Economic Preferences across Generations and Family Clusters: A Comment*

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Abstract

Chowdhury, Sutter and Zimmermann (2022) assessed the risk, time, and social preferences of family members in rural Bangladesh, presenting two main findings. First, there is a strong and positive association between family members' preferences, even when controlling for personality traits and family background. Second, families can be grouped into two clusters: approximately 20% of the families are characterized by relatively impatient, risk-averse, and spiteful members, while the rest of the families have relatively patient, risk-tolerant, and prosocial members. Recognizing the pivotal role of cluster analysis in deriving the second result, we first successfully computationally reproduced the results, and then we conducted two types of robustness checks. The first examines the transformation of variables (continuous or categorical), affecting the proximity measure that is crucial to cluster analysis. The second assesses the effect of varying the number of clusters on the findings. Some results are robust, as we consistently find the small cluster of families identified by Chowdhury et al. (2022). However, divergent outcomes emerge with categorical variables (a logical choice given their nature) and a larger number of clusters (3 or 4). We conclude that, although the cluster analysis by Chowdhury et al. (2022) is valid, its outcomes significantly depend on the researcher's assumptions and choices. Careful consideration of several alternatives is essential in exploratory cluster analysis to identify stable groups.

*Data and codes are available on https://github.com/ToniErtl/clusters.

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1 Introduction

A burgeoning body of literature underscores the crucial role that economic preferences play in various life outcomes, including educational attainment, labor market status, or health behavior and outcomes (Borghans et al., 2008; Almlund et al., 2011). Childhood and adolescence stand out as critical phases in the shaping of these preferences (Sutter et al., 2018, 2019), with family background being a relevant factor in the process (Falk et al., 2021; Samek et al., 2021).

Chowdhury, Sutter and Zimmermann (2022) aim to contribute to our understanding of economic preferences by measuring experimentally three distinct preferences — risk, time, and social — across parents and their offspring in 542 families from rural Bangladesh. Their research uncovers a positive and significant correlation in preferences between spouses, as well as between parents and children, showing that both mothers and fathers play an equally significant role in shaping their children's preferences. Furthermore, the significance of parents' socioeconomic status in predicting children's preferences vanishes when parents' preferences are accounted for.

Their second — and in their view more innovative — contribution is to investigate whether they can find groups of families that can be described by a set of well-defined preferences. This approach represents a significant departure from the conventional methodology of merely examining correlations between preferences (e.g., Dean and Ortoleva, 2019). Using cluster analysis, they discern compelling patterns in economic preferences that demarcate two main family clusters. In the first group, members of the families are relatively impatient (preferring smaller and earlier amounts over larger, but delayed amounts), risk-averse (opting for lotteries with lower expected value and variance), and spiteful (minimizing payoffs to others in allocation games). Conversely, the other cluster of families (encompassing about 80% of the families) is characterized by relative patience, risk tolerance, and lack of spitefulness. While this clustering exercise is interesting *per se*, there is also a strong relationship between clusters and socioeconomic background. Families with higher income and more members tend to belong to the group characterized by relative patience, risk tolerance, and non-spiteful attitudes.

While Chowdhury et al. (2022) are not the first to measure several economic preferences simultaneously (see Dean and Ortoleva, 2019; Snowberg and Yariv, 2021; Horn et al., 2022; Chapman et al., 2023; Stango and Zinman, 2023), they are pioneers in using cluster analysis to look for groups of individuals that can be described by a well-defined set of preferences. We concur with Chowdhury et al. (2022) that the main advantage of cluster analysis over other methods is that it is less restrictive (e.g. it does not assume a linear relationship between the different dimensions, as principal component analysis and factor analysis (Greenacre et al., 2022), and there is no need of *a priori* assumptions, as with mixture models).

However, finding well-defined groups can be a daunting task.[1] Clustering analysis

[1] With N individuals and k groups, the number of possible partitions can be approximated by $\frac{k^N}{k!}$ (Steinley, 2006).

provides principled ways to identify internally cohesive and externally isolated groups, yet there is no singular, unified approach that guarantees the best clustering.[2] This conclusion is echoed by Jain (2010) who states that "one of the important facts about clustering; there is no best clustering algorithm". Tackling this challenge requires the researcher to make key decisions on parameters such as the number of clusters and variable transformations, beyond just selecting from various methods and algorithms to identify groups stable across different clustering techniques. This strategy helps circumvent a major pitfall in cluster analysis, as described by Everitt et al. (2011): "The problem is, of course, that since in most cases the investigator does not know *a priori* the structure of the data (cluster analysis is, after all, intended to help uncover any structure), there is a danger of interpreting *all* clustering solutions in terms of the existence of distinct (natural) clusters. The investigator may then conveniently 'ignore' the possibility that the classification produced by cluster analysis is an artefact of the method and that actually she is *imposing* a structure on her data rather than discovering something about the actual structure."

In this comment, we first successfully computationally reproduce the results, then examine how different choices that the researcher has to make when applying cluster analysis affect the findings in Chowdhury et al. (2022). We focus on two crucial decisions, where the optimal choice is often not readily apparent. First, we consider alternative coding of non-trivially continuous data, as this significantly affects the use of proximity measures. These measures are essential in determining which responses are close to each other and, hence, who belongs to a certain group.[3] Second, we investigate how the number of clusters - for which there are numerous, generally not coinciding tests - influences the results.

Our findings highlight that both of these choices have non-negligible consequences on the findings. First, we question the assumption by Chowdhury et al. (2022) of treating social preferences as continuous variables. By considering the four binary variables related to social preferences as categorical and applying Gower's distance instead of Euclidean, we find that the core results remain unchanged. However, when we alter the assumption of the linearity of the time and risk preference measures and treat them as categorical, the results change drastically.[4] When clustering analysis treats all preference measures as categorical, it fails to replicate the two clusters identified in the original study. Importantly, there are no significant differences between the two groups in terms of time and risk preferences, although disparities in social preferences remain.

Moreover, when we test for more than two clusters (the number of clusters in Chowdhury et al. (2022)), the conclusions also change. Consistent with the original study, we identify the same small group of relatively impatient, risk-averse, and spiteful families.

[2] Fisher and Ness (1971) and Kleinberg (2002) show that there is no single clustering algorithm that can satisfy a set of simple and desirable properties.

[3] Following Everitt et al. (2011), we use the term 'proximity', although terms such as 'similarity,' 'dissimilarity,' and 'distance' are also prevalent in the literature.

[4] Time preferences initially ranged between 0 and 6 for children and 0 and 18 for adults, while risk preferences were coded between 1 and 6 for both groups.

However, the other larger group is divided in a manner that defies easy interpretation; that is, the larger group does not clearly separate into a very patient, risk-tolerant, and prosocial group and a group with intermediate scores on the preferences. Across all groups, there is consistently a group characterized by high scores in patience and risk tolerance, another with distinctly low scores on these attributes, and one or two intermediate groups (depending on whether 3 or 4 clusters are considered). Yet, when examining social preferences, the intermediate group(s) appear to be more prosocial compared to the group with the most patient and risk-tolerant families. In these intermediate groups, individuals are more egalitarian and altruistic, and less selfish than those in the latter group.

2 Computational reproduction

The nature of the preference measure data lies at the heart of the replication exercise and the robustness checks, so first we present the preference measures used in Chowdhury et al. (2022).

To assess *time preferences*, subjects were presented with binary choices in six choice sets for children and eighteen for adults, choosing between sooner (smaller) and later (larger) rewards. The measure used was the count of later (more patient) choices ranging from 0 to 6 for children, and from 0 to 18 for adults. A higher count indicates more patience.

Risk attitudes were evaluated using six lotteries, each offering a low or high payoff with equal probability. The first lottery involved no risk as the low and the high gambles' payoffs were identical. Subsequent lotteries exhibited an increasing expected value accompanied by a widening spread, with the final gamble always including zero as the low payoff. The measure of risk preference is represented by a number ranging from 1 to 6, corresponding to the chosen lottery. Higher numbers indicate a preference for riskier options, signifying a greater tolerance for risk.

The assessment of *social preferences* involved four binary choices, with one option consistently being '1 for me, and 1 for the other'. Drawing on existing literature (Bauer et al., 2014), subjects were classified into one of four types based on their choices: altruistic (focused on maximizing the payoff for others), egalitarian (aiming to minimize differences in payoffs), spiteful (intending to minimize the payoff for others), and selfish (prioritizing the maximization of their own payoff).

For replication, we use the data set and the Stata and R working files provided by Chowdhury et al. (2022). Given the materials provided, we were able to computationally reproduce all the figures and tables, after which we have conducted various robustness tests, which we present below.

3 Critical points - coding of variables and number of clusters

We focus on the coding of variables and the choice of the number of clusters. These elements are pivotal in cluster analysis and may affect substantially the findings.

3.1 Coding of variables

Given the preference measures described above, the calculation of distances between individuals poses a challenge. For instance, determining the distance between an adult who made 12 patient choices, selected gamble 4, and is categorized as egalitarian, and another who made only 9 patient choices, chose gamble 2, and is classified as spiteful is not straightforward. Chowdhury et al. (2022) approach this problem by standardizing all preference measures and applying Euclidean distance, which implies treating these measures as continuous. However, the assumption of continuity for these measures is not immediately evident. For instance, assuming a continuous scale in the case of time preferences choosing 2 vs 3 later rewards represents the same difference as selecting 10 vs 11. However, the actual differences in time preference may not be linear.

Similarly, in the context of risk preferences, the degree of difference in risk attitudes between choices like 2 versus 1 or 4 versus 3 remains ambiguous, even though the risk preference measure suggests an identical difference.[5] Therefore, using categorical variables to capture nuances in risk attitudes might be a more precise measure.

The assumption of continuity is particularly questionable for social preferences, which are binary, taking only the values of 0 and 1. In this context, standardizing these variables is problematic.

In this comment, we reconsider the assumptions of continuity and instead categorize preferences as categorical variables. Specifically, we divide both time and risk preferences into three distinct categories: low, middle, and high. Regarding time preferences, as illustrated in Figure 4 in the Appendix, a significant portion of individuals are categorized as either very impatient (around 14.1% for children, 40.7% for fathers, and 32.8% for mothers) or very patient (around 9.7%, 16.0% and 15.2%, respectively), with between 43.2-76.1% falling into the intermediate category. This distribution supports treating time preference not as a continuum but rather as a categorical variable (very impatient, middle, very patient). Conversely, as Figure 5 in the Appendix indicates, the distribution of risk preferences does not present clear demarcation points, leading us to simplify the original 1 to 6 scale into three categories: 1-2 as risk-averse, 3-4 as middle, and 5-6 as risk-tolerant. For social preferences, we have adhered to the original binary coding (0 and 1) as presented in the dataset.

When analyzing data with categorical variables, it is advised to utilize proximity measures that align more closely with the nature of the data, rather than defaulting to

[5] Crosetto and Filippin (2013, 2016) provide examples of how to assess risk attitudes measured in choice tasks using CRRA utility functions.

Euclidean distance. Numerous studies advocate for the use of Gower's distance (Gower, 1967; Everitt et al., 2011; Ahmad and Khan, 2019), which incorporates appropriate distance measures for continuous and categorical variables, applying proper weights to the different variables.

Table 1 in the Appendix shows how the use of non-continuous variables, and hence the alternative proximity measure affects the results.[6] The first section of Table 1 reproduces Table A.22 in Chowdhury et al. (2022), standardizing all variables and using the same Euclidean distance measure. The subsequent section maintains the standardization of time and risk preferences (treating them as continuous) but modifies the treatment of social preferences to match their binary nature in the data, utilizing Gower's distance. The final section further modifies the approach by treating time and risk preferences also as categorical (dividing them into three categories each) and also applies Gower's distance.

Compared to the original results, maintaining time and risk preferences as continuous and treating social preferences as categorical does not significantly alter the results. However, challenging the continuity assumption for time and risk preferences markedly changes the cluster analysis outcome. The analysis produces two groups that differ markedly from those previously defined. Notably, there are no significant differences in time and risk preferences between these groups. In terms of social preferences, one group emerges as more spiteful yet less selfish compared to the other.[7]

Figure 1 offers a two-dimensional visualization of this clustering exercise. Chowdhury et al. (2022) utilized Principal Component Analysis (PCA) for their Figure 1 to display clustering results in two dimensions. PCA inherently assumes linear relationships among economic preferences and within family members. To relax this linearity assumption, we adopt the Uniform Manifold Approximation and Projection technique (in short, UMAP, McInnes et al., 2018; Allaoui et al., 2020; Hozumi et al., 2021) for dimensionality reduction, enhancing cluster visualization. A major advantage of UMAP over PCA is its applicability to categorical data. However, UMAP cannot process missing observations, necessitating their removal from our analysis. In Figure 1, the left panel illustrates the UMAP visualization with two clusters applying Euclidean distance as in Chowdhury et al. (2022), after the exclusion of missing observations. The two clusters identified in the original study are clearly distinguishable, with the smaller cluster of families located at the top of the left panel. The middle panel incorporates mixed variables - continuous (time and risk preferences) and categorical (social preferences) - using Gower's distance, while the right panel displays the UMAP visualization employing solely categorical variables and Gower's distance. The findings corroborate previous

[6]Note that the use of Gower's distance does not allow for missing values. Whereas dropping or imputing missing values would in itself be an important choice to consider, Chowdhury et al. (2022) have already addressed this issue, showing that their choice of imputing the data has not impacted their outcome. We have also replicated their results, and we have also used their imputation method with the Gower's distance with virtually the same results. The reason we opt for dropping the missing values is due to our choice of visualization method (see below).

[7]Our findings remain qualitatively consistent when we treat time and risk preference categories separately, utilizing 6 categories for children and 18 categories for adults for time preferences, along with 6 categories for risk preferences.

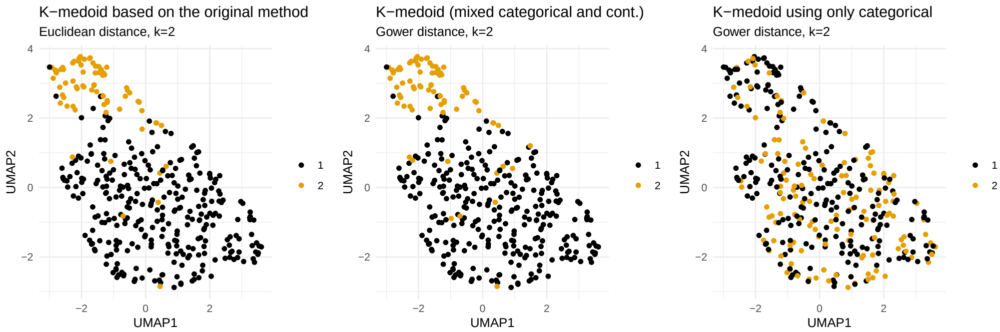

Figure 1: Replication: Family clusters with Euclidean (left) and Gower's (right) distances using the UMAP visualization (Note: Number of clusters: 2.)

observations: treating social preferences solely as a categorical variable does not change the results of Chowdhury et al. (2022), but categorizing time and risk preferences, instead of treating them as continuous, significantly changes the clustering outcomes. Groups are not easily distinguishable as they do not differ significantly in terms of time and risk preferences.

3.2 Number of clusters

The objective of cluster analysis is to identify distinct groups, and the researcher has to determine the number of clusters. While most studies rely on statistical criteria, often termed rules, to determine the optimal cluster count, these rules can vary widely and may suggest different numbers of clusters. It is common for studies to consider multiple rules (e.g. Tibshirani et al., 2001; Sugar and James, 2003). Following this approach, Chowdhury et al. (2022) applied two widely used rules, the average silhouette width and the Calinski-Harabasz statistic, both indicating two as the optimal number of clusters.

We consider a broader set of rules using the 'nclust' function from the 'parameters' package (Lüdecke et al., 2020) in R. Table 2 in the Appendix presents the proposed optimal number of clusters as suggested by different rules. On the left side of the table, we follow the same procedure as Chowdhury et al. (2022), standardizing all variables and applying the Euclidean distance, (but omitting observations with missing values). On the right side, we standardize time and risk preference variables but retain the original binary encoding for social preferences, employing Gower's distance for calculation. According to the first set of rules, the consensus leans towards 2 or 3 clusters (notably, we observe the same result for the silhouette and the Calinski-Harabasz method as Chowdhury et al. (2022)), though several rules indicate a preference for more clusters. When applying Gower's distance with categorical treatment of social preferences, 2 clusters emerge as the most common recommendation, followed by 4 clusters. Therefore, to assess the robustness of Chowdhury et al. (2022)'s findings, we explore the consequences of considering 3 or 4 clusters, in addition to the originally used 2 clusters. Given that

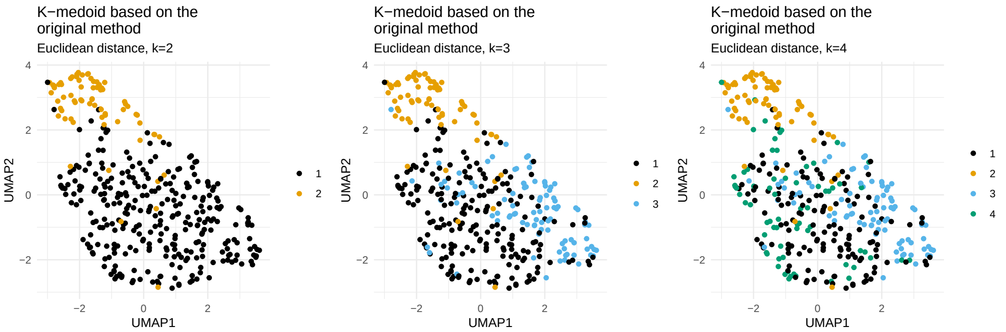

Figure 2: K-medoid clustering with Euclidean distance and continuous data using 2, 3 or 4 clusters.

our previous analysis showed employing two clusters and Gower's distance with mixed types of variables does not significantly alter the core conclusions in Chowdhury et al. (2022), we proceed to examine whether shifting to 3 or 4 clusters impacts the results using both the original and mixed coding methods.

While Figure 2 and Table 3 in the Appendix show the results for the original analysis that treats all preference measures as continuous data, Figure 3 and Table 4 in the Appendix present the findings when time and risk preference measures are considered continuous, but social preference is regarded as categorical, implying the use of the Gower's distance.[8] The main finding from this analysis is the consistency of the cluster comprising relatively impatient, risk-averse, and spiteful families (highlighted in yellow in figures and labeled as 2 in tables). In contrast, the larger cluster, characterized by patience, risk tolerance, and a lack of spitefulness, divides into two or three smaller clusters when the analysis is expanded to 3 or 4 clusters.

This exercise suggests that the less patient, more risk-averse, and spiteful group remains stable regardless of the number of clusters, while the more heterogeneous, larger group fragments as the number of clusters increases. However, the resulting sub-clusters are not straightforward to interpret. For example, when reanalyzing Chowdhury et al. (2022) with three clusters (see Table 3), we observe that, apart from the stable group of impatient, risk-averse, and spiteful families, one of the newly formed groups (group 3) exhibits greater patience and risk tolerance compared to the other (group 1). Nonetheless, the distribution of social preferences complicates the interpretation: the more patient and risk-tolerant group (group 3) appears more selfish than the other newly formed group (group 1), with the latter showing more egalitarian and altruistic tendencies. Interestingly, the stable group with relatively impatient, risk-averse, and spiteful families (group 2) is found to be less selfish than the group marked by the highest levels of patience and risk tolerance (group 3). In summary, while groups can be clearly ranked according to time and risk preferences, no such clear ordering emerges for social preferences. This conclusion persists with four clusters as well.

[8]The left panel in Figure 2 is the same as the left panel in Figure 1, and the left panel in Figure 3 is the same as the middle panel in Figure 1.

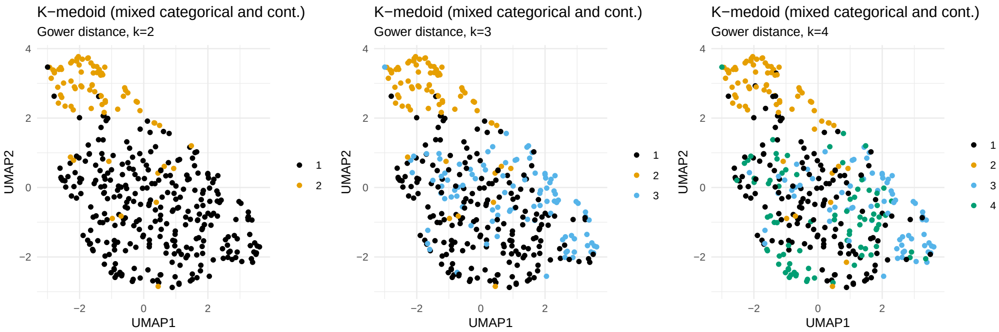

Figure 3: K-medoid clustering with Gower's distance and categorical social preferences using 2, 3 or 4 clusters.

4 Conclusion

We revisited the work by Chowdhury et al. (2022) on the economic preferences of families in rural Bangladesh. We first computationally reproduce their results, and then focus on the robustness of their cluster analysis. Our examination concentrated on the coding of the preference measures and the choice of the number of clusters.

We find that the study's conclusions are sensitive to these methodological choices. With two clusters, while treating only social preferences as categorical and maintaining time and risk preferences as continuous essentially preserved the original clusters, but converting time and risk preferences to categorical variables resulted in markedly different results. When altering the number of clusters, we consistently identified the smaller cluster of families characterized by impatience, risk aversion, and spitefulness, as initially identified by Chowdhury et al. (2022). However, the characteristics and interpretations of the newly formed clusters, which evolved from the initially larger cluster with relatively patient, risk-tolerant and non-spiteful families, became more intricate. While it was possible to distinctly rank these groups according to time and risk preferences, the social preferences did not follow a clear hierarchical pattern, complicating their interpretation.

Our findings suggest that adopting a variety of methodological approaches is essential when utilizing exploratory cluster analysis to identify stable groups based on economic preferences, ensuring the robustness and interpretability of the findings.

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5 Appendix

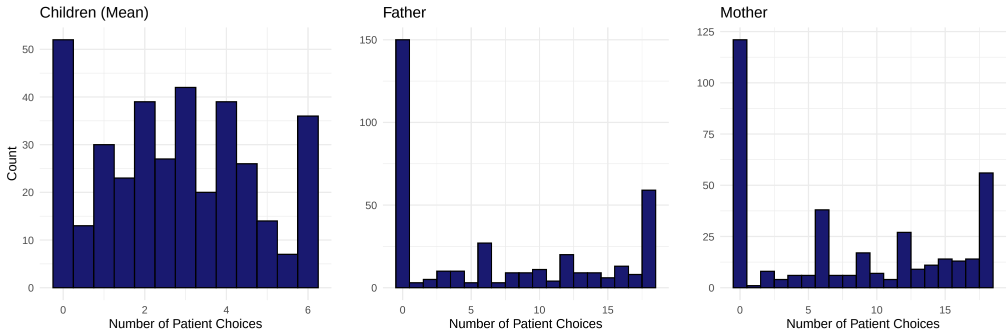

Figure 4: Distribution of time preferences

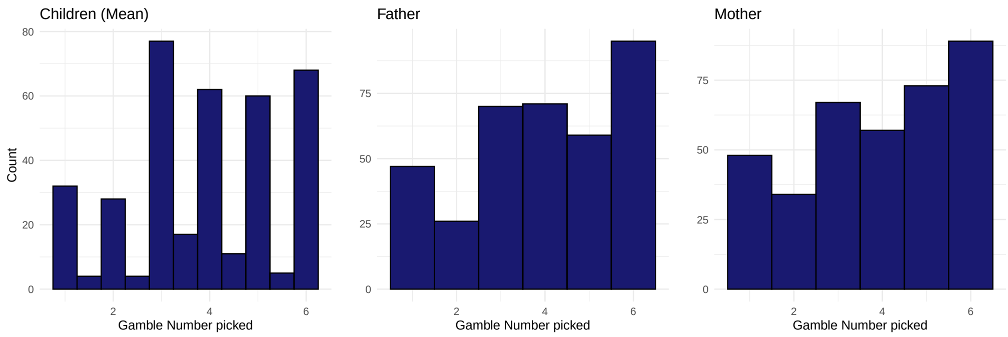

Figure 5: Distribution of risk preferences

	All continuous (Chowdhury et al., 2022) Euclidean distance			Time and risk cont., social categorical) Gower's distance			All categorical Gower's distance		
	1 (N=298)	2 (N=70)	p value	1 (N=294)	2 (N=74)	p value	1 (N=238)	2 (N=130)	p value
Time preferences: Number of Patient choices									
Children	2.842	2.329	0.037	2.825	2.426	0.099	2.693	2.838	0.475
Father	8.040	2.443	<0.001	8.139	2.351	<0.001	6.567	7.723	0.138
Mother	9.272	2.343	<0.001	9.296	2.622	<0.001	7.706	8.408	0.357
Risk preferences: Gamble Number picked									
Children	3.926	3.679	0.223	3.908	3.764	0.467	3.840	3.950	0.511
Father	4.164	3.100	<0.001	4.173	3.122	<0.001	4.008	3.877	0.474
Mother	4.003	3.586	0.064	4.017	3.554	0.036	3.861	4.038	0.340
Social preferences									
Spiteful									
Children	0.084	0.793	<0.001	0.083	0.757	<0.001	0.271	0.123	<0.001
Father	0.064	0.800	<0.001	0.054	0.797	<0.001	0.244	0.131	0.010
Mother	0.047	0.900	<0.001	0.041	0.878	<0.001	0.252	0.131	0.006
Egalitarian									
Children	0.193	0.057	0.001	0.190	0.074	0.004	0.185	0.135	0.141
Father	0.228	0.143	0.117	0.228	0.149	0.137	0.244	0.154	0.044
Mother	0.094	0.029	0.072	0.095	0.027	0.055	0.076	0.092	0.577
Altruistic									
Children	0.087	0.000	<0.001	0.088	0.000	<0.001	0.063	0.085	0.323
Father	0.121	0.014	0.008	0.122	0.014	0.005	0.088	0.123	0.289
Mother	0.074	0.014	0.064	0.075	0.014	0.052	0.067	0.054	0.613
Selfish									
Children	0.324	0.079	<0.001	0.325	0.088	<0.001	0.244	0.338	0.022
Father	0.332	0.029	<0.001	0.340	0.014	<0.001	0.223	0.369	0.003
Mother	0.453	0.000	<0.001	0.452	0.027	<0.001	0.319	0.454	0.010

Table 1: Replication: Family clusters with Euclidean (left) and Gower's (middle and right) distances using k-medoid clusters with k=2.

All preference measures continuous			Time and risk preference measures continuous, social preferences categorical		
Nr. of clusters	Method	Package	Nr. of clusters	Method	Package
1	Gap - uniform (Tibshirani et al., 2001; Maechler et al., 2019)	easystats	1	Frey and Van Groenewoud (1972)	NbClust
1	Frey and Van Groenewoud (1972)	NbClust	2	Elbow (Thorndike, 1953)	easystats
2	Caliński and Harabasz (1974)	NbClust	2	Silhouette (Rousseeuw, 1987)	NbClust
2	Davies and Bouldin (1979)	NbClust	2	Krzanowski and Lai (1988)	NbClust
2	Silhouette (Rousseeuw, 1987)	NbClust	2	Caliński and Harabasz (1974)	NbClust
2	McClain and Rao (1975)	NbClust	2	Duda et al. (1973)	NbClust
2	SD-index (Halkidi et al., 2000)	NbClust	2	Pseudot2 (Duda et al., 1973)	NbClust
3	Elbow (Thorndike, 1953)	easystats	2	Beale (1969)	NbClust
3	Trace Cov W (Milligan and Cooper, 1985)	NbClust	2	McClain and Rao (1975)	NbClust
3	Duda et al. (1973)	NbClust	3	Gap - uniform (Tibshirani et al., 2001; Maechler et al., 2019)	easystats
3	Pseudot2 (Duda et al., 1973)	NbClust	3	Ball et al. (1965)	NbClust
3	Beale (1969)	NbClust	4	Hartigan (1975)	NbClust
3	Ratkowsky and Lance (1978)	NbClust	4	Ratkowsky and Lance (1978)	NbClust
3	Ball et al. (1965)	NbClust	4	Point-Biserial (Milligan, 1980, 1981)	NbClust
4	Scott and Symons (1971)	NbClust	4	Dunn (1974)	NbClust
4	Marriott (1971)	NbClust	6	C-index (Hubert and Levin, 1976)	NbClust
5	Dunn (1974)	NbClust	9	Gap - pc (Tibshirani et al., 2001; Dudoit and Fridlyand, 2002)	easystats
6	C-index (Hubert and Levin, 1976)	NbClust	9	Davies and Bouldin (1979)	NbClust
6	Point-Biserial (Milligan, 1980, 1981)	NbClust	9	SD-index (Halkidi et al., 2000)	NbClust
7	Hartigan (1975)	NbClust	10	SDbw (Halkidi and Vazirgiannis, 2001)	NbClust
7	Trace W (Milligan and Cooper, 1985)	NbClust			
7	Friedman (Friedman and Rubin, 1967)	NbClust			
7	Rubin (Friedman and Rubin, 1967)	NbClust			
10	Gap - pc (Tibshirani et al., 2001; Dudoit and Fridlyand, 2002)	easystats			
10	Krzanowski and Lai (1988)	NbClust			
10	Cubic Clustering Criterion (Sarle, 1983)	NbClust			
10	SDbw (Halkidi and Vazirgiannis, 2001)	NbClust			

Table 2: Outputs from parameters::nclust(); optimal choice of the number of clusters with different methods

		Original method, k = 2			Original method, k = 3				Original method, k = 4				
		1 (N=298)	2 (N=70)	p value	1 (N=204)	2 (N=70)	3 (N=94)	p value	1 (N=142)	2 (N=69)	3 (N=88)	4 (N=69)	p value
Time preferences: Number of Patient choices													
	Children	2.842	2.329	0.037	2.434	2.329	3.729	<0.001	2.553	2.348	3.767	2.232	<0.001
	Father	8.040	2.443	<0.001	7.270	2.443	9.713	<0.001	7.979	2.478	9.591	6.072	<0.001
	Mother	9.272	2.343	<0.001	8.711	2.343	10.489	<0.001	10.099	2.377	10.420	5.971	<0.001
Risk preferences: Gamble Number picked													
	Children	3.926	3.679	0.223	3.718	3.679	4.378	0.001	3.789	3.667	4.352	3.674	0.009
	Father	4.164	3.100	<0.001	3.873	3.100	4.798	<0.001	3.986	3.101	4.875	3.609	<0.001
	Mother	4.003	3.586	0.064	3.882	3.586	4.266	0.035	3.894	3.594	4.307	3.826	0.062
Social preferences													
Spiteful													
	Children	0.084	0.793	<0.001	0.086	0.793	0.080	<0.001	0.092	0.790	0.085	0.080	<0.001
	Father	0.064	0.800	<0.001	0.078	0.800	0.032	<0.001	0.077	0.812	0.034	0.072	<0.001
	Mother	0.047	0.900	<0.001	0.069	0.900	0.000	<0.001	0.077	0.913	0.000	0.043	<0.001
Egalitarian													
	Children	0.193	0.057	0.001	0.250	0.057	0.069	<0.001	0.155	0.058	0.045	0.457	<0.001
	Father	0.228	0.143	0.117	0.314	0.143	0.043	<0.001	0.120	0.130	0.011	0.739	<0.001
	Mother	0.094	0.029	0.072	0.123	0.029	0.032	0.006	0.127	0.014	0.034	0.116	0.008
Altruistic													
	Children	0.087	0.000	<0.001	0.103	0.000	0.053	<0.001	0.116	0.000	0.051	0.072	<0.001
	Father	0.121	0.014	0.008	0.147	0.014	0.064	0.002	0.183	0.014	0.068	0.058	<0.001
	Mother	0.074	0.014	0.064	0.093	0.014	0.032	0.023	0.099	0.014	0.034	0.072	0.066
Selfish													
	Children	0.324	0.079	<0.001	0.201	0.079	0.590	<0.001	0.236	0.080	0.602	0.145	<0.001
	Father	0.332	0.029	<0.001	0.157	0.029	0.713	<0.001	0.218	0.029	0.739	0.043	<0.001
	Mother	0.453	0.000	<0.001	0.294	0.000	0.798	<0.001	0.211	0.000	0.784	0.522	<0.001

Table 3: Clustering with k-medoid using the Euclidean distance, varying the number of clusters (k=2,3,4)

		K-medoid with Gower's distance, k = 2			K-medoid with Gower's distance, k = 3				K-medoid with Gower's distance, k = 4				
		1 (N=294)	2 (N=74)	p value	1 (N=198)	2 (N=72)	3 (N=98)	p value	1 (N=146)	2 (N=70)	3 (N=71)	4 (N=81)	p value
Time preferences: Number of Patient choices													
	Children	2.825	2.426	0.099	2.636	2.410	3.209	0.010	2.342	2.529	3.817	2.716	<0.001
	Father	8.139	2.351	<0.001	8.621	2.417	7.000	<0.001	5.623	2.957	8.282	11.741	<0.001
	Mother	9.296	2.622	<0.001	9.106	2.542	9.602	<0.001	9.671	2.914	10.859	6.667	<0.001
Risk preferences: Gamble Number picked													
	Children	3.908	3.764	0.467	3.818	3.715	4.122	0.163	3.729	3.707	3.972	4.216	0.089
	Father	4.173	3.122	<0.001	3.965	3.111	4.582	<0.001	3.877	3.143	5.014	3.901	<0.001
	Mother	4.017	3.554	0.036	3.909	3.500	4.265	0.014	3.678	3.714	3.901	4.568	0.001
Social preferences													
Spiteful													
	Children	0.083	0.757	<0.001	0.086	0.771	0.082	<0.001	0.103	0.786	0.077	0.062	<0.001
	Father	0.054	0.797	<0.001	0.066	0.792	0.051	<0.001	0.048	0.800	0.000	0.148	<0.001
	Mother	0.041	0.878	<0.001	0.056	0.903	0.010	<0.001	0.068	0.943	0.000	0.012	<0.001
Egalitarian													
	Children	0.190	0.074	0.004	0.247	0.069	0.077	<0.001	0.226	0.079	0.077	0.216	<0.001
	Father	0.228	0.149	0.137	0.293	0.153	0.092	<0.001	0.342	0.129	0.042	0.198	<0.001
	Mother	0.095	0.027	0.055	0.116	0.028	0.051	0.028	0.137	0.014	0.070	0.049	0.009
Altruistic													
	Children	0.088	0.000	<0.001	0.106	0.000	0.051	<0.001	0.116	0.000	0.021	0.093	<0.001
	Father	0.122	0.014	0.005	0.172	0.014	0.020	<0.001	0.137	0.000	0.028	0.185	<0.001
	Mother	0.075	0.014	0.052	0.101	0.014	0.020	0.004	0.130	0.000	0.014	0.037	<0.001
Selfish													
	Children	0.325	0.088	<0.001	0.192	0.076	0.597	<0.001	0.212	0.086	0.669	0.216	<0.001
	Father	0.340	0.014	<0.001	0.167	0.014	0.684	<0.001	0.205	0.029	0.817	0.136	<0.001
	Mother	0.452	0.027	<0.001	0.268	0.000	0.837	<0.001	0.082	0.000	0.761	0.852	<0.001

Table 4: Clustering with Gower's distance using both numerical (Patience and Risk) and categorical (for Social Preferences) variables , varying the number of clusters (k=2,3,4)