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Analysis of Archetypes to Determine Time Use and Workload Profiles of Spanish University Professors

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Abstract: Allocation of time use is important to develop appropriate policies, especially in terms of gender equality. Individual well-being depends on many factors, including how time is spent. Therefore, knowing and analysing the time use and workload of academic staff is relevant for academic policy making. We analyse the responses of 703 Spanish academic staff regarding different activities of paid work and household work (unpaid). We use an innovative machine learning technique in this field, archetype analysis, which we introduce step by step while exploring our data. We identify five profiles, and we examine gender inequalities. The findings indicate that there is a higher prevalence of women in the profiles with a greater workload in household activities and teaching-related activities, but the prevalence is the same in the profile with a greater workload in research activities.

Keywords: archetype analysis; academia; gender; housework time; working hours; work–life balance

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1. Introduction

Time-use data are a key element for developing adequate regulations in all fields. Time-use data expose differences in how women and men spend their time, mostly as a result of gender roles [1]. Universities are not immune to gender norms, which also affect academic staff [2]. Previous works reveal gender differences in academia according to the distribution of time spent on different tasks [3]. In the case of Spain, a recent paper by Cabero and Epifanio [4] lays bare the gender gap in tasks related to both quality teaching and housework, as other papers point out [5,6]. This difference in time use also influences how long it takes to be promoted within the university. It is therefore crucial, both for social and academic equity, that university equality policies take these differences into account and implement policies to eradicate gender inequalities. This work is relevant to highlight these inequalities in order to recognise and tackle them.

As regards the methodologies used to analyse time-use data, they range from the simplest ones, such as descriptive techniques, to multivariate analysis techniques, which are not so common in this field, such as principal component analysis (PCA) [7] and cluster analysis (CLA) [4,7]. Those tools return exploratory analyses that provide a better understanding of the dataset. Their objective is to discover what data can reveal beyond the formal modelling or hypothesis-testing task.

Here, we propose to use a new exploratory statistical learning technique called archetype analysis (AA) [8], which is halfway between PCA and CLA. AA is more flexible than CLA and allows us to explain the data better; at the same time, however, its results are easily interpretable, even for non-experts, unlike those of PCA. Although there are previous works about time-use data among academic staff [3,4,9], none of them consider AA. Therefore, as a novelty, this is the first time that AA is applied to time-use data. As AA is an exploratory technique, this study is strictly exploratory and descriptive. No inferential statistics for testing a hypothesis are considered.

The contributions of this work are twofold. On the one hand, we introduce the AA technique for time-use data, step by step. In this way, we also introduce the use of AA as a useful tool in the field of education. Although it has been used elsewhere [10–17], unlike previous works, we adopt a pedagogical approach here, explaining the technique to facilitate the more widespread use of AA in the educational community. On the other hand, we apply AA for time-use data in the academic context. The advantages of using AA rather than other techniques are that we obtain archetypal profiles, "pure academic models", and we can represent the academic staff as mixtures of those prototypes. The archetypal profiles are in the periphery of the data, unlike centroids or average groups. The fact that archetypes are extreme profiles is more useful in decision making [18] than considering averages, since we obtain contrastive classes. In order to make decisions, opposite or dualism allows us to understand the dataset better [19,20]. This is why AA has been used in management for many years [21,22], and it is also helpful for drawing up university policy programmes.

There is a gender pay gap in Spanish academic staff [23]. Gender inequalities are present in academia, as proven by numerous works [24–27]. Here, we explore the different archetypal profiles in Spanish academia, and the analysis is broken down by gender to discover hidden patterns. The most similar previous work is that of Cabero and Epifanio [4], since we use the same data, although univariate descriptive analysis and CLA are used in Cabero and Epifanio's work [4] rather than AA.

In Cabero and Epifanio's work [4], it was shown that the number of hours worked by academic staff is significantly higher than the legally stipulated hours (37.5 h) and there was also a difference according to gender and professional category. Women worked more hours per week than men on average (50.8 h compared to 47.3 h for full-time academic staff). The staff categories with the highest mean workload correspond to full-time temporary positions, but also to the highest category (professor). In this last case, the mean workload of female professors (55 h) was 7 h per week higher than that of male professors (48 h).

With AA, we obtain a richer description of the data than in Cabero and Epifanio's work [4]. On the one hand, AA is a multivariate technique, meaning that we can handle relationships between variables, as opposed to univariate descriptive analysis. On the other hand, unlike AA, in Cabero and Epifanio's work [4], CLA provides hard assignments of the academic staff to different groups defined by centroids. Hard assignment means that academic staff belong to a single group, but nothing is said about how strong this assignment is. However, assignments are soft in AA; therefore, we can characterise the structure of time-use data more deeply and extensively: the groups are defined by archetypes and academics can be expressed as belonging to one group or to a mixture of groups, which provides finer details. Note also the difference between groups characterised by centroids in CLA or archetypes in AA, which favours better decision making, as explained above.

In summary, this work has two main objectives: (1) to provide a step-by-step guide for using AA; and (2) to apply AA for the analysis of time-use data for the first time to show how Spanish academic staff spend their time, which is very useful for devising appropriate gender equality policies in universities.

2. Materials and Methods

2.1. Sample and Instruments

We have used the data that can be accessed in Cabero and Epifanio's work [4]. The questionnaire used was created with Google Forms and is available at https://forms.gle/XCFHZqzYao19KdPz5 (accessed on 8 March 2023).

This questionnaire is divided into two sections; the first contains questions of a more personal nature, such as professional category, branch of knowledge, gender, age and number of children. The second section contains fourteen numbered questions in which the participating teaching staff specify the hours they spend per week on different tasks, such as face-to-face classes, answering queries, preparing teaching activities, correcting work, tutoring students, university management, research, transfer, caring for people, leisure and personal entertainment and household chores, in addition to the number of credits they have assigned, the credits of teaching reduction and the average number of hours they sleep on working days. Since the weekly timetable can vary greatly depending on the semester and even the week, the questionnaire specifies that participants should refer to work in a standard week; however, we are aware that these raw measures cannot capture all qualitative aspects of academic work, though the results of the analysis may help to clarify some doubts.

This questionnaire was answered by 703 people from 10 Spanish universities. Moreover, the percentage distribution of these people among the different categories of university teaching staff is very similar to the overall distribution of Spanish university teaching staff, except that in the case of part-time teaching staff, the percentage in the sample is lower than the percentage in the overall population. The percentage distribution in the sample according to branches of knowledge is also similar to the percentage distribution in the overall population, although the percentage in the sample is lower than in the overall population for health sciences, which is precisely where most part-time teaching staff are concentrated.

Each of the 703 participants is assigned a vector based on the answers to the questionnaire $x_i = (x_{i1}, x_{i2}, x_{i3}, x_{i4})$, $i = 1, 2, \ldots, 703$, where x_{i1} denotes the number of hours per week that the i-th person spends on tasks related to university teaching, x_{i2} denotes the number of hours per week that the i-th person spends on research and transfer, x_{i3} denotes the number of hours per week that the i-th person spends on management and x_{i4} denotes the number of hours per week that the i-th person spends on caring for people and household chores.

2.2. Statistical Technique: Archetype Analysis

We ask ourselves whether we can obtain a number p of profiles of people, represented by vectors $z_j = \left(z_{j1}, z_{j2}, z_{j3}, z_{j4}\right)$, $j = 1, 2, \ldots, p$, so that the 703 participating individuals can be obtained as a 'mixture' of these p profiles of individuals, which we will call archetypes. The mathematical approach to answering this question is based on minimising a sum of distances in the space; that is, the archetypes z_j must minimise the expression:

$$\sum_{i=1}^{703} dist^2\left(x_i\ ,\ \sum_{j=1}^{p} \alpha_{ij} z_j\right) \quad on\ \ \alpha_{ij} \geq 0 \quad and\ \ \sum_{j=1}^{p} \alpha_{ij} = 1. \tag{1}$$

$$z_j = \sum_{i=1}^{703} \beta_{ij}\, x_i \quad on\ \ \beta_{ij}\ \geq 0 \quad and \quad \sum_{j=1}^{703} \beta_{ij} = 1.$$

The experienced reader will have noticed that the number of archetypes p to be considered is fundamental; in fact, if p = 703 the solution to the problem posed is trivial, since the sum is minimised (in fact, it gives zero) when the archetypes are $z_j = x_j$ and α_{ii} =1, α_{ij} =0 if $i \neq j$. This leads us to comment on some interesting geometrical deductions [4]. Although our data x_i are in R^4, the deductions will be explained for the case of the R^2 plane, where they are easier to visualise. Given a set of points in the plane, its convex envelope is defined as the convex polygon of minimum area covering all points (i.e., all points are inside the polygon). The archetypes are always inside the convex envelope of the set of points. Moreover, if the polygon defining the convex envelope has q vertices, and we are looking for a number of archetypes p = q, then the archetypes are precisely the vertices of the convex envelope. In Figure 1, we see what happens as the number of archetypes approaches the number of vertices of the convex envelope. In Figure 1a, we have a dataset in the plane and its convex envelope. In Figure 1b, we have the data, together with p = 3 archetypes and the polygon they define. In Figure 1c, we have the data and p = 5 archetypes. In Figure 1d, we have the data and p = 10 archetypes, which coincide with the vertices of the convex envelope.

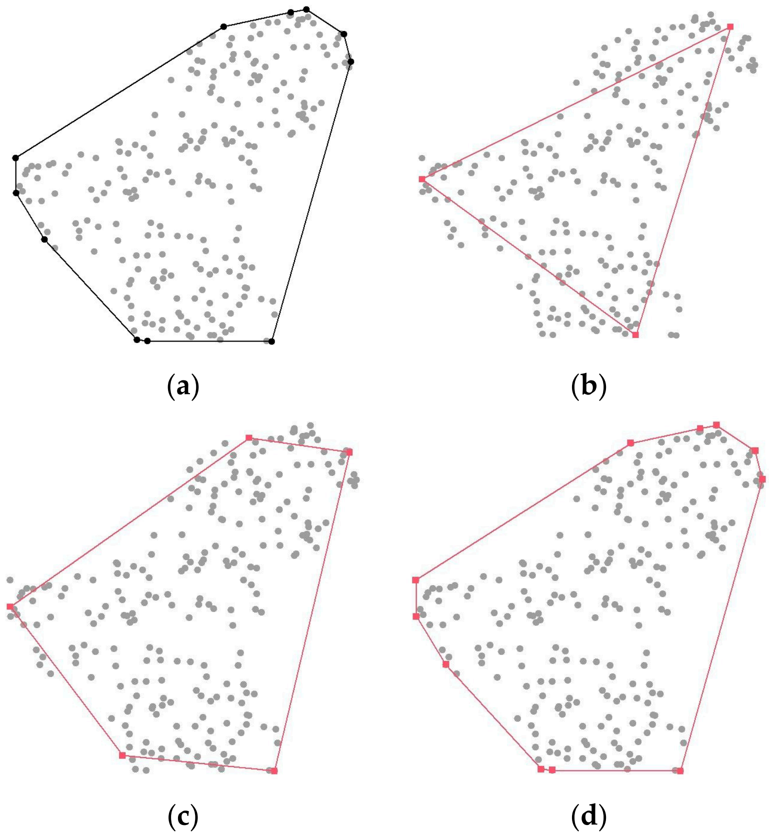


Figure 1. Evolution of the situation of archetypes according to p.

If the data are points in space, this consideration is generalised, but polygons are replaced with polyhedra. In the case of higher dimensions, as in our case, it is also generalised, but it is difficult, if not impossible, to visualise. We recommend, for example, the work of the Swiss geometrician Ludwig Schläfli (1814–1895), which presents a series of regular polyhedra in dimension four.

Therefore, a distinctive property of archetype analysis is that archetypes correspond best to extreme points with respect to the dataset x_i. In fact, it is shown, using simple geometric tools, that archetypes belong to the boundary of the convex envelope of the dataset.

Again, the experienced reader will have thought that, if we obtain the vertices of the convex envelope from the data, we already have not only the maximum number of archetypes but the archetypes themselves. This is true; however, obtaining the vertices is usually a difficult task. Moreover, the number of vertices may be too high, and we are statistically interested in summarising the data. Therefore, we will consider another way to analyse the "ideal" number of archetypes p to consider, and then obtain the value of the archetypes. The ideal situation is to consider few archetypes, but in such a way that the convex envelope of the archetypes and the convex envelope of the vertices are not very different (see Figure 1). However, this is equivalent to the minimum value of Equation (1) (RSS(p)), which does not vary much from a certain value of p.

In Figure 2, the minimum value (RSS(p)) of Equation (1) is plotted as a function of the number of archetypes p considered. It can be seen that, for our 703 standardised data, at the value p = 5, we have what is called an elbow, and from the number of archetypes p = 5, the value of RSS(p) remains 'stable'; therefore, we select p = 5 as the ideal number of archetypes.

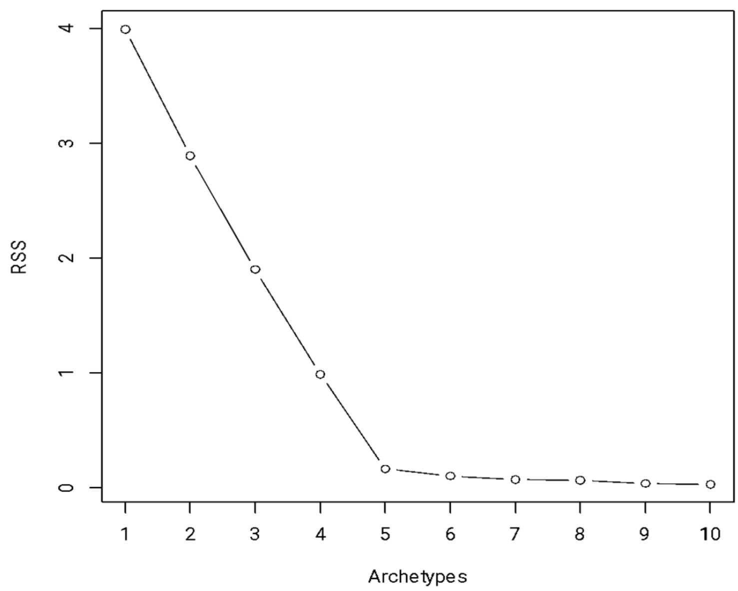
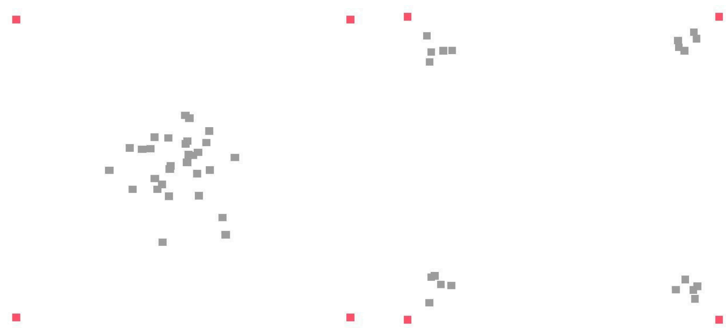


Figure 2. Screeplot of the number of archetypes versus RSS(p).

Once we have the p = 5 archetypes, all the data can be expressed approximately as:

$$x_i \approx \sum_{j=1}^{5} a_{ij}\, z_j\,, \quad 0 \leq a_{ij} \leq 1, \qquad \sum_{j=1}^{5} a_{ij} = 1, \quad i = 1, \ldots, 703, \qquad j = 1, \ldots, 5. \tag{2}$$

That is, each datum x_i, which in our case represents one of the 703 people participating in the survey, is expressed as a mixture of the p archetypes. Moreover, as the values of a_{ij} are between 0 and 1, it is easy to explain the weight of each archetype in percentages. In Figure 3, we have two datasets that are represented by the same four archetypes. In Figure 3a, all archetypes have a significant weight in the sum, i.e., the coefficients a_{ij} have a similar value for the points in the central cloud. In Figure 3b, each datum is practically explained by one archetype, i.e., one value of a_{ij} is close to 1 and the rest are close to zero.



(**a**) (**b**)

Figure 3. Datasets with the same archetypes but different weights. Archetypes are represented with red squares. Data are represented with (red and grey) squares.

3. Results and Discussion

In this section, the results of AA are analysed. We will consider the archetypal academic staff and their analysis by gender to observe if there is a gender gap for the different blocks (teaching, research, management and care). Table 1 shows the values obtained for the five archetypes z_j , $j = 1, 2, 3, 4, 5$.

Table 1. Number of hours per week devoted by each archetype to the different activities.

	z_{j1} = Teaching Hours	z_{j2} = Research Hours	z_{j3} = Management Hours	z_{j4} = Home and Personal Care Hours
z_1	12.26	0	0	2.57
z_2	14.61	14.63	40.02	14.86
z_3	14.98	4.11	0	99.03
z_4	12.43	59.65	0.4	5.69
z_5	70.94	11.25	4.12	21.86

Linking the archetypes, which have extreme values as seen before, to the teaching staff, we find that archetype z_1 generally devotes few hours to the activities mentioned in the questionnaire. Archetype z_2 devotes many hours per week to management tasks. Archetype z_3 spends many hours caring for people and the home. Archetype z_4 spends many hours on research and transfer. Finally, archetype z_5 devotes many hours to university teaching.

When it comes to analysing the data on the basis of the five archetypes, we will carry so out in two different ways. The first consists of dividing the 703 data into five groups and assigning each datum to the archetype group it most resembles; that is, each datum x_i is assigned to the archetype group z_j for which the value of the coefficient a_{ij} in Equation (2) is largest. This way of clustering the data is similar to that used in other clustering methods [4]. Table 2 shows the number of participating teachers belonging to each of the five groups.

Table 2. Groups according to the most similar archetype.

Group G1 (Minimal Effort) (Archetype 1)	Group G2 (High Management) (Archetype 2)	Group G3 (High Domestic) (Archetype 3)	Group G4 (High Research) (Archetype 4)	Group G5 (High Teaching) (Archetype 5)
353 (50%)	39 (6%)	93 (13%)	85 (12%)	133 (19%)

With this way of grouping the teaching staff, we find that approximately half belong to the group defined by the archetype that spends few hours on the different activities in the questionnaire. It should be noted that 89 of the 123 people who took part in the survey and form part of the group of part-time lecturers belong to this group, which is consistent with the fact that these people devote time to their main job outside the university. It is also logical that group G2 (high management), defined by the archetype that devotes the most hours to university management, is the least numerous.

If we construct a table similar to Table 2, but distinguishing between men and women, we obtain the results shown in Table 3. From Table 3, we can conclude that the percentages of women belonging to group G3 (high domestic) (defined by the archetype that spends many hours caring for people) and the percentage of women belonging to group G5 (high teaching) (defined by the archetype that spends many hours teaching) are higher than the respective percentages for men. On the other hand, the percentage of men in group G1 (minimal effort) is higher than that of women.

Table 3. Groups according to archetype distinguishing between men and women.

	Group G1 (Minimal Effort) (Archetype 1)	Group G2 (High Management) (Archetype 2)	Group G3 (High Domestic) (Archetype 3)	Group G4 (High Research) (Archetype 4)	Group G5 (High Teaching) (Archetype 5)
Men (347)	208 (60%)	15 (4%)	36 (10%)	41 (12%)	47 (14%)
Women (356)	145 (41%)	24 (7%)	57 (16%)	44 (12%)	86 (24%)

This way of assigning each datum x_i to the archetype group, for which the value of the coefficient a_{ij} is largest, does not distinguish between very different situations as depicted in Figure 3. Since our data are in R^4, to obtain an idea of each coefficient's weight in the representation, we will conduct an indicative geometric visualisation based on two orthogonal projections. First, we project the data onto the convex envelope formed by the archetypes; then, we project the new points onto a plane [28]. Obviously, the result of the projection depends on the plane; thus, the visualisation is only indicative. Figure 4 shows the result of this projection; the colour (and shape) of the points relates the projected points to the group to which the original data belong. A_j points are the projections of the archetypes z_j.

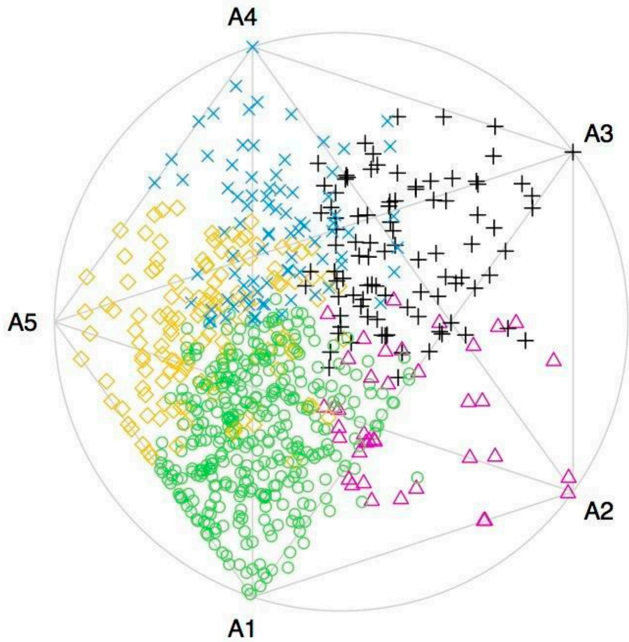


Figure 4. Orthogonal projection of the data on a plane (simplexplot function of the R software).

From Figure 4, we can conclude that there are many data that can be practically explained by the value of one of the archetypes; however, there are also others which seem to be explained as a combination of several archetypes. Therefore, we propose a second way of analysing the data in terms of archetypes, which is as follows. Any datum x_i of the 703 that has a coefficient $a_{ij} > 0.5$, i.e., is expressed mostly (more than 50%) by archetype z_j, is assigned to archetype group z_j. If the sum of two coefficients a_{ij} is greater than 0.5 and none of them separately, we create a new group that will be the mixture of the two corresponding archetypes and so forth until we have each datum in one of the generated groups.

In Table 4, we have the number of groups that have been generated and the number of participating teachers belonging to each of the groups. Only three participants belong to a group defined with three archetypes, and this group does not appear in the table.

As can be seen in Table 4, 350 out of the 703 people (50%) are expressed as a single archetype, 350 as a mixture of two archetypes, and only 3 are a mixture of three archetypes. The most numerous group with a mixture of two archetypes is G1-5 (minimal effort-high teaching), a mixture of archetypes z_1, which spends few hours on the activities mentioned in the questionnaire, and z_5, which spends many hours on university teaching.

Table 4. More detailed groups according to archetype distinguishing between men and women.

Group G1 (Minimal Effort) (Archetype 1)	**Group G2 (High Management) (Archetype 2)**	**Group G3 (High Domestic) (Archetype 3)**	**Group G4 (High Research) (Archetype 4)**	**Group G5 (High Teaching) (Archetype 5)**
197 (28%)	9 (1%)	38 (5%)	37 (5%)	69 (10%)
Group G1-2 (minimal effort-high management) (archetypes 1-2)	**Group G1-3 (minimal effort-high domestic) (archetypes 1-3)**	**Group G1-4 (minimal effort-high research) (archetypes 1-4)**	**Group G1-5 (minimal effort-high teaching) (archetypes 1-5)**	**Group G2-3 (high management and domestic) (archetypes 2-3)**
25 (4%)	33 (5%)	73 (10%)	99 (14%)	15 (2%)
Group G2-4 (high management and research) (archetypes 2-4)	**Group G2-5 (high management and teaching) (archetypes 25)**	**Group G3-4 (high domestic and research) (archetypes 3-4)**	**Group G3-5 (high domestic and teaching) (archetypes 3-5)**	**Group G4-5 (high research and teaching) (archetypes 4-5)**
4 (1%)	11 (2%)	27 (4%)	30 (4%)	33 (5%)

From Table 5, where we distinguish the results between men and women, we draw the same conclusions that we discussed as a consequence of Table 3. In addition, for the groups defined by two archetypes, the number of women belonging to group G1-4 (minimal effort–high research) (defined by the archetype that spends few hours on the activities in the questionnaire and the archetype that spends many hours on research and transfer) is lower than that of men, while in groups G1-3 (minimal effort–high domestic) (defined by the archetype that spends few hours per week on the activities in the questionnaire and the archetype that spends many hours per week on caring for people and the home) and G3-5 (high domestic and teaching) (defined by the archetype that spends many hours per week on caring for people and the home and the archetype that spends many hours per week on university teaching) the opposite is true.

Table 5. Groups defined by one and two archetypes distinguishing between men and women.

	Group G1 (Minimal Effort)	**Group G2 (High Management)**	**Group G3 (High Domestic)**	**Group G4 (High Research)**	**Group G5 (High Teaching)**
Men	123	6	9	19	22
Women	74	3	29	18	47
	Group G1-2 (minimal effort–high management)	**Group G1-3 (minimal effort–high domestic)**	**Group G1-4 (minimal effort–high research)**	**Group G1-5 (minimal effort–high teaching)**	**Group G2-3 (high management and domestic)**
Men	12	12	42	50	6
Women	13	21	31	49	9
	Group G2-4 (high management and research)	**Group G2-5 (high management and teaching)**	**Group G3-4 (high domestic and research)**	**Group G3-5 (high domestic and teaching)**	**Group G4-5 (high research and teaching)**
Men	2	5	14	10	14
Women	2	6	13	20	19

Obviously, more detailed information could be provided by considering, for example, results according to different categories of teaching staff or different branches of knowledge; however, we leave it to each university to analyse and expand the information as they consider appropriate and to start a political debate on whether to maintain the groups of teaching staff that appear in the analysis presented or to take measures to redress the balance in each group.

4. Conclusions

The main tasks carried out by academic staff include teaching, research and transfer, and management. In addition to these tasks that are carried out to a large extent at the university, we must add the task of caring for people (children and dependent elderly people) and the home.

When making political decisions that, for instance, favour equality between men and women or distinguish between teachers with an exclusively teaching profile and teachers with a double teaching and research profile, it is very important to know the number of hours devoted to each of the five tasks mentioned above, as well as having an explanation of this distribution of hours through the application of an appropriate statistical model.

In this study, 703 university professors have answered a questionnaire, from which a vector with four entries has been associated with each professor. Each entry shows the number of hours per week that each teacher spends on each of the four activities. With these 703 vectors, we apply the statistical technique of archetype analysis, and the first result we obtain is that the ideal number of archetypes for analysing the information is $p = 5$.

These five archetypes are extreme vectors that belong to the frontier of the convex hull of the 703 vectors. Firstly, we have used these five archetypes for clustering the 703 vectors, assigning each vector to the group defined by the closest archetype. The most outstanding conclusions of this grouping are that the largest group is defined by teachers who spend little time on the four tasks (this is explained by the fact that a high percentage of teachers work part-time and have another job outside the university) and the least numerous group is defined by devoting more hours to university management. However, when we differentiate between men and women in the grouping, the most interesting finding is that the percentage of women belonging to the group defined by the archetype that devotes many hours to caring for people and the percentage of women belonging to the group defined by the archetype that devotes many hours to teaching are higher than the respective percentages of men.

Secondly, because AA allows academic staff to be represented as mixtures of these five prototypes, we analyse mixtures of groups and conclude that 350 out of the 703 people (50%) are expressed as a single archetype, 350 as a mixture of two archetypes, and only 3 as a mixture of three archetypes. The main conclusions in this case are that the most numerous group with a mixture of two archetypes is the group that devotes few hours to the activities mentioned in the questionnaire and many hours to university teaching (Group G1-5 (minimal effort–high teaching)). If we distinguish between men and women, we can highlight as conclusions that for the groups defined by two archetypes, the number of women belonging to the group defined by the archetype that spends few hours on the activities in the questionnaire and the archetype that spends many hours on research and transfer (Group G1-4 (minimal effort–high research)) is lower than that of men, while in the group defined by the archetype that spends few hours a week on the activities in the questionnaire and the archetype that spends many hours a week caring for people and the home (Group G1-3 (minimal effort–high domestic)) and in the group defined by the archetype that spends many hours a week caring for people and the home and the archetype that spends many hours a week on university teaching (Group G3-5 (high domestic and teaching)), the number of women is higher than that of men.

In view of the conclusions of this work, Spanish university policies should favour the hiring of full-time teaching staff and fight against the current gender gap.

As regards the gender gap, some specific measures that could be implemented in Spain are suggested by the Royal Spanish Mathematical Society's Women's Commission [29]. However, they are not specific to Spain; for example, gender neutral policies should not be used since not only do they not reduce the gender gap, but they actually increase it [30]. Meritocracy should be revised [31], and promotion criteria should include teaching performance [32]. In fact, a high research production can affect teaching quality [33]. A monographic study about gender equality in higher education and research institutions can be found in the work of Lopez, Silvestre and García [34], which presents many possible initiatives that can be carried out to reduce the gender gap, ranging from the analysis of university rankings [35] to implementing appropriate equality plans with gender-sensitive indicators [36]. Nevertheless, another line of action to change visions is to incorporate gender perspective into teaching in all disciplines, including STEM [37], despite the resistance that can be found [38], even in the use of inclusive language [39].

Finally, the authorities should also pay attention to the high number of hours spent working by many individuals, especially in G5 (high teaching), the majority of whom are women (much more than the 37.5 weekly hours stipulated in Spanish law). Those individuals could be accelerated researchers, which implies psychosocial risks [40]. Coneso and González [40] propose a change to the model of work organisation considering an 'ethics of care' feminist approach.

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