group" would then be compared to that of the "testing group". If for both subgroups, the number of clusters and the attributes within the clusters are similar, this would indicate a high stability or consistency of the final clusters [70].

More stable or consistent solutions are preferred over less stable ones. In case of low consistency, qualitative assessments of identified clusters could be used to qualify the relevance of the lack of consistency. The consistency of cluster solutions can be impacted by minor data changes such as changes in the sample of data points used for clustering [96]. High consistency may not always be achievable, yet cluster solutions should remain reflective of distinctive clusters with differing characteristics. Hence, final clusters with a rather high distinctiveness and a rather low consistency may require less attention in terms of reiteration or revisiting of the clustering than clusters with rather lower distinctiveness and rather high consistency.

In addition to the use of statistical measures to determine the quality of identified clusters, also the users' perspectives play an important role. The derived clusters may comprise a set of attributes that are not deemed meaningful or may not correspond to the users' 'expected' clusters. Then, a re-iteration of the steps of attribute selection, attribute reduction, and clustering may be considered. Yet, any reiteration introduces additional subjectivity and users must be alert to the fact that they may "pick" up clusters that – in their eyes - are more 'desirable' or stereotypical but have a lower statistical reliability.

3.6 Interpretation and Labelling of Archetypes

Once final clusters have been identified, the next step is to describe the defining features of each archetype and label the different archetypes. Beyond clustering attributes, additional labels may be used. Describing and naming archetypes helps in the interpretation of distinct archetypes and allows easy communication about the archetypes [74].

In general, the labelling of archetypes should closely relate to the purpose of the underlying interest. In some cases, it may be appropriate to make the labelling process a participatory process, with potential users of the identified archetypes on board.

Archetypes are typically labelled with names to represent and convey the core insights or defining characteristics [71, 75]. Berry et al., for instance, labelled in their study one cluster as 'Retirees' to represent the core defining characteristic of individuals in this cluster. Compared to other clusters, this cluster comprised an overproportionate share of people above the age of 55 (97%), who stopped active employment due to retirement (82%), and received some kind of age-related income support [72]. Another cluster was labelled as

‘Disadvantaged Australians’, to represent a cluster in the Australian population that had a high proportion (nearly 50%) of people with below-average incomes, as well as overproportionate shares of people with worse scores for mental or physical health and elevated levels of childhood adversity [72].

In some cases, labels may be more abstract, with no direct references made to the underlying attributes. Ortiz et al., for instance, named one of their identified archetypes the ‘Incautious Realists’. With this label, they wanted to highlight the attitude-behaviour gap in most individuals in this cluster: they were characterized by a high awareness of the need to conserve energy, yet had low internal control and high energy-wasting patterns [76].

The naming of groups may also rely on the theoretical framework used to identify the clustering attributes. An alternative would be to return to the pre-defined clustering attributes (see Chapter 3.3). Nunez et al., for instance, differentiate between ‘traditional’ archetypes, by which they understand groups of individuals with a low willingness to interact with new technologies and ‘visionary’ archetypes, describing those with a higher willingness to adopt new technologies [73].

The use of evocative labels can bring strong imagery to mind and may hence create an impactful narrative for its intended audience. This may be of special interest if there is the aim for continued participation in data collection or in receiving feedback.

As the labelling of archetypes may not always be intuitive, ‘naming workshops’ with stakeholders can be conducted. Such workshops may also contribute to creating ownership among potential users of the archetypes [80]. They could also help to perform a reality check, comparing identified archetypes against the mental models of stakeholders [68].

To enhance the interpretation of archetypes, descriptive statistics such as frequencies, percentages, means, standard deviations, maxima, or minima may be leveraged [74]. Hugh et al., for instance, provided a general overview of the attributes of each cluster and indicated how the attributes varied between different clusters [74]. They distinguished, for instance, a cluster with a high representation of individuals with environmentally friendly beliefs, higher electricity use and high income, from other clusters, which had a much lower representation of the aforementioned three criteria. They labelled the cluster as ‘Lavish Lifestyles’ to capture the key defining attributes [74].

Making use of individuals' archetypes enables users to split a large number of individuals into fairly homogenous groups of people, i.e., into clusters or archetypes. Targeted interventions may be designed for such archetypes. Planners and decision-makers, or stakeholders in general, should be involved in the labelling and interpretation efforts related to clusters identified based on statistical methods. Hereby, the likelihood of translating insights from archetypes’ identification into targeted policies can be enhanced.

4 Summary and Final Remarks

This document provides a brief introduction to the concept of social archetypes and their relevance in assessing social resilience caused by various forms of disruptions. A conceptual framework and a five-step approach are presented to show in detail how social archetypes can be identified empirically. Given the importance of threats and challenges in the next decades, social resilience impacts must be assessed to make sure that future societies can flourish and guarantee individuals' well-being. Also, government interventions should not only be analysed with respect to their costs and immediate impacts, but also with respect to social resilience impacts. Only if societies manage to keep social support and trust between individuals and between individuals and decision-makers, they will strive despite adverse conditions. The concept of social archetypes is presented as an innovative analytical tool to assess social resilience impacts of shocks, stressors, and government interventions and their related changes in social, political, and economic structures.

Using the concept of social archetypes brings interesting advantages compared to the traditional focus on socio-demographic or socio-economic groups. Yet, some precautionary remarks must be taken into account. Users of the tool must be aware that within each cluster, not every individual performs in the exact same way as his or her cluster colleagues. Considerable within-cluster variations may exist [80]. Archetypes are often rooted within specific contexts, which may restrict the generalizability of the respective insights to other contexts [14].

Despite these limitations, the identification of social archetypes and the subsequent impact analysis provide relevant insights for decision-makers and may guide them to design tailored strategies for building social resilience within specific groups (with specific preferences or requirements) and within society as a whole.

5 Bibliography

1. Saja, A.M.A., et al., A critical review of social resilience assessment frameworks in disaster management. *International Journal of Disaster Risk Reduction*, 2019. 35: p. 101096.
2. Saja, A.M.A., et al., An inclusive and adaptive framework for measuring social resilience to disasters. *Int. J. Disaster Risk Reduct.*, 2018. 28: p. 862-873.
3. Aldrich, D.P. and M. Michelle. A., Social Capital and Community Resilience. *American Behavioral Scientist*, 2014. 59(2): p. 254-269.
4. Maguire, B. and P. Hagan, Disasters and Communities: Understanding Social Resilience. *Australian Journal of Emergency Management*, 2007. 22.
5. Layla, K., S. Renate, and J. Jonas, Social resilience indicators for disaster-related contexts: Literature Review. *Singapore ETH Centre (news),* Accessed Jun 1, 2023., 2020. https://frs.ethz.ch/news-events/frs-news-channel/2020/07/Social-resilience-indicators-for-disaster-related-contexts.html.
6. World Economic Forum, The Global Risks Report 2024, Accessed on 12 Jan 2024 from https://www3.weforum.org/docs/WEF_The_Global_Risks_Report_2024.pdf.
7. Lloyd's Register Foundation Institute for the Public Understanding of Risk, Singapore 2023 Risk Barometer, Available on 13 Feb 2024 from https://ipur.nus.edu.sg/wp-content/uploads/2024/01/Singapore-2023-Risk-Barometer.pdf. 2024.
8. World Economic Forum, The future of jobs report 2023. 2023, Accessed on 1 Feb 2024 from https://www.weforum.org/publications/the-future-of-jobs-report-2023/.
9. Copeland, S., et al., Measuring social resilience: Trade-offs, challenges and opportunities for indicator models in transforming societies. *International Journal of Disaster Risk Reduction*, 2020. 51: p. 101799.
10. Busic, A. and R. Schubert, Social Resilience Indicators for Pandemic Crises. *SSRN*, 2022.
11. Godschalk, D., Urban Hazard Mitigation: Creating Resilient Cities. *Natural Hazards Review*, 2003. 4.
12. Keck, M. and P. Sakdapolrak, What Is Social Resilience? Lessons Learned and Ways Forward. *Erdkunde*, 2013. 67: p. 5-18.
13. Norris, F.H., et al., Community resilience as a metaphor, theory, set of capacities, and strategy for disaster readiness. *American Journal of Community Psychology*, 2008. 41(1-2): p. 127-50.
14. Oberlack, C., et al., Archetype analysis in sustainability research meanings, motivations, and evidence-based policy making. *Ecology and Society*, 2019. 24(2).
15. Karimi, S., C.P. Holland, and K.N. Papamichail, The impact of consumer archetypes on online purchase decision-making processes and outcomes: A behavioural process perspective. *Journal of Business Research*, 2018. 91: p. 71-82.
16. Green, M.C., K. Fitzgerald, and M.M. Moore, Archetypes and Narrative Processes. *Psychological Inquiry*, 2019. 30(2): p. 99-102.
17. Altuwairiqi, M., N. Jiang, and R. Ali, Problematic Attachment to Social Media: Five Behavioural Archetypes. *International Journal of Environmental Research and Public Health*, 2019. 16(12).

18. Sadigov, T., Social Archetypes: How Ideas Shape Citizen-initiated Corruption. International Journal of Sociology and Social Policy, 2016. 38(5), p. 484-508.
19. Housing Development Board Singapore, New Urban Kampung, 2021, Accessed on 19 Dec 2023 from https://www.clc.gov.sg/docs/default-source/urban-solutions/urbsol21pdf/13_case-study_singapore_new-urban-kampung-research-programme.pdf.
20. Bhooma, C., Social Archetypes: A study on fact and fiction. *International Journal of Social Science and Humanities Research*, 2018. 6(2): p. 839-42.
21. Eisenack, K., C. Oberlack, and D. Sietz, Avenues of archetype analysis: Roots, achievements and next steps in sustainability research. *Ecology and Society*, 2021. 26.
22. National Youth Council Singapore, The state of youth in Singapore Research Compilation. 2018. Accessed on 11 Nov 2023 from https://www.nyc.gov.sg/-/media/mccy/projects/nyc/files/innitiatives/resource/national-youth-council-research-compilation-2018.
23. Amadeus Group, Traveler Tribes 2030 report. 2021. Accessed on 14 Nov 2023 from https://amadeus.com/documents/en/blog/pdf/2015/07/amadeus-traveller-tribes-2030-airline-it.pdf.
24. Design Singapore Council, Design for Ageing Gracefully (Rethinking Health & Wellness for the Elderly: Public Services). 2015, Accessed on 16 Feb 2023 from https://designsingapore.org/wp-content/uploads/2022/06/EXP_DSG_Ageing_Booklet_Ebook_Issuu_edited.pdf.
25. Yale University, Archetypes and Personas. 2024, Accessed on 11 Feb 2024 from https://usability.yale.edu/understanding-your-user/archetypes-and-personas.
26. Vaillancourt, S., et al., Using archetypes to design services for high users of healthcare. *Healthc Pap*, 2014. 14(2): p. 37-41; discussion 58-60.
27. Page, L., Nielsen Norman Group: Personas vs. Archetypes. 2022, Accessed on 12 Nov 2023 from https://www.nngroup.com/articles/personas-archetypes/.
28. Thompson, K., et al., Experiences of resilience during the COVID-19 pandemic: A qualitative study among high and low socio-economic status individuals in the Netherlands. *SSM - Qualitative Research in Health*, 2023. 4: p. 100322.
29. Cagney, K.A., et al., Social Resources and Community Resilience in the Wake of Superstorm Sandy. *PloS One*, 2016. 11(8): p. e0160824.
30. Schubert, R., Busic, A., Joerin, J, Social Resilience during the COVID-19 Pandemic: Comparisons between Singapore and Switzerland. Future Resilient Systems. Technical Note Series No.01, 2021, Accessed on 16 Feb 2024 from https://ethz.ch/content/dam/ethz/special-interest/dual/frs-dam/documents/FRS_Technical_Note_Social_Resilience_11Jun2021.pdf.
31. Li, M., Wu, T., Schubert, R., Joerin, J, Changes in Social Capital During the Covid-19 Pandemic: Empirical Evidence from Singapore and Switzerland. *Natural Hazards Review*, 2024.25(4).
32. Paveglio, T.B., et al., Categorizing the Social Context of the Wildland Urban Interface: Adaptive Capacity for Wildfire and Community "Archetypes". *Forest Science*, 2014. 61(2): p. 298-310.
33. Amadei, B. *A Systems Approach to Building Community Capacity and Resilience*. Challenges, 2020. 11(28).

34. Maltby, J. and S.S. Hall, Less is more. Discovering the latent factors of trait resilience. *Journal of Research in Personality*, 2022. 97: p. 104193.
35. Den Hartigh, R.J.R. and Y. Hill, Conceptualizing and measuring psychological resilience: What can we learn from physics? *New Ideas in Psychology*, 2022. 66: p. 100934.
36. Rockström, J., et al., Shaping a resilient future in response to COVID-19. *Nature Sustainability*, 2023. 6(8): p. 897-907.
37. Kieu, M. and G. Senanayake, Perception, experience and resilience to risks: a global analysis. *Scientific Reports*, 2023. 13(1): p. 19356.
38. Lavergne, R. and J. Saxby, Capacity Development: Vision and implications. Canadian International Development Agency, 2001, Capacity Development Occasional Series No.3.
39. Ong, Y.X., et al., Profile identification and characterization of risk perceptions and preventive behaviors during the COVID-19 pandemic: A latent profile analysis. *Frontiers in Psychology*, 2023. 14.
40. Twigg, J., Characteristics of a Disaster-resilient Community A Guidance Note Characteristics of a Disaster-resilient Community: A Guidance Note. 2007.
41. Hernández, D., et al., Public Housing on the Periphery: Vulnerable Residents and Depleted Resilience Reserves post-Hurricane Sandy. *Journal of Urban Health*, 2018. 95(5): p. 703-715.
42. Paek, H.-J. and T. Hove, *Risk Perceptions and Risk Characteristics*. 2017, Oxford University Press.
43. Paton, D., M. Millar, and D. Johnston, Community Resilience to Volcanic Hazard Consequences. *Natural Hazards*, 2001. 24: p. 157-169.
44. Brown, V.J., Risk perception: it's personal. *Environmental Health Perspectives*, 2014. 122(10): p. A276-9.
45. Slovic, P., Perception of Risk. *Science*, 1987. 236: p. 280-285.
46. Buckle, P., Assessing social resilience. *Disaster resilience: An integrated approach*, 2006. 88: p. 104.
47. Bodas, M., et al., Risk Perception of Natural and Human-Made Disasters—Cross Sectional Study in Eight Countries in Europe and Beyond. *Frontiers in Public Health*, 2022. 10.
48. Ungar, M., Community resilience for youth and families: Facilitative physical and social capital in contexts of adversity. *Children and Youth Services Review*, 2011. 33(9): p. 1742-1748.
49. Ungar, M. and L. Theron, Resilience and mental health: how multisystemic processes contribute to positive outcomes. *The Lancet Psychiatry*, 2019. 7.
50. Theron, L. and M. Ungar, Resilience in Situational and Cultural Contexts, in *Handbook of Resilience in Children*, S. Goldstein and R.B. Brooks, Editors. 2023, Springer International Publishing: Cham. p. 105-119.
51. Southwick, S.M., et al., Why are some individuals more resilient than others: the role of social support. *World Psychiatry*, 2016. 15(1): p. 77-9.
52. Terpstra, T. and M. Lindell, Citizens' Perceptions of Flood Hazard Adjustments An Application of the Protective Action Decision Model. *Environment and Behavior*, 2013. 45: p. 993-1018.

53. Radell, M.L., et al., The personality trait of behavioral inhibition modulates perceptions of moral character and performance during the trust game: behavioral results and computational modeling. *PeerJ*, 2016. 4: p. e1631.
54. Li, T., et al. Exploring the Dynamic Characteristics of Public Risk Perception and Emotional Expression during the COVID-19 Pandemic on Sina Weibo. Systems, 2023. 11(1).
55. Ivanisevic, J. and H. Nordenstedt, Values in risk perception - A study of the relationship between values and risk perception in three countries. *Jàmbá: Journal of Disaster Risk Studies*, 2010. 3.
56. Wu, Z. and S. Zhong, Individualism-Collectivism and Risk Perception Around the World. *SSRN Electronic Journal*, 2022.
57. Aschwanden, D., et al., Psychological and behavioural responses to coronavirus disease 2019: The role of personality. *European journal of personality*, 2021. 35(1): p. 51-66.
58. Haggard, L. and D. Williams, Identity Affirmation through Leisure Activities: Leisure Symbols of the Self. *Journal of Leisure Research*, 1992. 24: p. 1-18.
59. Rashidfarokhi, A. and V. Danivska, Managing crises 'together': how can the built environment contribute to social resilience? *Building Research & Information*, 2023. 51(7): p. 747-763.
60. Castaño-Rosa, R., et al., Resilience in the built environment: Key characteristics for solutions to multiple crises. *Sustainable Cities and Society*, 2022. 87: p. 104259.
61. Vaughan, E.H.-S., S., Resilience Measurement Practical Guidance Note Series 1: Risk and Resilience Assessments. . *USAID. Produced by Mercy Corps as part of the Resilience Evaluation, Analysis and Learning (REAL) Associate Award.*, 2018.
62. Mattisson, K., C. Håkansson, and K. Jakobsson, Relationships Between Commuting and Social Capital Among Men and Women in Southern Sweden. *Environment and Behavior*, 2015. 47(7): p. 734-753.
63. Sun, B., J. Lin, and C. Yin, How does commute duration affect subjective well-being? A case study of Chinese cities. *Transportation*, 2021. 48(2): p. 885-908.
64. Saraniemi, S., et al. Silenced Coffee Rooms: The changes in social capital within social workers work Communities during the first wave of the COVID-19 Pandemic. 2022. 13 (1): p. 8.
65. Juchnowicz, M. and H. Kinowska Employee Well-Being and Digital Work during the COVID-19 Pandemic. Information, 2021. 12.
66. Centre for Research on Successful Ageing, Singapore Resilience Study, 2023, Accessed on 16 Nov 2023 from https://rosa.smu.edu.sg/sites/rosa.smu.edu.sg/files/Briefs/Singapore%20Resilience%20Study.pdf. 2023.
67. Schubert, R., Wu, TT., Joerin, J, Changes in Social Capital During the Covid-19 Pandemic: A Comparative Study for Singapore and Switzerland. *SSRN*, 2023.
68. Piemontese, L., et al., Validity and validation in archetype analysis: practical assessment framework and guidelines. *Environmental Research Letters*, 2022. 17(2): p. 025010.
69. Oberlack, C., et al., Sustainable livelihoods in the global land rush? Archetypes of livelihood vulnerability and sustainability potentials. *Global Environmental Change*, 2016. 41: p. 153-171.
70. Ketchen, D.J. and C.L. Shook, The application of cluster analysis in strategic management research. *Strategic Management Journal*, 1996. 17(6): p. 441-458.

71. Backhaus, K., et al., Cluster Analysis, in *Multivariate Analysis: An Application-Oriented Introduction*, K. Backhaus, et al., Editors. 2021, Springer Fachmedien Wiesbaden: Wiesbaden. p. 451-530.
72. Berry, H., et al., Contemporary Australian Archetypes: Different People, Different Needs. *SSRN Electronic Journal*, 2008.
73. Viloria-Núñez, C., M. Tovar, and A.C. Millán, Digital archetypes: a tool for understanding personality characteristics in the digital culture. *Humanities and Social Sciences Communications*, 2023. 10(1): p. 952.
74. Hughes, M., Moreno, J, Further Analysis of Data from the HEUS: Increasing Insight and UK Applicability. UK Department of Energy & Climate Change, 2014, Accessed on 6 Dec 2023 from https://www.gov.uk/government/publications/household-electricity-survey--2.
75. Ortiz, M.A. and P.M. Bluyssen, Developing home occupant archetypes: First results of mixed-methods study to understand occupant comfort behaviours and energy use in homes. *Building and Environment*, 2019. 163: p. 106331.
76. Ortiz, M.A. and P.M. Bluyssen, Proof-of-concept of a questionnaire to understand occupants' comfort and energy behaviours: First results on home occupant archetypes. *Building and Environment*, 2018. 134: p. 47-58.
77. Ben, H. and K. Steemers, Household archetypes and behavioural patterns in UK domestic energy use. *Energy Efficiency*, 2018. 11(3): p. 761-771.
78. Grasso, A.C., et al., Understanding meat consumption in later life: A segmentation of older consumers in the EU. *Food Quality and Preference*, 2021. 93: p. 104242.
79. Thies, A.J., M. Staudigel, and D. Weible, A segmentation of fresh meat shoppers based on revealed preferences. *Agribusiness*, 2023. 39(4): p. 1075-1099.
80. Poortinga, W. and A. Darnton, Segmenting for sustainability: The development of a sustainability segmentation model from a Welsh sample. *Journal of Environmental Psychology*, 2016. 45: p. 221-232.
81. Civil Service College Singapore, Reimagining productive longevity. Ethos Issue 20. 2019, Accessed on 12 Dec 2023 at https://file.go.gov.sg/ethos-issue-20.pdf.
82. Weden, M.M., et al., Neighborhood archetypes for population health research: is there no place like home? *Health Place*, 2011. 17(1): p. 289-99.
83. Singh, S. and R. Sagar, A critical look at online survey or questionnaire-based research studies during COVID-19. *Asian Journal of Psychiatry*, 2021. 65: p. 102850.
84. Szolnoki, G. and D. Hoffmann, Online, face-to-face and telephone surveys—Comparing different sampling methods in wine consumer research. *Wine Economics and Policy*, 2013. 2(2): p. 57-66.
85. Vafakhah, M. and S. Janizadeh, Chapter 6 - Application of artificial neural network and adaptive neuro-fuzzy inference system in streamflow forecasting, in *Advances in Streamflow Forecasting*, P. Sharma and D. Machiwal, Editors. 2021, Elsevier. p. 171-191.
86. Jolliffe, I.T., Principal component analysis for special types of data. 2002: Springer.
87. Cattell, R.B., The Scree Test For The Number Of Factors. *Multivariate Behavioral Research*, 1966. 1(2): p. 245-276.
88. Kaiser, H.F., An index of factorial simplicity. *Psychometrika*, 1974. 39(1): p. 31-36.
89. Bartlett, M.S., A Note on the Multiplying Factors for Various Approximations. *Journal of the Royal Statistical Society.* , 1954. 16(2): p. 296-298.
90. Punj, G. and D.W. Stewart, Cluster Analysis in Marketing Research: Review and Suggestions for Application. *Journal of Marketing Research*, 1983. 20(2): p. 134-148.

91. Hair, J., M. Howard, and C. Nitzl, Assessing measurement model quality in PLS-SEM using confirmatory composite analysis. *Journal of Business Research*, 2020. 109: p. 101-110.
92. Pagès, J., *Multiple factor analysis by example using R*. 2015, CRC Press Boca Raton: Boca Raton.
93. Sietz, D., et al., Archetype analysis in sustainability research methodological portfolio and analytical frontiers. *Ecology and Society*, 2019. 24(3).
94. Lim-Camacho, L., et al., Climate adaptation of food value chains: the implications of varying consumer acceptance. *Regional Environmental Change*, 2017. 17(1): p. 93-103.
95. Kok, M., et al., A new method for analysing socio-ecological patterns of vulnerability. *Regional Environmental Change*, 2016. 16(1): p. 229-243.
96. Gao, C.X., et al., An overview of clustering methods with guidelines for application in mental health research. *Psychiatry Research*, 2023. 327: p. 115265.
97. Gower, J.C., A General Coefficient of Similarity and Some of Its Properties. *Biometrics*, 1971. 27(4): p. 857-871.
98. Ahmed, M., R. Seraj, and S.M. Islam, The k-means Algorithm: A Comprehensive Survey and Performance Evaluation. Electronics, 2020. **9**.
99. Benassi, M., et al., Using Two-Step Cluster Analysis and Latent Class Cluster Analysis to Classify the Cognitive Heterogeneity of Cross-Diagnostic Psychiatric Inpatients. *Frontiers in Psychology*, 2020. 11.
100. Norusis, M., Cluster analysis. *SPSS 17.0 Statistical Procedures Companion*, 2009: p. 361-391.
101. Rundle-Thiele, S., et al., Using two-step cluster analysis to identify homogeneous physical activity groups. *Marketing Intelligence & Planning*, 2015. 33(4): p. 522-537.
102. Chiu, T., et al. A robust and scalable clustering algorithm for mixed type attributes in large database environment. in Proceedings of the seventh ACM SIGKDD international conference on knowledge discovery and data mining. 2001.
103. Kent, P., R.K. Jensen, and A. Kongsted, A comparison of three clustering methods for finding subgroups in MRI, SMS or clinical data: SPSS TwoStep Cluster analysis, Latent Gold and SNOB. *BMC Medical Research Methodology*, 2014. 14: p. 1-14.
104. Mooi, E. and M. Sarstedt, A concise guide to market research: The process, data, and methods using IBM SPSS Statistics. New York: Springer. 2011. 307.
105. Spurk, D., et al., Latent profile analysis: A review and “how to” guide of its application within vocational behavior research. *Journal of Vocational Behavior*, 2020. 120: p. 103445.
106. Eisenack, K., et al., Design and quality criteria for archetype analysis. *Ecology and Society*, 2019. 24: p. 6.
107. Merlo, O., et al., Exploring the changing role of brand archetypes in customer-brand relationships: Why try to be a hero when your brand can be more? *Business Horizons*, 2023. 66(5): p. 615-629.
108. Syakur, M.A., et al., Integration K-Means Clustering Method and Elbow Method For Identification of The Best Customer Profile Cluster. *IOP Conference Series: Materials Science and Engineering*, 2018. 336(1): p. 012017.
109. Milligan, G.W. and M.C. Cooper, An examination of procedures for determining the number of clusters in a data set. *Psychometrika*, 1985. 50(2): p. 159-179.

110. Wicki, S., et al., Archetypes of social-ecological-technological systems for managing ecological infrastructure. *Environmental Research Letters*, 2024. 19(1): p. 014038.
111. Rousseeuw, P., Silhouettes: A Graphical Aid to the Interpretation and Validation of Cluster Analysis. *Journal of Computational and Applied Mathematics*, 1987. 20: p. 53-65.

6 Appendix

Example case studies on identified archetypes by public agencies in Singapore.

Name of archetypes /Agency	Application	Attributes	Method for archetype identification	Archetype groups	Sample profile	Sources of data
Youth Aspiration Archetypes National Youth Council (2018)**[22]**	To understand youth perceptions of the world and gather insights on current and future actions, values and aspirations.	• Demographic • Values and aspirations (multicultural, liberal, altruistic, non-material, material, family orientations) • Behaviours	Principal Component Factor Analysis; Hierarchical and K-means cluster analyses	6 youth archetypes (Active Aaron; Community Chloe; Old school Olly etc)	Active Aaron: High scores on all values and aspiration dimensions. Driven to achieve goals and new experiences, engaged in a wide range of social activities and networks	Representative youths aged 15-34 years from the National Youth Survey 2016 (n=3531); survey administered per 3-5 years
Senior Productive Longevity Archetypes Civil Service College (2019)**[81]**	To understand challenges of employing seniors To guide age-friendly re-design of workplace practices and jobs	• Demographic • Socio-economic • Lifestyle • Attitudes • Motivations • Status and vocation of respondents' social circle	Cluster analyses (unspecified); ethnographic interviews	6 senior archetypes (Privileged retiree, independent workaholic, burdened breadwinner etc)	Independent Workaholic: Well-educated private housing, professionals, works past retirement age to pass time and maintain autonomy	Seniors aged 45-85 years from the Retirement and Health Survey 2014-17 (n=10,300); survey administered per 2 years
New Urban Kampung Resident Archetypes Housing Development Board (2021)**[19]**	To understand the needs and aspirations of residents. To guide neighbourhood designs for better quality of life.	• Demographic • Socio-economic • Perceptions • Behaviours • Lifestyle (e.g. time at work) • Social connections (# of household members; family members living ≤10 mins walk)	Two-level clustering	8 resident archetypes (Empowered Millennials, Golden Seniors, Silver contributors etc)	Empowered Millennials: Young adults, no HDB, poly/university graduates, high technology self-efficacy, less affected by social change	Residents from the HDB census surveys (n=5155); survey administered per 5 years

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