Article

Not peer-reviewed version

Caritas for the Goals of the Agenda 2030: A Study on the Services Provided in Campania

Mario Musella , Ida Camminatiello * , Francesco Izzo

Posted Date: 30 May 2024

doi: 10.20944/preprints202405.2065.v1

Keywords: sustainable development goals (SDGs); poverty; inequality; caritas; tandem clustering; classification, multiple factor analysis

Article

Caritas for the Goals of the Agenda 2030: A Study on the Services Provided in Campania

Mario Musella [1], Ida Camminatiello [2,*] and Francesco Izzo [2]

[1] Department of Social Sciences, University of Naples Federico II, Vico Monte della Pietà, 80138 Napoli, Italy; mario.musella2@unina.it

[2] Economics Department, University of Campania, Corso Gran Priorato di Malta, 81043 Capua, CE, Italy; francesco.izzo@unicampania.it

* Correspondence: ida.camminatiello@unicampania.it

Abstract: The United Nations' Agenda 2030 has established a series of Sustainable Development Goals to address global challenges, including poverty, food insecurity, access to education, and social inequality. In this context, charitable organizations such as Caritas play a crucial role in mitigating the negative effects of these challenges and promoting fair and sustainable development. This study aims to analyze prevalent needs among individuals seeking assistance from Caritas in Campania and examine how the organization contributes to achieving the Agenda 2030 Goals in the region. The statistical investigation techniques considered include tandem analysis [28], which considers a dimension-reduction technique, such as multiple factor analysis, and, then cluster analysis to identify similar groups of individuals. These exploratory data analysis methods have allowed for the identification of common needs, including food assistance, support for education, employment, and housing assistance. Subsequently, Caritas programs and initiatives aimed at meeting these needs and promoting sustainable development are explored. The results indicate that Caritas plays a significant role in addressing the urgent needs of the vulnerable population in Campania and contributes to the goals of Agenda 2030, particularly those related to poverty alleviation, immigration, health promotion, education, employment, and reduction of social inequalities. This study provides an important perspective on the relevance and effectiveness of Caritas' work in the context of Agenda 2030.

Keywords: sustainable development goals (SDGs); poverty; inequality; caritas; tandem clustering; classification, multiple factor analysis

1. Introduction

In a world marked by constant change, characterized by increasingly complex socioeconomic challenges and growing disparities among populations, the need for transformative action has become ever more urgent.

In response to these pressing issues, the United Nations' Agenda 2030 emerges as a guiding light towards a more sustainable and equitable future for all. This ambitious action plan, adopted in 2015 by all 193 UN member states, sets forth 17 Sustainable Development Goals (SDGs) that encompass a wide range of critical issues whose main objectives is the achievement of a sustainable and inclusive development [26].

The definition of sustainable and inclusive development is highly debated in literature. The classical definition of sustainable development was first given by the Bruntland Commission in 1987 which says that the sustainable development is

> "the development that meets the needs of the present without compromising the ability of future generations to meet their own needs".

Inclusive development, on the other hand, refers to the economic growth that ensures fair distribution across society and creates opportunities for all [21]. For an in-depth reading on

 doi:10.20944/preprints202405.2065.v1

"Sustainable Development", see "The Sustainable Development Goals Report 2023 (United Nations)" [27]. In this rapidly evolving global landscape, humanitarian and social assistance organizations like Caritas play a fundamental role in translating the ideals and objectives of the Agenda 2030 into concrete and tangible actions at the community level. Founded on the principles of solidarity, compassion, and love for one's neighbor, Caritas has been committed for decades to combating poverty, social injustice, and providing support and assistance to vulnerable individuals, regardless of their social, religious, or geographical conditions.

The 17 SDGs are categorized into three main areas: the "Social domain", focusing on poverty alleviation, reduction of social and economic inequalities, and improvement of access to education and healthcare; the "Economic domain", aimed at fostering innovative economic growth, generating employment opportunities, and sustain economic resilience; and the "Environmental domain", dedicated to biodiversity conservation, mitigation of climate change, and preservation of ecosystems.

In this context, Caritas primarily contributes to the Social domain by "promoting the testimony of charity, which is the concrete love for others. The dimension of charity permeates and enriches the life of communities" [5].

Through its global network, Caritas delivers a range of services from food support to healthcare, education, and vocational training, aimed at improving the lives of vulnerable populations. Beyond providing assistance, Caritas mobilizes resources and fosters a culture of solidarity and active participation in society through awareness-raising projects, advocacy, and training.

In this present work, we will focus on analyzing the important connection between the Agenda 2030 and Caritas, examining how the latter fits into the broader framework of global efforts to achieve the SDGs and how it contributes concretely to realizing a more just, fair, and sustainable world for all.

To explore in depth the impact and effectiveness of Caritas' initiatives in implementing the Agenda 2030, with particular attention to the local context and social dynamics at play, we will employ Tandem Analysis tandem analysis [6,28], which considers a dimension-reduction technique, such as multiple factor analysis, and, then cluster analysis to identify similar groups of countries.

Through this deep dive, we hope to offer new perspectives and valuable insights that can inform and guide future efforts towards achieving the SDGs and improving the well-being and dignity of all people, everywhere in the world.

This paper is organized as follows: section 2 is a discussion of the theoretical framework; section 3 presents the data; section 4 introduces the data analysis methodology; section 5 is an analysis of the results; sections 6 and 7 provides the discussion and conclusion of the study.

2. Inequality and Poverty

In contemporary discourse, the intricate relationship between inequalities and poverty has garnered significant attention as researchers and policymakers seek to understand and measure these interconnected challenges [1].

In literature, inequalities have been studied from various perspectives. Smith [25] has defined them as "differences in the distribution of income and wealth, as well as economic and social opportunities, among different groups within a society".

The linkages between inequalities and poverty are profound and multifaceted, shaping the lived experiences of individuals and communities.

At its core, inequalities serve as fundamental drivers of poverty, amplifying and perpetuating economic and social disparities. Socioeconomic inequalities, such as unequal access to education, employment, and healthcare opportunities, can significantly limit upward mobility and economic independence for disadvantaged individuals. This restricted access often correlates with higher levels of poverty, trapping individuals in cycles of deprivation and marginalization.

Conversely, poverty exacerbates and reinforces existing inequalities, creating barriers to social inclusion and equitable participation in society. Limited access to resources and opportunities due to poverty further entrenches disparities based on factors such as race, ethnicity, gender, and geographical

 doi:10.20944/preprints202405.2065.v1

location. As a result, those living in poverty face heightened vulnerabilities and diminished prospects for socioeconomic advancement.

The UN recognizes the importance of combating poverty by including this Goal in the Agenda 2030, specifically Goal 1, defining it as "Eradicating extreme poverty for all people everywhere by 2030" [26]. The Agenda 2030 is an international plan, whereas our study focuses on the Italian context, specifically in Campania. We will now proceed with a description of the phenomenon of poverty in Italy, followed by an analysis of how Caritas contributes to addressing this issue.

2.1. Poverty in Italy in the Context of the Agenda 2030

Focusing solely on Europe, it's clear that we are still far from achieving Goal 1 of the Agenda 2030, which aims to reduce by 15 million the number of people at risk of poverty or social exclusion in Europe. Eight years after the adoption of the Sustainable Development Goals and three and a half years into the socio-health crisis caused by Covid, we have experienced significant setbacks. Regrettably, the pandemic, the energy crisis, and the war in Ukraine are having a highly negative impact on our progress toward these targets.

Currently in Europe, more than 95 million people, comprising 21.8% of the population, are living in conditions of poverty and/or social exclusion. This percentage remains relatively stable compared to 2021 when it was at 22% [9]. However, the impact of the Coronavirus is evident, as indicated by Figure 1, showing a reversal of the previously observed signs of improvement starting from 2020.

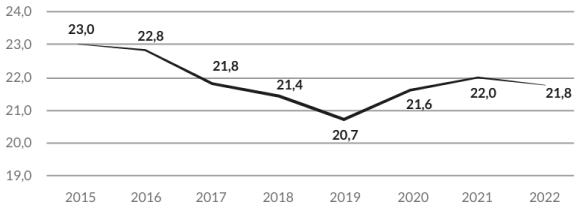

Figure 1. People at risk of poverty and/or social exclusion in the EU (incidence %) - Years 2015-2022. Source: Eurostat.

Through a comparison among European countries ([9]), we can notice that in Italy, people at risk of poverty and/or social exclusion account for 24.4% of the population, which is higher than the EU average [9].

As it is not the objective of this paper to define the risk of poverty or social exclusion,it suffices to know that individuals in this category include those who live in at least one of the following situations: in households at risk of poverty, defined as having an income below sixty percent of the national median income; in conditions of severe material and social deprivation; in households with low work intensity. For further details, please refer to the literature (they are, for example, defined in the annual report on poverty by ISTAT [14]. If we shift from a European context to a national context, the southern part of Italy, known as the Mezzogiorno, emerges as the most affected area by poverty according to ISTAT data [14].

3. A Look at Data

Caritas is making a relevant contribution to the cause by conducting research and promoting concrete actions. For a comprehensive exploration of this topic, refer to the Caritas Report published in 2023 [8]. In this context, we analyze a dataset concerning individuals who visited Caritas. The data are accessible on the Ospoweb platform, which is used by Listening Centers for entering data related to the beneficiaries of Caritas services.

The dataset consists of $n = 1837$ observations representing individuals who sought support from Caritas. In particular, the information was collected by Caritas staff from the relevant provinces and

 doi:10.20944/preprints202405.2065.v1

subsequently aggregated to form the dataset used for analysis. Various types of information were collected for these individuals, amounting to a total of $p = 37$ variables, as detailed in Table 1.

For each variable, the nature of the variable and its respective categories (in the case of qualitative variables) have been specified.

A problem encountered during data analysis concerns the presence of missing values. There are several ways to handle missing data [20], among these, one can choose, when feasible, to perform imputation using specific techniques. However, when the data do not allow for this, for instance due to an extremely high rate of missing values (in our case, exceeding 2/3 for certain variables), one may opt to remove that variable. This is the approach we have chosen.

Below, we report which variables have been removed:

RP; MIG ; NM ; SAF ; MD ; OIND ; EM ; UEM ; CI ; OS ; TN ; ACM ; COINV; LAV; SAN; CONP; ISTR; SSA; SE; SEAL.

After making the changes, the dataset consists of 17 variables. For the needs of the statistical techniques used which we will describe later, transformations were performed on the quantitative variables. Specifically, such variables - i.e. DRES; NC; CHD; FC were transformed into categorical variables, dividing them into non-empty and equidistant classes of values.

In the next paragraph, we will proceed with the description of the statistical techniques used.

Table 1. Description of variables

Variables Label	Variables	Categories Label	Categories
ACM	Services offered to the beneficiary: housing	YES; NO	
AGE	Age Brackets	11-17; 18-34; 35-44; 45-54; 55-64; 65-99	
CHD	Indicate the presence of chlidren	0; 1; 2; 3 or more	
CI	Indicate whether you receive citizenship income	YES	
COU	Indicate the country of origin if users are not Italian	AL; DZ; AR; BR; BG; BF; CU; EG; PH; GE; DE; GR; IN; IR; IT; KZ; KG; LT; MA; MD; NG; PK; PL; UK; DO; RO; RU; SD; SN; ES; LK; TJ; TN; UA; UZ	
DRES	Indicate years of Residence. If born in the municipality of residence, indicate N	N; 1-10; 11-20; 21-30; 31-40; 41-50; 51-60; 60+	
EM	Employed (including irregular) in the family unit	0; 1; 2; 3; 4+	
EQ	Specify the educational qualification	MS ; HS ; BD ; Ill	Middle School Diploma; High School Diploma; Bachelor's Degree; Illiterate
ES	Indicate the employment status	UNW; UW; IE; PT; TC; PC; HM; RE; UN; OT	Unemployed Not Seeking Work; Unemployed Seeking Work; Irregularly Employed; Part-Time Employed; Temporary Contract; Permanent Contract; Homemaker; Retired; Unable To Work; Other
FC	Year of the first contact with the center (specify the year)	Quantitative variable	
FRQ	Specify the frequency of contact	W; B; M ; T ; Y	Weekly; Biweekly; About once a month; At least once every three months; At least once a year
GEN	Indicate Gender	M;F	Male; Female
HS	Indicate type of housing	RR; UR; SR; OP; GS; HL	Regular Rent; Unregistred Rent; Single Room; Owned Property; Guests; Homeless
LIS	Services offered to the beneficiary: listening	YES; NO	
MD	Indicate the presence of declared pathologies within the family unit	YES; NO	
MGS	Services provided to the beneficiary: material goods and services	YES; NO; FP; F/C; GV; GV/UB; IND; SUP; UB;	Food Parcel; Food/Clothes parcel; Grocery Vouchers; Grocery Vouchers/Utility Bills; Induments; Support; Utility Bills
MIG	If migrant, indicate the year of arrival in Italy	70'; 80'; 90'; 2000'; 2010'; 2020'	
MS	Indicate Marital Status	M ; D ; S ; W ; NS	Married; Divorced; Single; Widower; Not Specified
NC	Indicate the number of family members	0-3; 4-6; 7-9	
NM	Indicate the presence of minors	0; 1; 2; 3 or more	
OIND	Declared situation of over-indebtedness	YES; NO	
OS	Indicate if supported by other public services	YES	
PN	Main need for which Caritas support is requested	HI; DJ; ADD; FAM; HAN; EDI ; IMM; EI; POV; HP; PRO	Housing Issues; Detention and Justice; Addiction; Family Issues; Handicap and Disabilities; Educational Issues; Migration/Immigration Issues; Employment Issues; Poverty/Economic Issues; Health Problems; Other Problems
RES	Indicate the usual municipality of residence	AFR; CA; CR; CV; CE; CC; CI; MA; MAR; MT; RE; SA; SF; SME; SNS; SMV; SMCV	
RP	For foreign users, please indicate the residence permit	YES; NO	
SAF	In case of minors, indicate whether they attend school regularly	0; 1; 2; 3 or more; NO	
SN	Indicate if you have received additional support	HI; DJ; ADD; FAM; HAN; EDI ; IMM; EI; POV; HP; PRO	Housing Issues; Detention and Justice; Addiction; Family Issues; Handicap and Disabilities; Educational Issues; Migration/Immigration Issues; Employment Issues; Poverty/Economic Issues; Health Problems; Other Problems
TN	Indicate if you have received additional support	HI; DJ; ADD; FAM; HAN; EDI ; IMM; EI; POV; HP; PRO	Housing Issues; Detention and Justice; Addiction; Family Issues; Handicap and Disabilities; Educational Issues; Migration/Immigration Issues; Employment Issues; Poverty/Economic Issues; Health Problems; Other Problems
UEM	If long-term unemployed, indicate the last year of employment	Quantitative variable	

 doi:10.20944/preprints202405.2065.v1

4. Methodology: Tandem Clustering

For the multivariate analysis of our data, among the most widely techniques proposed in literature (such as multiple factor analysis for mixed data by Pagés [22], and non-linear principal component analysis by Gifi [11]) we consider Tandem Clustering [6,28], which can be viewed as a method of minimizing redundancies in the data.

Here, tandem clustering uses a dimensional reduction technique, specifically multiple correspondence analysis [2,11,12,19], to create new variables that are uncorrelated, and then applies cluster analysis to form classes using these new variables.

Starting from the factors extracted by multiple factor analysis (MCA), instead of using the original variables, the statistical units (the individuals who have sought assistance from Caritas, in our case) will be grouped by using a Hierarchical agglomerative clustering algorithm [24]. As a result, only the most important variables will lead to the identification of similar groups of individuals.

Indeed, the factors, being orthonormal, have the advantage of providing the same impact on the (dis)similarity index used to measure the distance between the groups of units. The results of this integrated analysis approach allow us to better specify the needs of individuals and find confirmation of the individuals' profiles already identified in MCA.

It is common in the literature to use this type of technique for this kind of analysis. [7,16,23]

4.1. Multiple Correspondence Analysis

The Multiple Correspondence Analysis is utilized to explore the relationships among a group of categorical variables observed across a population of statistical individuals or units. By generating new variables (latent variables) and pinpointing an optimal lowe-dimensional space, MCA serves as statistical technique for assigning scores to units and to each category of variables. Analyzing survey data by using MCA can be made calculating a super-indicator matrix $\mathbf{X} = \left[\mathbf{X_1}| \quad \cdots \quad |\mathbf{X_k}| \quad \cdots \quad |\mathbf{X_p}\right]$ of p ordered categorical variables observed on the same set of n individuals. Let D be the super-diagonal table of dimension J *x* J where the *(k, k)*th diagonal matrix contains the relative column marginal frequencies,

$$p_{.jk} = \frac{\sum_{i=1}^{n} x_{ij_k}}{n}$$

for the k-th variable. Observe that an indicator matrix implies coding the data in a complete disjunctive form [12,18]. For example, the matrix $\mathbf{X}_k$ consists of elements 0 and 1, where 1 represents that an individual/unit is classified into a category and a 0 indicates that it does not share that characteristic. Therefore, the total number of categories under consideration is

$$J = \sum_{k=1}^{p} j_k$$

where the generic variable k has $\mathbf{j}_k$ categories. There are many ways with which multiple correspondence analysis can be presented, one of those is to perform a (generalized) singular value decomposition of the super-indicator matrix

$$\frac{1}{p\sqrt{n}} X D^{-\frac{1}{2}} = U \Lambda V^T \tag{1}$$

Where $\mathbf{\Lambda}$ is the diagonal matrix of the singular values, $\mathbf{U}$ and $\mathbf{V}$ are the right and left singular vector matrix, respectively, which allow the computation of the coordinates for units and variable categories. The coordinates of the categories allow to display also graphically the relationships existing among the variables. In particular, since each category is the center of gravity of the units (assisted by Caritas) that have chosen it, the proximity between two categories highlights those chosen by the same people or by very similar individuals: the proximity between two categories can therefore be

 doi:10.20944/preprints202405.2065.v1

interpreted in terms of association between them. Similarly, the proximity between two units allows to highlight the (dis)similarity among people.

4.2. Hierarchical Agglomerative Clustering

To identifying homogeneous groups of units, we perform a cluster analysis [13] on the unit coordinates obtained through MCA which contains a synthesis of all original variables information.

In the literature [13], the term cluster analysis indicates a set of statistical techniques used to group statistical units based on the similarity of their profile, described by a set of variables. The resulting units' group should be characterized by a high degree of internal homogeneity and there should be a high degree of variability between the individuals' groups. Not knowing a priori the suitable number of clusters to analyze, among the plethora of classification methods, we preferred to consider the hierarchical agglomerative clustering, whose logic can be summarized through the following steps.

In the initial stage, each individual forms a separate cluster. In the second step those two individuals, which have minimum distance, are merged. For the calculation of the distance, the WARD method has been used; it is based on the decomposition of the total deviance into deviance between groups and deviance within groups. At each step, then, those two groups that get the minimum within-group deviance are merged. The third step calculates the distance between the new cluster (group) and all the other units. Finally, steps two and three are repeated until a configuration is reached where there is only one group.

The clustering process can be graphically represented through a dendrogram, from which it is also possible to read the aggregation index appreciate how much a group is separated from the others. Of course, the aggregation index can be used in order to identify the suitable number of clusters: cutting the cluster tree after the fusion that correspond to low values of the aggregation index and before those corresponding to high values of the aggregation index [10].

5. Results

Let's proceed with the presentation of the results. The quality of representation of each category can be assessed by examining the contributions of the categories in Table 2.

Table 2. Contributions and Coordinates

Categories	Contributions		Coordinates	
	Dim 1	Dim 2	Dim 1	Dim 2
Albania	0.2494	0.6348	-0.6663	0.9157
Algeria	0,0000	0,0133	-0.0010	0.6484
Argentina	0,0030	0,0038	-0.5025	0.4893
Brazil	0.0122	0.0529	0.4562	0.8189
Bulgaria	0,0003	0.0001	-0.1686	0.0712
Burkina Faso	0.0000	0.0011	-0.0135	-0.2668
Cuba	0.0318	0.0001	1.6483	0.0753
Egypt	0.0052	0.0002	-0.6697	0.0979
Philippines	0.0071	0.2513	-0.1218	0.6234
Georgia	0.6414	0.0069	4.2738	0.3810
Germany	0.0175	0.0055	0.7067	0.3412
Greece	0.0551	0.0020	2.1693	-0.3571
India	0.0156	0.0125	-0.6667	0.5140
Iran	1.0352	0.0210	4.7022	0.5767
Italy	0.8350	0.6538	-0.2312	-0.1762
Kazakhstan	0.0007	0.0013	-0.2381	0.2839

 doi:10.20944/preprints202405.2065.v1

Categorie	Contributions		Coordinates	
	Dim 1	Dim 2	Dim 1	Dim 2
Kyrgyzstan	0.3394	0.0388	1.3060	0.3806
Lithuania	0.0005	0.0303	-0.1527	0.9804
Morocco	0.0627	0.1306	-0.5788	0.7195
Moldova	0.0004	0.0036	-0.1233	0.3379
Nigeria	0.1192	0.8363	0.7371	0.2985
Pakistan	0.0040	0.0008	0.4109	0.1636
United Kingdom	0.0017	0.0002	0.3582	0.4327
Polonia	0.0271	0.0013	0.3840	-0.1250
Dominican Republic	0.0006	0.0000	0.2214	0.0328
Romania	0.0223	0.0013	0.6899	0.1415
Russia	0.0113	0.0229	0.4395	0.5397
Senegal	0.0198	0.1088	3.3073	0.1710
Spain	0.0002	0.0078	0.2228	0.4505
Sri Lanka	0.0123	0.0009	0.1439	0.7013
Kyrgyzstan	0.0004	0.0051	0.7242	0.1675
Tunisia	0.0001	0.0421	-0.4910	1.2169
Tajikistan	0.0264	0.0435	-0.1374	0.4023
Tunisia	0.0020	1.4628	-0.0350	0.7307
Ukraine	3.2956	0.4785	1.0634	0.3491
Uzbekistan	0.0016	0.0001	0.3668	-0.0917
13-17	0.5920	0.0211	5.0301	0.8149
18-34	0.6406	0.1881	0.5992	-0.2783
35-44	0.0066	0.0325	-0.0394	0.0771
45-54	0.0127	0.0628	-0.0492	-0.0979
55-64	0.0058	0.0105	0.0318	-0.0368
65-99	0.0109	0.1155	-0.0522	0.1464
GEN.F	0.0040	0.1405	0.0168	0.0863
GEN.M	0.0077	0.2722	-0.0325	-0.1671
Afragola	0.0011	0.0105	0.2218	0.5729
Caivano	0.0009	0.0879	-0.2815	2.3796
Capodrise	0.0001	0.0049	-0.0905	0.5550
Casagiove	0.0079	0.0101	0.3097	0.3007
Caserta	2.6139	0.729	0.5024	0.2220
Castel Campagnano	0.0076	0	-0.8026	-0.0099
Cervino	0.0376	0.0007	-0.8952	-0.1178
Maddaloni	2.7782	2.2105	-0.7406	0.5758
Marcianise	0.601	12.3915	-0.4574	-1.7767
Montedecoro	0.0072	0.0522	-0.7864	1.8315
Recale	0.0018	0.2526	0.0887	-0.9119
Salerno	0.0051	0.0954	0.6606	2.4625
San Felice a Cancello	0.0227	0.0082	1.3954	0.7035
San Marco Evangelista	0.0018	0.0006	-0.0396	0.0261
San Nicola La Strada	0.0207	0.013	-0.1355	-0.0879
Santa Maria a Vico	0.0484	0.1461	-1.4390	2.1716
Santa Maria Capua Vetere	0.0148	0.0007	0.7951	0.1394
11to20	0.2694	0.006	0.3600	0.0434

 doi:10.20944/preprints202405.2065.v1

Categorie	Contributions		Coordinates	
	Dim 1	Dim 2	Dim 1	Dim 2
1to10	1.6208	0.0819	0.5461	0.10327
21to30	0.0698	0.536	-0.3683	-0.8828
31to40	0.0533	2.1049	-0.3914	-2.1091
41to50	0.0983	1.1696	0.4978	-1.4800
51to60	0.0212	0.0396	-0.6021	-0.7105
60+	0.0007	0.0133	-0.1712	-0.6596
DRES.N	0.0520	1.0030	-0.0767	-0.2901
N	0.0026	0.0057	-0.4685	0.6003
MS.M	0.6169	0.1261	-0.2334	-0.0909
MS.D	0.0016	0.0447	0.0241	-0.1088
MS.S	2.9642	0.1032	0.8099	0.1302
MS.W	0.4344	0.2471	-0.4145	0.2692
0 to 3	0.3442	0.1254	0.1526	0.0793
4 to 6	0.6839	0.4336	-0.3446	-0.2363
7 to 9	0.0977	0.0019	-0.4815	-0.0580
0	12.0556	0.1097	2.3722	0.1949
1	0.1046	0.0292	-0.1525	-0.0694
2	0.3598	0.1569	-0.2803	-0.1595
3 or more	0.4530	0.2247	-0.4213	-0.2555
UR	0.0002	0.2983	0.0162	0.5916
RR	0.0357	0.4530	0.0475	-0.1456
GS	0.0001	0.0023	-0.0182	0.0689
SR	6.7695	0.1685	3.1575	0.4290
OP	0.5757	0.9386	-0.5526	-0.6078
HL	0.0014	0.0991	0.2452	1.7718
HS	0.0954	0.0011	0.2019	-0.0186
MS	0.2358	1.2473	0.1266	-0.2507
BD	0.0254	0.2202	0.2126	0.5392
Illiterate	0.0516	0.0001	-0.7421	0.0230
HM	0.6740	0.0078	-0.3725	0.0346
UW	0.3794	0.2950	-0.2959	-0.2248
UNW	0.0087	0.3586	0.1059	0.5868
UN	0.0151	0.0067	-0.2271	0.1300
IE	1.6168	0.4105	0.5920	-0.2569
RE	0.0156	0.1285	-0.0692	0.1708
PT	0.0632	0.0048	0.2582	0.0611
TC	0.0426	0.1078	-0.2844	0.3895
PC	0.0004	0.2811	-0.0204	0.4973
OT	1.7880	0.0000	2.1846	0.0060
PN.HI	0.0000	0.0249	-0.0012	-0.2463
PN.HP	0.5246	17.4752	-0.4453	-2.2134
PN.IMM	7.6240	0.0067	1.9807	0.0507
PN.PAC	0.0013	0.0000	-0.3271	-0.0083
PN.DJ	0.0099	0.0012	0.5301	0.1593

 doi:10.20944/preprints202405.2065.v1

Categorie	Contributions		Coordinates	
	Dim 1	Dim 2	Dim 1	Dim 2
PN.FAM	0.0119	0.0121	-0.2691	0.2339
PN.ADD	0.0001	0.0027	-0.0613	0.2934
PN.HAN	0.0640	0.0381	0.8270	0.5490
PN.EDI	0.0013	0.0021	0.2334	-0.2560
PN.EI	1.6004	0.0048	0.7847	0.0372
PN.POV	1.8813	3.1435	-0.4083	0.4545
PN.PRO	0.0294	0.0388	0.1429	-0.1415
SN.ADD	0.0074	0.0061	-0.3256	0.2548
SN.HI	0.0001	0.0027	0.0483	0.2062
SN.DJ	0.1294	0.2208	-1.2566	1.4138
SN.FAM	0.0231	0.0052	-0.2932	0.1201
SN.HAN	0.0132	0.0006	-0.4335	0.0772
SN.EDI	0.0029	0.0036	-0.5012	0.4768
SN.EI	0.3485	0.1577	-0.4920	0.2851
SN.POV	0.4039	15.1835	-0.3504	-1.8503
SN.PRO	0.0102	0.2828	-0.0748	0.3389
SN.IMM	5.9819	0.0034	2.8037	0.0572
SN.HP	0.0086	0.2007	-0.1015	0.4232
2000	0.0010	0.0237	-0.2111	-0.8670
2001	0.0000	0.0014	-0.0474	-0.2931
2003	0.0001	0.0007	-0.0693	-0.1447
2004	0.0002	0.0024	-0.1006	-0.2750
2005	0.0015	0.0008	0.3602	-0.2187
2008	0.0006	0.0004	-0.1332	-0.0947
2009	0.0002	0.0036	-0.0836	-0.3365
2010	0.0058	0.0129	0.1958	-0.2508
2011	0.0055	0.0068	0.4829	-0.4647
2013	0.0000	0.0015	0.0188	0.0944
2014	0.1083	1.3733	-0.3993	-1.2249
2015	0.0450	1.1157	-0.2033	-0.8719
2016	0.1599	0.0426	-0.3080	0.1368
2017	0.2065	0.4358	-0.2716	0.3399
2018	0.1261	0.0553	-0.3422	0.1952
2019	0.0532	0.0411	-0.2187	-0.1655
2020	0.2010	0.0428	-0.2769	-0.1100
2021	0.4102	0.0672	-0.3837	0.1337
2022	0.3117	0.3069	-0.3290	-0.2811
2023	0.1387	0.3374	-0.4001	0.5375
FRQ.Y	0.0903	0.0088	1.3888	0.3724
FRQ.M	0.0079	0.0017	-0.0204	0.0082
FRQ.T	0.0194	0.0282	-0.4286	-0.4456
FRQ.B	0.0044	0.0216	-0.0747	-0.1418
FRQ.W	0.0050	0.0128	-0.0749	-0.1034
LIS.NO	0.1003	0.0854	0.7100	0.5643
LIS.YES	1.8280	4.5479	-0.4404	0.5983

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 30 May 2024 doi:10.20944/preprints202405.2065.v1

Categorie	Contributions		Coordinates	
	Dim 1	Dim 2	Dim 1	Dim 2
MGS.FOOD PARCEL	2.1021	0.0695	-0.3484	-0.0546
MGS.FOOD PARCEL/INDUMENTS	0.0513	0.1407	-1.0464	1.4931
MGS.GROCERY VOUCHERS	0.4383	0.0044	1.6352	-0.1406
MGS.GROCERY VOUCHERS/UTILITY	1.4355	0.0144	1.6152	-0.1392
MGS.INDUMENTS	0.0083	0.0114	-0.8422	0.8515
MGS.NO	0.0081	0.0001	0.8311	0.0634
MGS.YES	0.0142	0.3412	-0.2162	0.9118
MGS.SUPPORT	0.0034	0.0128	0.3787	-0.6377
MGS.UTILITY BILLS	0.1653	0.0019	0.9114	0.0844

In general, the further categories are from the origin, the better the quality of the graphical representation. In Figure 2, the most characteristic categories are those farthest from the origin (which represents independence from the variables).

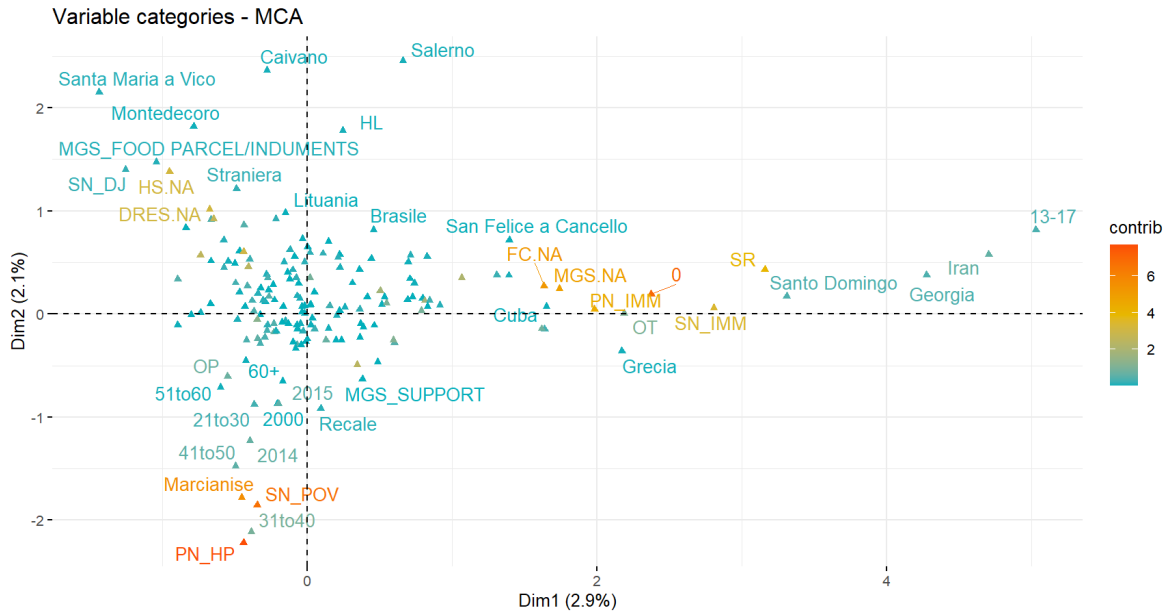

Figure 2. MCA bidimensional Graph

The categories that most characterize the survey participants are indicated by warm colors, while the less significant categories are indicated by cool colors. On the right side of the image along the horizontal axis, there are variables and categories characterizing the first dimension. From this graph, we can start forming an idea about the associations of the modalities. On the right side of the figure along the horizontal axis, there are those individuals who come from a foreign country (Georgia, Iran, Santo Domingo, etc.) and with immigration issues; they are mostly young (see Table 2). The second dimension, the vertical axis, is characterized by those individuals who mainly reside in the province of Caserta, are homeless and have turned to Caritas for economic issues (they received clothing and food parcels).

After conducting MCA, the research proceeds with the implementation of hierarchical clustering based on the coordinates of the individuals extracted by MCA. For selecting the optimal number of dimensions to consider, we chose to use the elbow method. Considering the Figure 3, it is evident that from the second dimension onwards, the eigenvalues stabilize, suggesting that we consider the number of dimensions preceding the flattening.

 doi:10.20944/preprints202405.2065.v1

The implementation of hierarchical clustering based on the coordinates of the individuals extracted by the MCA produces the dendrogram as shown in Figure 3.

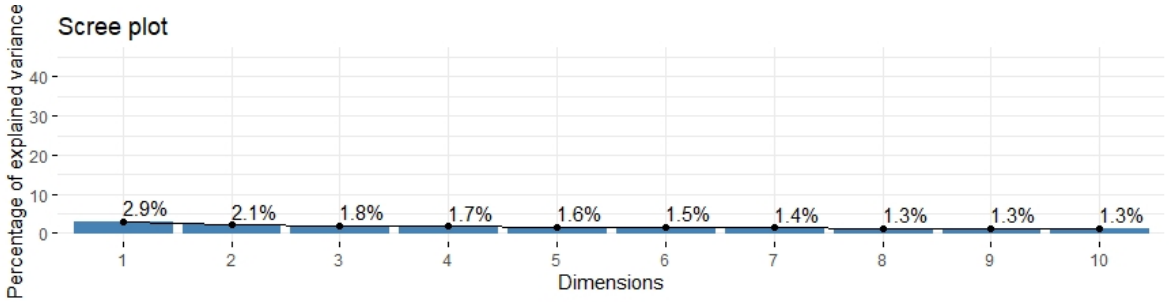

Figure 3. Eigenvalues in to Elbow method

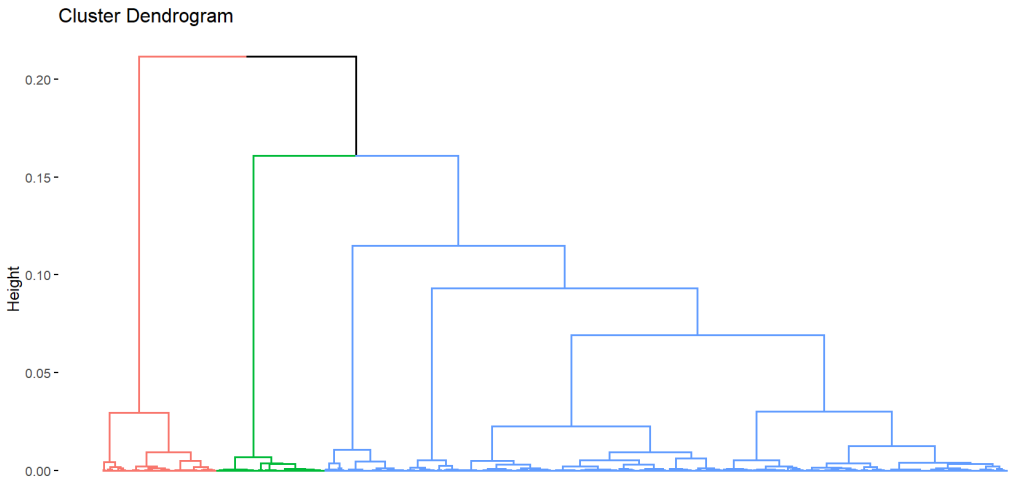

Figure 4. Dendrogram : the colors indicate the groupings

The dendrogram suggest us to consider three cluster. To confirm this choice, we used the silhouette index ([24]), which returned a value of 0.59, indicating that a structure in the data was found. Too see the characteristics of each cluster, refer to Tables 3, 4 and 5. Below is a guide on how to interpret it. The first column of each table, titled CLA/MOD, represents the percentage of individuals with a specific category within a cluster relative to the total individuals who possess that specific category in the dataset. The second column, named MOD/CLA, expresses the percentage of individuals with a specific category relative to the total individuals in the cluster. The third column, indicated as Global, indicates the percentage of visitors with a specific category in the entire dataset. The fourth column displays the p-value, which represents the statistical significance of the category in each cluster. Finally, the last column provides the test value related to the considered categories.

5.1. Clusters Description

In this paragraph, we will describe the three clusters, highlighting the characteristics that represent them. For each cluster, one or more primary needs for which they sought help were defined.

The first cluster (Table 3) is mainly characterized by individuals with health problems (HP) and economic issues (POV). The services provided to them are material goods and services. It is evident that these individuals are strongly characterized by being Italians, residents of Marcianise, which could indicate a significant issue affecting this province.

 doi:10.20944/preprints202405.2065.v1

Regarding the second cluster (Table 4), it shows that the defining variables and categories are those related to work. Indeed, the individuals in this cluster have been listened to by Caritas and have sought support concerning poverty and employment issues (EI). These individuals have reported living in houses with irregular contracts (Unregistred Rent, UR) and having temporary employment contracts (TC). We can say that this cluster refers to employment and poverty issues faced by individuals residing in the province of Caserta, mainly in Maddaloni, San Marco Evangelista, and other areas.

Finally, the third cluster (Table 5) reflects all those foreign individuals who have immigration issues. As we can see, in this cluster, most individuals are non-italian nationals (Santo Domingo, Georgia, Kyrgyzstan, etc.), characterized by having immigration-related primary and secondary needs. They do not have children (CHD) and are young (13-17 and 18-34). Finally, they are Irregularly Employed (IE). Given these characteristics, we can say that the individuals in this cluster are young immigrants looking to settle down by seeking employment.

Table 3. Firt Cluster

Description	Cla/Mod	Mod/Cla	Global	p-value	v.test
PN=PN_HP	95.575	97.738	12.370	< 0,0001	34.512
SN=SN_POV	78.292	99.548	15.380	< 0,0001	32.097
RES=Marcianise	81.855	91.855	13.574	< 0,0001	30.195
COU=Italia	16.479	99.548	73.071	< 0,0001	11.617
MGS=MGS_FOOD PARCEL	14.875	99.548	80.952	< 0,0001	9.330
DRES=31to40	73.333	9.955	1.642	< 0,0001	7.797
EQ=MS	15.513	88.235	68.801	< 0,0001	7.142
DRES=41to50	55.882	8.597	1.861	< 0,0001	6.168
FC=2015	34.409	14.480	5.090	< 0,0001	5.780
FC=2014	41.379	10.860	3.175	< 0,0001	5.724
HS=OP	26.708	19.457	8.812	< 0,0001	5.327
ES=IE	19.797	35.294	21.565	< 0,0001	5.023
DRES=21to30	40.909	8.145	2.408	< 0,0001	4.880
FC=2022	19.919	22.172	13.465	< 0,0001	3.798
GEN=GEN_M	15.916	44.796	34.045	< 0,0001	3.531
FRQ=FRQ_M	12.963	95.023	88.670	< 0,0001	3.429
NC=4to6	16.057	35.747	26.929	< 0,0001	3.072
RES=Recale	36.842	3.167	1.040	< 0,0001	2.762
CHD=2	16.113	28.507	21.401	< 0,0001	2.668
ES=UW	16.216	27.149	20.252	< 0,0001	2.639
MS=MS_M	13.857	60.633	52.928	< 0,0001	2.450
HS=RR	13.072	80.090	74.111	< 0,0001	2.199
DRES=N	13.907	47.511	41.325	< 0,0001	1.979
MGS=MGS_YES	0.000	0.452	1.423	< 0,0001	-2.118
COU=Albania	2.083	0.452	2.627	< 0,0001	-2.396
COU=Senegal	0.000	0.000	1.861	< 0,0001	-2.513
MS=MS_S	8.290	14.480	21.128	< 0,0001	-2.658
ES=PC	2.778	0.905	3.941	< 0,0001	-2.761
COU=Filippine	0.000	0.000	2.244	< 0,0001	-2.823
FC=2017	6.695	7.240	13.082	< 0,0001	-2.894
ES=TC	0.000	0.000	2.463	< 0,0001	-2.989
NC=0to3	10.530	60.181	69.130	< 0,0001	-3.011
EQ=BD	0.000	0.000	2.627	< 0,0001	-3.108
HS=UR	0.000	0.000	2.956	< 0,0001	-3.337
HS=SR	0.000	0.000	3.175	< 0,0001	-3.482
GEN=GEN_F	10.124	55.204	65.955	< 0,0001	-3.531
DRES=1to10	7.527	15.837	25.452	< 0,0001	-3.631
SN=SN_IMM	0.000	0.000	3.558	< 0,0001	-3.725
ES=UNW	0.000	0.000	3.612	< 0,0001	-3.759
SN=SN.HP	0.000	0.000	3.886	< 0,0001	-3.923
FC=2023	0.000	0.000	4.050	< 0,0001	-4.020
ES=PT	0.000	0.000	4.433	< 0,0001	-4.237
SN=SN.EI	0.813	0.452	6.732	< 0,0001	-4.817
PN=PN.PRO	0.813	0.452	6.732	< 0,0001	-4.817
RES=San Marco Evangelista	0.000	0.000	5.692	< 0,0001	-4.894
SN=SN.PRO	0.000	0.000	8.539	< 0,0001	-6.167
PN=PN.IMM	0.000	0.000	9.086	< 0,0001	-6.388
PN=PN.EI	0.901	0.905	12.151	< 0,0001	-6.628
CHD=0	0.000	0.000	10.016	< 0,0001	-6.751
COU=Ucraina	0.000	0.000	13.629	< 0,0001	-8.044
RES=Maddaloni	0.461	0.905	23.755	< 0,0001	-10.372
LIS=LIS.YES	0.497	1.810	44.061	< 0,0001	-15.416
RES=Caserta	0.337	1.357	48.714	< 0,0001	-16.961
PN=PN.POV	0.104	0.452	52.764	< 0,0001	-18.646

 doi:10.20944/preprints202405.2065.v1

Table 4. Second Cluster

Description	Cla/Mod	Mod/Cla	Global	p-value	v.test
PN=PN.POV	99.481	69.898	52.764	< 0,0001	28.096
LIS=LIS.YES	98.758	57.945	44.061	< 0,0001	23.251
MGS=MGS.FOOD PARCEL	84.652	91.254	80.952	< 0,0001	18.261
RES=Maddaloni	99.539	31.487	23.755	< 0,0001	16.267
SN=SN.PRO	98.718	11.224	8.539	< 0,0001	8.619
SN=SN.EI	98.374	8.819	6.732	< 0,0001	7.407
PN=PN.PRO	98.374	8.819	6.732	< 0,0001	7.407
FC=2017	92.050	16.035	13.082	< 0,0001	7.134
RES=San Marco Evangelista	99.038	7.507	5.692	< 0,0001	7.062
FC=2023	98.649	5.321	4.050	< 0,0001	5.722
ES=PT	97.531	5.758	4.433	< 0,0001	5.603
HS=UR	100.000	3.936	2.956	< 0,0001	5.256
SN=SN.HP	97.183	5.029	3.886	< 0,0001	5.107
MS=MS.W	87.963	13.848	11.823	< 0,0001	4.945
RES=San Nicola La Strada	93.878	6.706	5.364	< 0,0001	4.940
ES=PC	95.833	5.029	3.941	< 0,0001	4.734
FC=2016	89.583	9.402	7.882	< 0,0001	4.503
COU=Filippine	100.000	2.988	2.244	< 0,0001	4.499
FC=2018	91.304	6.122	5.036	< 0,0001	4.012
FRQ=FRQ.W	92.105	5.102	4.160	< 0,0001	3.828
EQ=BD	95.833	3.353	2.627	< 0,0001	3.799
ES=TC	95.556	3.134	2.463	< 0,0001	3.604
ES=HM	81.687	24.708	22.715	< 0,0001	3.604
FC=2021	84.034	14.577	13.027	< 0,0001	3.539
MGS=MGS.YES	100.000	1.895	1.423	< 0,0001	3.455
COU=Albania	93.750	3.280	2.627	< 0,0001	3.332
ES=UNW	90.909	4.373	3.612	< 0,0001	3.261
SN=SN.FAM	100.000	1.676	1.259	< 0,0001	3.213
CHD=1	81.250	22.741	21.018	< 0,0001	3.197
FRQ=FRQ.B	89.706	4.446	3.722	< 0,0001	3.029
FC=2020	83.036	13.557	12.261	< 0,0001	3.018
COU=Senegal	94.118	2.332	1.861	< 0,0001	2.822
PN=PN.HI	96.154	1.822	1.423	< 0,0001	2.752
HS=GS	93.548	2.114	1.697	< 0,0001	2.584
MS=MS.M	77.559	54.665	52.928	< 0,0001	2.577
GEN=GEN.F	76.929	67.566	65.955	< 0,0001	2.504
PN=PN.FAM	100.000	1.020	0.766	< 0,0001	2.369
FC=2010	100.000	0.948	0.712	< 0,0001	2.260
ES=UW	79.459	21.429	20.252	< 0,0001	2.196
FC=2019	84.211	5.831	5.200	< 0,0001	2.171
DRES=21to30	59.091	1.895	2.408	< 0,0001	-2.349
COU=Georgia	0.000	0.000	0.164	< 0,0001	-2.424
GEN=GEN.M	71.543	32.434	34.045	< 0,0001	-2.504
FC=2014	58.621	2.478	3.175	< 0,0001	-2.786
COU=Iran	0.000	0.000	0.219	< 0,0001	-2.894
FC=2015	61.290	4.155	5.090	< 0,0001	-3.014
COU=Ucraina	67.068	12.172	13.629	< 0,0001	-3.071
COU=Santo Domingo	0.000	0.000	0.274	< 0,0001	-3.307
FRQ=FRQ.M	73.889	87.245	88.670	< 0,0001	-3.464
DRES=N	70.728	38.921	41.325	< 0,0001	-3.603
DRES=41to50	44.118	1.093	1.861	< 0,0001	-3.849
AGE=18-34	59.211	6.560	8.320	< 0,0001	-4.497
MGS=MGS.GROCERY VOUCHERS	14.286	0.146	0.766	< 0,0001	-4.676
DRES=31to40	23.333	0.510	1.642	< 0,0001	-5.929
ES=OT	18.750	0.437	1.752	< 0,0001	-6.682
MS=MS.S	60.622	17.055	21.128	< 0,0001	-7.140
HS=SR	8.621	0.364	3.175	< 0,0001	-10.894
ES=IE	51.777	14.869	21.565	< 0,0001	-11.518
EQ=MS	67.621	61.953	68.801	< 0,0001	-11.73
SN=SN.IMM	1.538	0.073	3.558	< 0,0001	-13.097
CHD=0	8.743	1.166	10.016	< 0,0001	-20.355
PN=PN.IMM	4.217	0.510	9.086	< 0,0001	-20.805
RES=Marcianise	17.742	3.207	13.574	< 0,0001	-20.840
SN=SN.POV	20.996	4.300	15.380	< 0,0001	-21.205
PN=PN.HP	4.425	0.729	12.370	< 0,0001	-24.823

 doi:10.20944/preprints202405.2065.v1

Table 5. Third Cluster

Description	Cla/Mod	Mod/Cla	Global	p-value	v.test
CHD=0	91.257	71.368	10.016	< 0,0001	26.948
PN=PN.IMM	95.783	67.949	9.086	< 0,0001	26.924
RES=Caserta	25.843	98.291	48.714	< 0,0001	18.069
SN=SN.IMM	98.462	27.350	3.558	< 0,0001	16.299
HS=SR	91.379	22.650	3.175	< 0,0001	13.918
MGS=MGS.GROCERY VOUCHERS	95.745	19.231	2.573	< 0,0001	13.182
MS=MS.S	31.088	51.282	21.128	< 0,0001	11.062
ES=IE	28.426	47.863	21.565	< 0,0001	9.661
COU=Ucraina	32.932	35.043	13.629	< 0,0001	9.074
EQ=MS	16.866	90.598	68.801	< 0,0001	8.403
ES=OT	75.000	10.256	1.752	< 0,0001	8.099
PN=PN.EI	28.829	27.350	12.151	< 0,0001	6.854
MGS=MGS.GROCERY VOUCHERS	85.714	5.128	0.766	< 0,0001	6.093
NC=0 to 3	15.044	81.197	69.130	< 0,0001	4.430
COU=Santo Domingo	100.000	2.137	0.274	< 0,0001	4.150
DRES=1to10	18.280	36.325	25.452	< 0,0001	3.955
AGE=18-34	23.684	15.385	8.320	< 0,0001	3.853
COU=Iran	100.000	1.709	0.219	< 0,0001	3.649
MGS=MGS.UTILITY BILLS	47.059	3.419	0.930	< 0,0001	3.417
COU=Georgia	100.000	1.282	0.164	< 0,0001	3.079
COU=Kirghizstan	41.176	2.991	0.930	< 0,0001	2.896
DRES=N	15.364	0.729	12.370	< 0,0001	2.723
AGE=13-17	100.000	0.855	0.109	< 0,0001	2.401
COU=Nigeria	50.000	1.282	0.328	< 0,0001	2.119
PN=PN.DJ	66.667	0.855	0.164	< 0,0001	1.987
SN=SN.FAM	0.000	0.000	1.259	< 0,0001	-2.035
MGS=MGS.YES	0.000	0.000	1.423	< 0,0001	-2.203
PN=PN.HI	0.000	0.000	1.423	< 0,0001	-2.203
FRQ=FRQ.B	4.412	1.282	3.722	< 0,0001	-2.276
DRES=41to50	0.000	0.000	1.861	< 0,0001	-2.610
FC=2015	4.301	1.709	5.090	< 0,0001	-2.755
CHD=2	8.696	14.530	21.401	< 0,0001	-2.828
SN=SN.HP	2.817	0.855	3.886	< 0,0001	-2.880
COU=Filippine	0.000	0.000	2.244	< 0,0001	-2.930
DRES=21to30	0.000	0.000	2.408	< 0,0001	-3.058
ES=PT	2.469	0.855	4.433	< 0,0001	-3.239
ES=PC	1.389	0.427	3.941	< 0,0001	-3.456
HS=UR	0.000	0.000	2.956	< 0,0001	-3.459
FC=2023	1.351	0.427	4.050	< 0,0001	-3.526
FC=2018	2.174	0.855	5.036	< 0,0001	-3.606
FC=2014	0.000	0.000	3.175	< 0,0001	-3.608
NC=4 to 6	8.130	17.094	26.929	< 0,0001	-3.758
FC=2019	1.053	0.427	5.200	< 0,0001	-4.209
FRQ=FRQ.W	0.000	0.000	4.160	< 0,0001	-4.227
CHD=3 or more	4.587	4.274	11.932	< 0,0001	-4.258
FC=2016	2.778	1.709	7.882	< 0,0001	-4.291
RES=San Marco Evangelista	0.962	0.427	5.692	< 0,0001	-4.478
RES=San Nicola La Strada	0.000	0.000	5.364	< 0,0001	-4.894
SN=SN.EI	0.813	0.427	6.732	< 0,0001	-5.009
PN=PN.PRO	0.813	0.427	6.732	< 0,0001	-5.009
ES=HM	6.024	10.684	22.715	< 0,0001	-5.017
SN=SN.PRO	1.282	0.855	8.539	< 0,0001	-5.396
CHD=1	5.208	8.547	21.018	< 0,0001	-5.425
HS=OP	1.242	0.855	8.812	< 0,0001	-5.518
MS=MS.M	8.583	35.470	52.928	< 0,0001	-5.663
FC=2020	2.232	2.137	12.261	< 0,0001	-5.878
ES=UW	4.324	6.838	20.252	< 0,0001	-6.013
MS=MS.W	1.852	1.709	11.823	< 0,0001	-6.034
FC=2021	1.681	1.709	13.027	< 0,0001	-6.508
FC=2017	1.255	1.282	13.082	< 0,0001	-6.874
FC=2022	0.813	0.855	13.465	< 0,0001	-7.384
RES=Marcianise	0.403	0.427	13.574	< 0,0001	-7.825
PN=PN.HP	0.000	0.000	12.370	< 0,0001	-7.863
SN=SN.POV	0.712	0.855	15.380	< 0,0001	-8.067
COU=Italia	8.689	49.573	73.071	< 0,0001	-8.229
RES=Maddaloni	0.000	0.000	23.755	< 0,0001	-11.485
LIS=LIS.YES	0.745	2.564	44.061	< 0,0001	-15.499
PN=PN.POV	0.415	1.709	52.764	< 0,0001	-18.511
MGS=MGS.FOOD PARCEL	0.473	2.991	80.952	< 0,0001	-29.250

6. Conclusion

The conclusions drawn from this study reflect a thorough analysis of the connection between the United Nations' Agenda 2030 and the organization Caritas, highlighting the crucial role the latter plays in implementing the SDGs and contributing to realizing a more just, fair, and sustainable world for all. The Agenda 2030, with its 17 SDGs, provides a global framework for addressing complex socioeconomic challenges and promoting equitable and sustainable development worldwide.

Caritas, founded on the principles of solidarity, compassion, and love for one's neighbor, has been committed for decades for combating poverty and social injustice, and providing support and assistance to vulnerable individuals, regardless of their social, religious, or geographical conditions. Through a wide range of programs and services, Caritas offers food assistance, shelter, medical care, education, and emotional support to those in need, thus contributing to the social domain of the Agenda 2030.

This study focuses on analyzing Caritas' impact on society using Tandem Analysis, a technique aimed at identifying the primary needs of individuals seeking assistance from Caritas. The results

 doi:10.20944/preprints202405.2065.v1

show that Caritas plays an important role in meeting the needs of the most vulnerable people while contributing to the achievement of the SDGs in the local context.

The analysis conducted highlights the fundamental role of Caritas as a humanitarian and social assistance organization in translating the ideals and objectives of the Agenda 2030 into concrete and tangible actions at the community level. Through its ongoing commitment and dedication to solidarity and compassion, Caritas remains a beacon of hope and a positive agent of change in the fight against poverty and social injustice, thereby contributing to a fairer and more sustainable future for all. From a statistical perspective, we considered tandem analysis due to its mathematical properties and the abundance of useful, interpretative graphical displays it offers. However, recent advancements in tandem analysis alternatives warrant investigation. These alternatives integrate dimensionality reduction and classification techniques simultaneously rather than sequentially. For handling qualitative variables, several promising techniques merit consideration, among these MCA K-means [17], iterative Factorial Correspondence Biplot [15], Cluster Correspondence Analysis [28]. These methods, providing a powerful tool for simultaneous dimensionality reduction and classification, could enhance our analytical framework.

Funding: This research was funded by Italian Ministerial grants PRIN-2022 SCIK-HEALTH (code: 2022825Y5E 02; CUP: B53D23009750006) and PRIN-2022 PNRR The value of scientific production for patient care in Academic Health Science Centres (code: P2022RF38Y; CUP: B53D23026630001).

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Aaberge, R.; Brandolini, A. Multidimensional poverty and inequality. *Handbook of Income Distribution*, **2015**,2,141-216
2. Benzécri, J.P. *L'Analyse des Données* (two volumes). Paris: Dunad. 1973.
3. Benzécri, J.P. Sur le calcul des taux d'inertie dans l'analyse d'un questionnaire (abbendum et erratum). *Cahiers de l'Analyse des Données* **1979**, 4, 377–378.
4. Calinski, T.; Harabasz, J. A Dendrite Method for Cluster Analysis. *Communications in Statistics*, **1974**, 3, 1–27.
5. Caritas Presentation. Available online: https://www.caritas.it/presentazione/.
6. Cho, C.; Kim, S.; Lee, J.; Lee, D.-W. A tandem clustering process for multimodal datasets. *European Journal of Operational Research* **2006**, *168*, 998-1008.
7. Camminatiello, I.; et al. A model for evaluating inequalities in sustainability. *Social Indicators Research*, **2023**, 1-20.
8. Caritas Italiana. *TUTTO DA PERDERE: Rapporto su povertà ed esclusione sociale in Italia 2023*. Edizioni Palumbi. Roma, Italia, 2023.
9. Eurostat Statistics. Available online: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Living_conditions_in_Europe_-_poverty_and_social_exclusion.
10. Gherghi, M.; Lauro, C. *Appunti di analisi dei dati multidimensionali.* In RCE edizioni. Napoli, 2008.
11. Gifi, A. *Nonlinear multivariate analysis.* Vol. 8. Chichester: Wiley, 1990.
12. Greenacre, M. *Theory and Application of Correspondence Analysis.* London: Academic Press, 1984.
13. Husson, F.; Le, S.; Pagés, J. *Exploratory Multivariate Analysis by Example Using R.* New York: Chapman and Hall, 2010
14. ISTAT, Annual Report on Poverty. Available Online: https://www.istat.it/it/files/2023/06/REPORT-REDDITO-CONDIZIONI-DI-121VITA2022.pdf
15. Iodice D'Enza, A.; Palumbo, F. Iterative factor clustering of binary data. *Computational Statistics*, **2013**, 28, 789-807.
16. Izzo, F.; *et al*. Creating customer, museum and social value through digital technologies: Evidence from the MANN Assiri project. *Socio-Economic Planning Sciences*, **2023**, 85: 101502.
17. Hwang, H.; Dillon, W. R.; Takane, Y. (2006). An extension of multiple correspondence analysis for identifying heterogeneous subgroups of respondents. *Psychometrika*, **2006**, 71(1), 161-171.
18. Lebart, L.; Morineau, A.; Piron, M. *Statistique Exploratoire Multidimensionnelle.* Paris: Dunod, 1997
19. Lebart, L.; Morineau, A.; Warwick, K. M. *Multivariate Descriptive Statistical Analysis.* New York: Wiley, 1984.

 doi:10.20944/preprints202405.2065.v1

20. Little, R. J. A.; Rubin, D. B. *Statistical analysis with missing data.* John Wiley & Sons, 2019, 793.
21. OECD. *Opportunities for all: A Framework for policy action on inclusive growth.* Organisation for Economic Cooperation and Development. 2018
22. Pages, J. Analyse factorielle de donnees mixtes. *Revue Statistique Appliquee*, **2004**, *52*(4), 93–111.
23. Rossi, L.; Camminatiello, I.; Zanetti, M. The learning style of teenagers with callous-unemotional traits. *Statistica Applicata-Italian Journal of Applied Statistics*, **2022**, 2.
24. Rousseeuw, P.J. Silhouettes: A Graphical Aid to the Interpretation and Validation of Cluster Analysis. *Journal of Computational and Applied Mathematics*. **1987**, 20, 53–56
25. Smith, A. *The wealth of nations*. The Modern Library, Random House Inc. 1937.
26. United Nations General Assembly. "Transforming our world: the 2030 Agenda for Sustainable Development." United Nations: New York, NY, USA, **2015**.
27. United Nations. The Sustainable Development Goals Report, 2023
28. van de Valden, M.; Iodice D'Enza, A.; Palumbo, F. Cluster Correspondence Analysis. *Psychometrika* **2017**, *82*, 158–185.