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Fotiadis, Thomas A.

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# Contemporary advanced statistical methods for the science of marketing: Implicative Statistical Analysis vs Principal Components Analysis

Thomas A. Fotiadis
Post Doc Candidate, University of Western Macedonia
Sofia D. Anastsiadou
University of Western Macedonia

**Introduction:** Even though there is a substantial development and utilization of pattering methods in the science of marketing, a direct comparison of multivariate methods in group/cluster identification in the field of Consumer Behavior has not been carried out.

**Objective:** This study analyses two different statistical techniques: i.e the Principal Components Analysis (PCA) and the Implicative Statistical Analysis (ASI). The main objective is to compare patterns derived from Principal Components Analysis (PCA) and Implicative Statistical Analysis (ASI) procedures with respect to Consumer Behavior.

**Design:** A survey was carried out using a structured questionnaire for a sample of 335 adults, customers of 125 Greek e-shops. These were conventionally approached by the Marketing Laboratory of a major public University in Northern Greece. Information Seeking, Information Sharing, Responsible Behavior subscales are related to Customer Participation Behavior**.** These subscales were measured by 15 items, rated on a seven-point Likert format, ranging from 1 (strongly disagree) to 7 (strongly agree).

**Methods:** The study focuses on the presentation of the two main types of clustering methods, Implicative Statistical Analysis (ASI) and Principal Components Analysis (PCA).

**Results:** PCA's results showed the existence of 3 Component, amongst which the first is shown to be the Component of Responsible Behavior, the second is shown to be the Component of Information Sharing, and the third is shown to be the Component of Information Seeking.

ASI results release a similarity tree and a cohesive tree. Similarity tree showed that *Information Seeking* is the par excellence most powerful constituent of the creation of Customer Participation behaviour values and *Information Sharing* is the next similarity tree also showed that customers' *Responsible Behaviour* is the weakest constituent for the creation of Customer Participation Behaviour values.

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Hierarchical group of the items in conceptual construct *Information Seeking* exhibits the externally significant cohesion. Beliefs on conceptual construct *Information Sharing* imply beliefs on *Responsible Behavior with* exceptionally high cohesion.

**Key words:** Principal Components Analysis, Implicative Statistical Analysis, Consumer, Behavior

## The Instruments/ Measures

Customer Participation Behavior scale was measured using Customer Value Co-creation Behavior multidimensional and hierarchical scale of Yi & Gong (2013) that consists of 15 items, rated on a seven-point Likert format, ranging from 1 (strongly disagree) to 7 (strongly agree). Customer citizenship behavior, in particular, contains the constructs of *Information Seeking, Information Sharing,* and *Responsible Behavior*.

The group regards conceptual construct *Information Seeking,* and comprises of 3 statements ($INF_i$) (eg. INF1: I have asked others for information on what this service offers), while the second group regards conceptual construct *Information Sharing* ($FDB_i$) and comprises of 4 statements (eg. FDB1: I clearly explained what I wanted the employee and the e-shop to do). The third group regards conceptual construct *Responsible Behavior* ($INS_i$) and comprises of 4 statements (eg. INS1: I performed all the tasks that are required). These three conceptual constructs contribute to the creation of Latent Variable Customer Participation Behavior.

## Data Clustering Techniques

This section is dedicated to the presentation of the three main types of clustering methods that is Implicative Statistical Analysis (ASI), and Principal Components Analysis (PCA).

***Implicative Statistical Analysis (ASI):*** Implicative Statistical Analysis (ASI**)** was initiated and developed by Régis Gras to be applied in the Didactic of Mathematics (Gras, 1979). Since the doctoral dissertation of Régis Gras, a great deal of research has been published concerning different paths of theory development (Gras et al., 1997; Gras, & Couturier, 2013; Gras et al., 2004; Gras, et al., 2008 ; Gras, Regnier, & Guillet, 2009; Gras, Régnier, Marinica, & Guillet, 2013). Consequently, the method has been advanced noticeably and has been applied to a wide range of data, such as mathematics education; psychology; physics, medicine, etc (Nikolaou et al., 2017). According to Coutourier (2008) the initial objective of this method is to define an

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approach that adequately confronts the question "if an object has a property, does it also have another one". This is seldom accurate although a tendency seems to emerge. ASI aims at highlighting such tendencies in a set of properties. According to Coutourier (2008), ASI can be regarded as a method used to generate association rules. Furthermore, it is considered to be a wide theoretical framework, a theory connected with causality due to the fact that it responds to the weakness regarding other multivariate methods, as well as highlighting formal tools and practical methods of data representation, evaluation and interpretation.

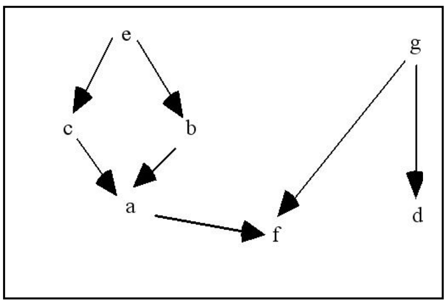
It is of a major importance to note that compared to other association rule methods; ASI distinguishes itself by providing a non linear measure that satisfies some important criteria.

In order for the implicative association rules to be extracted, the ASI assigns a numerical value between zero to R rules and one according to following form: If the variable a is observe then it is possible for the variable b to be observed. Consequently, if the variable a gets a specific value, then variable b possibly gets a higher value. The measure assigned is a probability, well known now as intensity of involvement. Consequently, causal and predictive relations are influenced by the intensity of involvement.

The principle of determining the intensity of involvement as a probability of a random event and it is defined as follows: if there was a non a priori asymmetric link between a and b, the number of counterexamples to the rule R, is under the unique effect of chance, usually higher than the number of counterexamples observed in the contingency. Thus, the method is based on implication intensity that measures the degree of astonishment inherent in a rule. For example, the set of items B, then it is legitimate and intuitive to expect that the counter part is and the set of non-B items is strongly associated with the set of non A-items.

According to Coutourier (2008), the implication intensity maybe reinforced by the degree of validity that is based on Shannon's entropy, in case that a researcher chooses this comparison approach.

The implicative representation of the associations is presented in figure 1 by a weighted graph without cycle where each edge corresponds to a rule, and in figure 2 by an ascending hierarchy oriented by meta-rules.



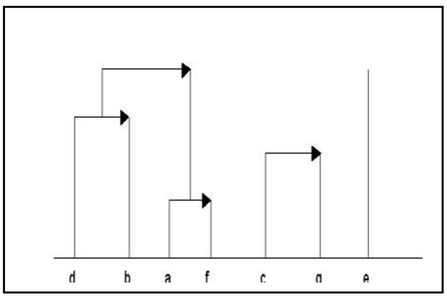



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Figure 1 Figure 2

Source: Wikipaideia

***Similarity: a symmetrical analysis*** according to the algorithm of the I.C. Lerman (Lerman, 1978) link brings together in a large class practically all the items whatever their a priori taxonomic classification maybe (Gras & Bodin, 2017). Similarity tree is based on the similarity indexes, defined by Lerman (1981). Similarity indices are used in data analysis to study objects described by binary variables. According to Blanchard (2009), they allow one to assess the likeness between two objects and two variables.

The likelihood index is based on Likelihood Linkage Analysis (LLA) (Lerman, 1981) and it is given by Lerman (1993) in Blanchard (2009) as:

Likelihood Linkage Index of Lerman $P(N_{ab}<n_{ab})$,

while the Implication Intensity of Gras (Gras, 1996; Gras & Kuntz, 2008) is given in Blanchard (2009) as:

Likelihood Linkage Index of Gras $P(N_{ab*}>n_{ab*})$,

where the hypothesis tested is Ho: there is independence between a and b, and $N_{ab}$ and $N_{ab*}$ are random variables for the numbers of examples and counterexamples $n_{ab}$ the number of examples and $n_{ab*}$ the number of counterexamples.

**Cohesive hierarchy:** It can now be expected that the cohesive hierarchy, always obtained by CHIC Software, which structures successes in groups guided by implication, respects, within them, the presumed taxonomic order.

For the analysis of the data Implicative Statistical Analysis is used. Specifically the Cohesion tree (Gras et al., 1997) as well as the Similarity tree (widely known as dendrogram (Lerman, 1981) resulted by CHIC Software (Couturier, 2008).

***Principal component analysis or PCA*** is a method for the analysis of multivariate data, and it is considered to constitute a part of factor Analysis.

The principal objectives of PCA are:

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- Data Reduction. PCA aims to replace highly correlated variables with a small number of correlated variables (Dafermos, 2013).
- To detect and establish a structure/model. The goal of PCA is, namely, to accentuate structures or fundamental relations existing between the existing variable (Dafermos, 2013). Moreover, PCA aims to bring to light and assess latent variables, and to detect and assess latent sources of variability and co-variability in observable measurements.
- To detect patterns. The goal of PCA is to detect prototype correlations which may potentially determine causality relations between the examined variables (Dafermos, 2013).

PCA is a descriptive or explanatory method and does not rest on conditions. In reality, PCA rests on the spectrum analysis of the variance or correlation matrix. Principal Components Analysis is by far the most widespread pattern recognition tool**.** It is a method for compressing a lot of data into patterns that capture the essence of the original data. Specifically, it constitutes a multivariate statistical analysis that is often used to reduce the dimension of data for easy exploration. Its objectives include: 1) to reduce the original into a lower number of orthogonal (uncorrelated), synthesized variables; 2) to visualize correlations among and between the original variables and the components, and 3) to visualize proximities among statistical units. Furthermore, PCA is considered to be a change of variable space.

It rests on the study of eigenvalues and eigenvectors in the correlations or covariance matrix.

As a multivariate analysis technique for dimension reduction, PCA aims to compress the data without losing much of the information contained in the original data. The process regards explaining the variance-covariance structure of a set of variables through a few new variables. All principal components are specific linear combinations of the p random variables exhibiting three important properties:

1. The principal components are uncorrelated. There are also orthogonal uncorrelated, linear combinations of standardized variables.
2. The first principal component has the highest variance; the second principal component has the second highest variance, and so on.
3. The total variation in all the principal components combined is equal to the total variation in the original variables.

In reality, PCA converts data into a set of linear components and, as it is characteristically alluded by Field (2009), it converts them to measurable ones.

Each component has the form: $Component_i = b_1X_1 + b_2X_2 + \ldots\ b_nX_m$. It is evident that PCA forecasts components based on measured variables. It is rendered clear that PCA break down the original data to a model of linear variables. PCA brings to light which linear components exist in the data and the manner by which one particular variable contributes to the shaping of each component (Field, 2009).

PCA rests on the overall variance of the variables in descending order. The first Principal Component (PC1) captures the most variance of the data; the second Principal Component (PC2), which is not correlated with PC1, captures the second variance etc.

The number of the components extracted is equal to the original variables and the sum of their variance is the sum of the variance of the original variables.

The sum of the squares of loadings to a principal component signifies the participation of the component to the overall variance of the variables. The value of the sum for each principal component is called eigenvalue. Eigenvalues are presented in descending order and allow for the exclusion of these components that do not interpret a satisfactory percentage of the overall variance, resulting only in only components interpreting a satisfactory percentage of the overall variance to be employed for the interpretation of the results. Selected are components whose eigenvalues are equal or greater than one (Kaiser, 1960) or equal or greater than 0.70 (Jolliffe, 1972, 1986).

The following table (Table 1) presents some of the basic differences of the two methods.

**Table 1:** Differences of the two methods

| ASI | PCA |
|---|---|
| • ASI rests on rules.<br>• It is based on a probabilistic model.<br>• It highlights tendencies in a set of properties (Coutourier, 2008).<br>• It generates association rules Coutourier, 2008).<br>• It provides a non linear measure Coutourier, 2008). | • PCA does not rest on conditions.<br>• It is based on metric space distances Coutourier, 2008).<br>• Its patterns are based on correlation between variables.<br>• It provides a linear measure. |

| | |
|---|---|
| | • It visualizes correlations among the original variables and between these variables and the components.<br>• It visualizes proximities among statistical units.<br>• It is a frequently employed statistical technique for unsupervised dimension reduction. |
| Properties between the variables<br>• Relationship between variables is dissymmetrical.<br>• The association measures are not linear and are based on probabilities. | Properties between the variables<br>• Relationship between variables is symmetrical.<br>• The association measures are linear. |
| | • Data Reduction (Dafermos, 2013).<br>• Data detection and establishment of a structure/model (Dafermos, 2013).<br>• Establishment of latent variables.<br>• Detection of latent sources of variability and co-variability in observable measurements (Dafermos, 2013).<br>• Detection of patterns (Dafermos, 2013). |
| • Represented by the similarity tree (lerman, 1981).<br>• Represented by the implication tree (Gras et al., 1997).<br>• Represented by the cohesion tree (Gras et al., 1997). | • Represented by factorial plane. |

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## Data Collection and Sample

***Data Collection:*** A survey was carried out using a structured questionnaire for a sample of 335 adults, customers of 125 Greek e-shops. These were conventionally approached by the Marketing Laboratory of a major public University in Northern Greece. Two post-graduate students were carefully trained in order to perform their duties as interviewers. The questionnaire was originally developed in English and then it was translated to Greek using the translation and back translation procedure, while tutors of English who speak fluent Greek assumed to provide the relevant translations.

***The sample:*** The sample comprised of 335 interviewees, of whom 185 (55.2%) were men and 150 (44.8%) were women. With respect to the ages of participants, 67 (20%) of them were between 18 to 24 years old, 67 (20%) of them were between 25-34, 68 (20.3%) of them were between 35-44, 67 (20%) of them were between 45-54 and, finally, 66 (19.7%) were between the ages of 55 to 64 years old. With respect to their family status, 143 (42.7%) were single, while 180 (53.7%) were married and 12 (3.6%) were separated or divorced. 288 of 335 interviewees, or a percentage of 86%, stated that they live in an urban setting, while 47 (14%) in a rural one.

Regarding the education of interviewees, one (0.3%) stated he graduated elementary education, 124 (37%) secondary, 160 (47.8) tertiary, while 50 (14.9%) hold a postgraduate diploma or doctorate. Out of the 154 interviewees, 137 (40.9%) declared that their income was less than €10,000 per year, 154 (46%) declared that their income was between € 10,000 and €24.999, while the income for 35 interviewees (10.4%) ranged between €25.000 to €49.999. According to 5 participants, (1.5%) their income ranged from €50.000 to €74,999. Finally, 4 interviewees (1.2%) declined to answer the question relating to their income.

## Results

***The similarity diagram:*** The similarity diagram presents groupings of statements based on customer behaviour as it is captured on the questionnaire. Similarities in emphasized black are significant, at a significance level of 99%. The similarity diagram (Figure 3) presents two distinct similarity groups (Group A, Group B). The first similarity group (Group A) refers to similarity relations between variables (((INF1 INF3) INF2) ((FDB1 FDB2) (FDB3 FDB4))) (similarity: 0.0172892) that regard the factor Information Seeking and the factor Information

Sharing, and represent the similar tactic employed by the interviewees to treat and perceive the implicit variable Customer Participation Behaviour. Specifically, this similarity is extremely weak because its value is equal to 0.0172892, almost 2%.

Specifically, similarity (INF1-INF3) (similarity: 0.918299), the most forceful in the first group, it is also the most forceful compared to all other similarity groups. A third variable, INF2 of the conceptual construct *Information Seeking*, completes this similarity group ((INF1 INF3) INF2) similarity: 0.768218). This reflects the degree of information searched regarding the e-shop location.

This Similarity between variables INS3-INS4- INS1-INS2 shows that *Information Seeking* is the par excellence most powerful constituent of the creation of Customer Participation Behaviour values.

The second most forceful similarity is the one between variables FDB1-FDB2 (similarity: 0.850801) that refer to the possibility interviewees clearly explained what they wanted the employee and the e-shop to do and consequently have provided the e-shop with the proper information.

The similarity FDB3-FDB4 (similarity: 0.775505) is equally important and refers to the necessary information given by customers to the shop so that the employee could perform his or her duties by answering all the employee's service-related questions. These two similarity groups form an equally forceful relation between the four items FDB1-FDB2 and FDB3-FDB4 (((FDB1 FDB2) (FDB3 FDB4)) similarity: 0.502155) which also approximates the amount 0.50 and, consequently, is a similarity of a medium importance. This specific similarity group refers to Information Sharing.

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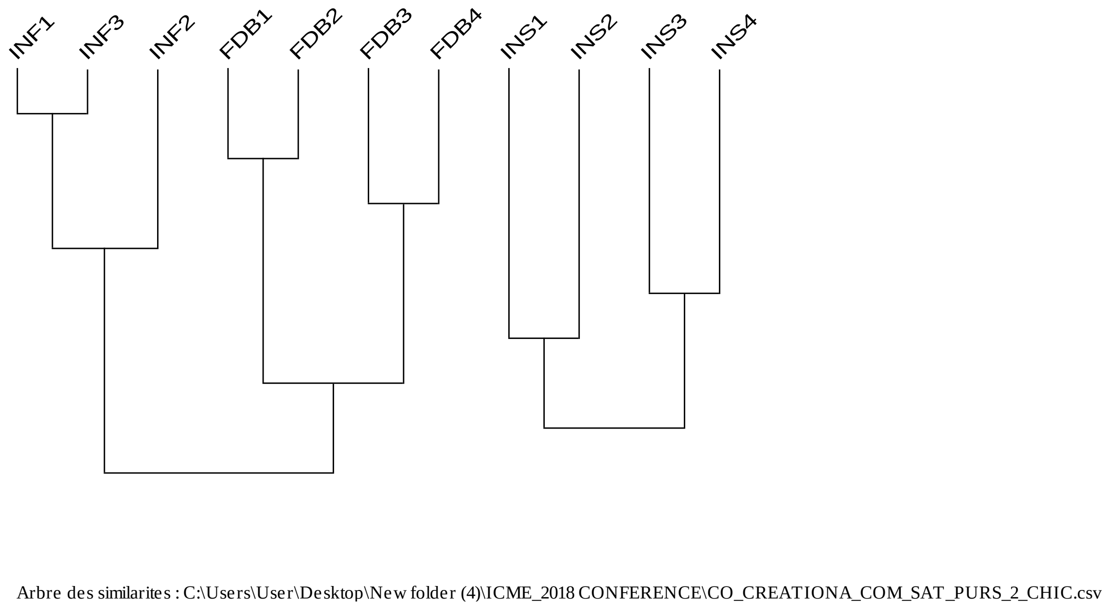


Figure 3: Similarity Tree

A third construct, *Responsible Behaviour*, contributes towards a second similarity group, Group B, which is an independent group. More specifically, the most powerful similarity in the second group, Group B, is that between variables INS3-INS4 (similarity: 0.716318), which refer to the possibility that customers followed the employee's or e-shop's directives and fulfilled their responsibilities to the business or e-shop.

Similarity INS1-INS2 (similarity: 0.711894) shows the similar tactic adopted by the interviewees to perform all the tasks required and adequately completed all the expected behaviors (similarity: 0.711894).

These two similarity groups form an equally forceful relation between the four items INS1-INS2 and INS3-INS4 ((INS1 INS2) (INS3 INS4)) (similarity: 0.256839) which also approximates value 0.27≈ 0.30 and, consequently, is of a limited acceptance accepted similarity.

This Similarity between variables INS3-INS4-INS1-INS2 shows that customers' *Responsible Behaviour* is the weakest constituent for the creation of Customer Participation Behaviour values.

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***The hierarchical diagram:*** The hierarchical diagram named cohesive tree (Figure 4) presents the implicative relations between the variable in order of significance. Additionally, the cohesive tree also shows the direction of such relations.

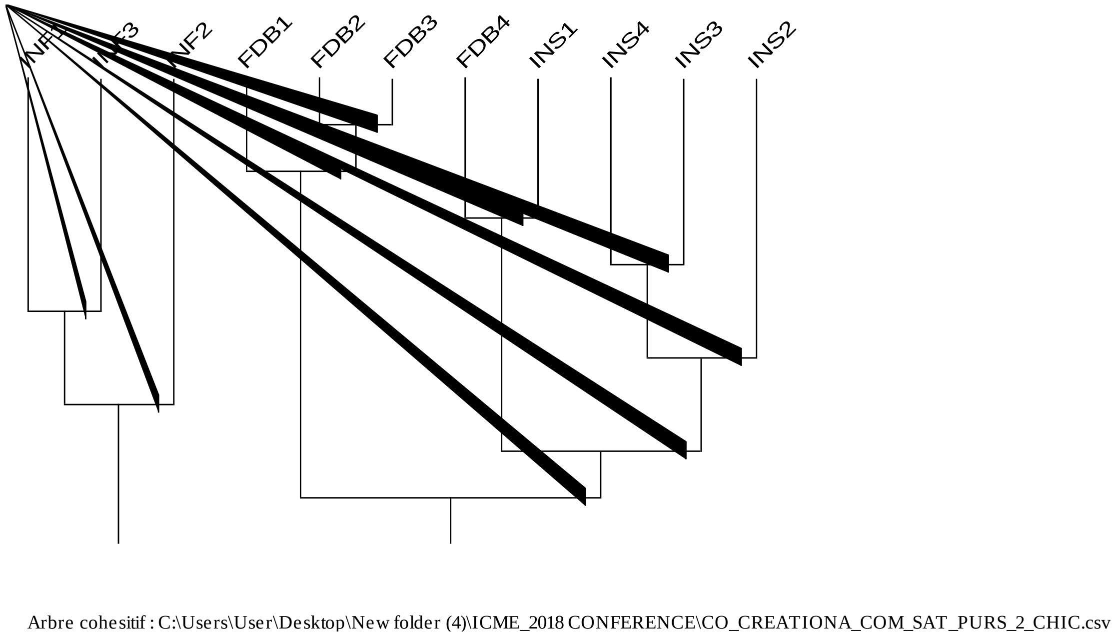


Figure 4: Cohesive Tree

With respect to the first hierarchical group, this refers to items INF1-INF3 (cohesion: 0.999) where the response to INF1 entails the response to INF3. Responses to items INF1 and INF3 entail the response to INF2. The hierarchical group (INF1-INF3)-INF2 exhibits the externally significant cohesion (cohesion: 0.994).

Specifically, when customers ask for information regarding the e-shop's offers and they pay attention on how others behave to use this service well, then they have search for information on where this e-shop is located.

The conclusion that this first hierarchical group is a hierarchy of the items in conceptual construct *Information Seeking* ensues effortlessly.

There are three hierarchical structures in the second hierarchical group. More specifically, the first refers to the three out of four items of the conceptual construct Information Sharing and its cohesion equals to 1, which constitutes a perfect cohesion [FDB1- (FDB2-FDB3)) cohesion: 1].

The figure renders it clear that the behaviour of customers who adequately explained what they wanted the e-shop to do (FDB1) the e-shop with proper information, so it could respond in a satisfactory manner.

With respect to the hierarchical relation (FDB2 FDB3) (cohesion: 1- which constitutes the maximum degree of cohesion), it is shown that when the customers provide the e-shop with proper information (FDB2), the e-shop is able to perform its duties flawlessly (FDB3).

Items FDB4 and INS1 [(FDB4 INS1) cohesion: 1] form another hierarchical group, with maximum cohesion. With respect to hierarchical relation FDB4-INS1 (cohesion: 1), it is shown that when customers answer all the employee's service-related questions (FDB4), then all required tasks are performed (INS1).

Items NS4, INS3 and INS2 [((INS4 INS3) INS2) cohesion: 0.998] form another hierarchical group whose cohesion is almost perfect.

With respect to hierarchical relation INS4-INS3 (cohesion: 0.999) whose cohesion is, again, perfect, it is shown that when followed the e-shops' directives or orders (INS4) then they fulfilled responsibilities to the e-shops (INS3). This implication in turn also implies the adequately complement of all the expected behaviors towards e-shop (INS2).

The hierarchy between these two groups cited above, [((FDB4 INS1) ((INS4 INS3) INS2))] is almost perfect (cohesion: 0.994).

The first hierarchical structure, appears between the one item out of four of the construct *Information Sharing* and items comprising the construct *Responsible Behavior*.

The entire second hierarchical group [((FDB1 (FDB2 FDB3)) ((FDB4 INS1) ((INS4 INS3) INS2))) cohesion: 0.982] exhibits exceptionally high cohesion (cohesion: 0.982) and shows that beliefs on conceptual construct *Information Sharing* implies beliefs on *Responsible Behavior*.

### *Principal Component Analysis (PCA) results*

Principal Component Analysis (PCA) results*:* Kaiser-Meyer-Olkin (KMO) Measure of the Sampling Adequacy and Bartlett's Test of Sphericity, and Measure for the suitability of the method were tested before the analysis of the factor analysis results (Table 2).

Both the Kaiser-Meyer-Olkin (KMO) factor, equal to 0.857 and deemed very satisfactory as it exceeds the acceptable value of 0.60, and Bartlett's Test of Sphericity ($x^2$=1408.907, df=55, p<0.001) have shown that the application of the Principal Component Analysis with varimax rotation method is permitted (Table 2) (Kaiser, 1974).

**Table 2:** KMO and Bartlett's Test

| KMO and Bartlett's Test | | |
|---|---|---|
| Kaiser-Meyer-Olkin Measure of Sampling Adequacy. | | ,857 |
| Bartlett's Test of Sphericity | Approx. Chi-Square | 1408,907 |
| | Df | 55 |
| | Sig. | ,000 |

The application of Principal Component Analysis with varimax rotation for all variables on the basis that the characteristic root or eigenvalue criterion is over one (eigenvalue≥ 1), was verified for 5 Components. These specific factors explained 65.527% of the variance. Similarly, according to the Scree Plot criterion, the steep descending trend of eigenvalues begins after the 3rd Principal Components (PC3) (Cattel, 1996). Consequently, the existence of the 3 Components was verified.

The first Principal Component (PC1), with an eigenvalue equal to 3.114, interprets 28.309% of the total variance of data, a percentage deemed satisfactory (Hair, 2005), gathers values for variables INS3, INS2, INS4, INS1 and FDB4 with very high loadings. These gathered values amount to 0.829, 0.821, 0.790, 0.763 and 0.483, respectively (Table 3).

The values of the Communalities of items INS3, INS2, INS4, INS1 and FDB4, take on values 0.739, 0.716, 0.636, 0.710 and 0.410, exceeding the 0.40 value criterion posed as the limit for the verification of the satisfactory quality for the variables of the First Component (PC1) (Table 3). The First Component (PC1) is constructed and interpreted by INS3, INS2, INS4, INS1 and FDB4.

The First Component (PC1) is shown to essentially be the Component of Responsible Behavior and with a spot of Information Sharing.

The Second Component (PC2) refers to FDB1, FDB2 and FDB3 related to Information Sharing. This Component has an eigenvalue of 2.382 and interprets 2.658 % of total data variance. The eigenvalue criterion, eigenvalue over one, verifies that the 3 variables FDB1, FDB2 and FDB3,

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which exhibit very high loadings 0.833, 0.775 and 0.770 correspondingly, are represented by the same conceptual construct (Table3). The values for the Communalities of FDB1, FDB2 and FDB3 take on prices 0.711, 0.749 and 0.733 respectively, and exceed the 0.40 value criterion posed as the verification limit for the satisfactory quality of statements of Second Component (PC2).

The Third Component (PC3) (Table 3) refers to Information seeking, which is represented by items INF1, INF2 and INF3 and exhibit high loadings of 0.827, 0.730 and 0.679 respectively, with an eigenvalue of 1.712, that interprets 15.560% of total data variance, a percentage deemed satisfactory (Hair et al., 2005), while falling under it are, in order, elements INF1, INF2 and INF3. The values of the Communalities of INF1, INF2 and INF3 take on prices 0.628, 0.591 and 0.585 exceeding the 0.40 value criterion posed as the limit for the verification of the satisfactory quality of Third Component (PC3). The Third Component (PC3) is essentially shown to be the Component of Information Seeking.

**Table 3:** Rotated Component Matrix

**Rotated Component Matrix[a]**

| | Component | | |
|---|---|---|---|
| | 1 | 2 | 3 |
| INS3 | ,829 | | |
| INS2 | ,821 | | |
| INS4 | ,790 | | |
| INS1 | ,763 | | |
| FDB4 | ,483 | ,397 | |
| FDB1 | | ,833 | |
| FDB2 | | ,775 | |
| FDB3 | | ,770 | |
| INF1 | | | ,784 |
| INF3 | | | ,756 |
| INF2 | | | ,694 |

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Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 5 iterations.

## Conclusion-Discussion

This study presents two different statistical techniques: i.e the Principal Components Analysis (PCA) and the Implicative Statistical Analysis (ASI). The main objective is to compare the outcomes derived from Principal Components Analysis (PCA) and Implicative Statistical Analysis (ASI) procedures with respect to Consumer Behavior and specifically with Customer Participation Behavior.

In addition, they showed that the two methods operate complementary, each one accentuating a different dimension for the interpretation of data, the interpretation of which would not have been determinative without the import Marketing Scientists.

Principal Components Analysis is an unsupervised pattern recognition method. It is based on the principal that there is no a priori information about the membership of the sample examined. PCA also falls under this category, since the Principal Components are not known beforehand, but ensues from the application of the method (Anastasiadou, 2018). Principal Components are hierarchically calculated (Anastasiadou, 2018).

Implicative Statistical Analysis (ASI), is connected with Implication Intensity of Gras (Gras, 1996; Gras & Kuntz, 2008). Specifically, similarity Likelihood Linkage Index of Lerman is connected with Likelihood Linkage Analysis (LLA) (Lerman, 1981). It is based on rules and especially on a probabilistic model. It highlights tendencies in a set of properties and generates association rules (Coutourier, 2008). ASI measure is assigned as a probability, named Intensity of Involvement.

Regarding the data analysisof the present research example connected with Customer citizenship behavior, that contains the constructs of *Information Seeking*, *Information Sharing*, and *Responsible Behavior* the similarity tree showed that *Information Seeking* is the par excellence most powerful constituent of the creation of Customer Participation behaviour values as similarity Likelihood Linkage Index amounts for 0.768218. Similarity Likelihood Linkage Index regarding Information *Sharing* amounts 0.502155 and shows is a similarity of a medium importance. Finally, similarity tree also showed that customers' *Responsible Behaviour* is the weakest constituent for the creation of Customer Participation behaviour values. Its similarity Likelihood Linkage Index amounts for 0.256839. Similarity tree identify the Similarity Intensity. In addition, similarity tree present an extremely weak Similarity Intensity between factors *Information Sharing* and *Information Seeking* amounts *for* 0.0172892.

Implication Intensity of Gras express as Likelihood Linkage Index of Gras or intensity of involvement determined the implicative relations between the variables in order of significance. Additionally, the cohesive tree showed the direction of such relations.

Hierarchical group of the items in conceptual construct *Information Seeking* exhibits the externally significant cohesion, amounts for 0.994 and revealed the direction of its items.

The hierarchy between the items FDB4, INS1, INS4, INS3, and INS2 whose intensity of involvement is almost perfect cohesion: 0.994. This hierarchical structure, appears between the item of the construct *Information Sharing and items* comprising the construct *Responsible Behavior, implies cohesion between them*.

The hierarchy between the items FDB1, FDB2, FDB3, FDB4, INS1, INS4, INS3, INS2 that exhibits exceptionally high cohesion amounts for 0.982 revealed that beliefs on conceptual construct *Information Sharing* implies beliefs on *Responsible Behavior*.

Finally, the intensity of involvement between the items INS4, INS3, INS2 related to beliefs on conceptual construct *Responsible Behavior* is almost perfect as it amounts for 0.998.

One can concisely cite that the application of PCA resulted to a data reduction and showed that there are three Principal Components (Latent Variables) which interpret all of the total variability/information of data, as well as their structure. It is worth noting that the First Principal Component is in a line with hierarchy structure between the all items comprising the construct *Information Seeking and* an item of the construct *Information Sharing (*INS3, INS2, INS4, INS1 and FDB4). Thus, the First Principal Component is a Latent Variable immerged by these items based on their loadings. These gathered values amount to 0.829, 0.821, 0.790, 0.763 and 0.483, respectively highlighting items INS3, INS2 as the most significant variables as the values of the corresponding loadings are over 0.820.

First Principal Component is a Latent Variables constituted from items FDB1, FDB2 and FDB3 whose loadings amounts for 0.833, 0.775 and 0.770 correspondingly highlighting item FDB1

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as the most significant variable as its loading value is higher than 0.830 and it is higher regarding all loadings' values to three Principal Components.

Finally, the third is a latent variables constituted from items emerged as the component *Information Seeking* comprises of variables INF1, INF2 and INF3 whose loadings amounts for 0.784, 0.756 and 0.694 correspondingly highlighting item INF1 as the most significant variable as its loading value is higher for this Component.

The results from the application of the methods have pointed at their differences and similarities but also their complementarity. One can concisely cite that the application of PCA resulted to a data reduction and showed that there are three Principal Components (Latent Variables) which interpret all of the total variability/information of data, as well as their structure and the of ASI result in hierarchy and cohesive structures based on similarity and Intensity of Involvement.

## References

Anastasiadou, S. (2018). Comparison of multivariate methods in group/cluster identification. Dissertation thesis of the degree of MSc. in Research Methodology in Biomedicine, Biostatistics and Clinical Bioinformatics, Fuculty of Medicine, University of Thessaly.

Blanchard, J., Guillet, F.,& Kuntz, P. (2009). Semantics-based classification of rule interestingness measures. Yanchang Zhao, Chengqi Zhang, Longbing Cao. Post-Mining of Association Rules: Techniques for Effective Knowledge Extraction, IGI Global, pp.56-79, 2009. <hal-00420971>.

Coutourier, R. (2008). CHIC: Cohensive Hierarchical Implicative Classification. Studies in Computational Intelligence (SCI), pp.41-53. Springer-Verlag Berlin Heidelberg.

Dafermos, B. (2013). *Factor Analysis*, Thessaloniki: Ziti.

Field. A. (2009). *Discovering statistic using SPSS*. SAGE Publications India Pvt Ltd.

Gras, R., P. Peter, H. Briand, & J. Philippé. *(1997).* Implicative Statistical Analysis. *In C. Hayashi, N. Ohsumi, N. Yajima, Y.* Tanaka, *H. Bock, Y. Baba (Eds.).* Proceedingsofthe5th Conference of the International Federation of Classication Societies, Volume 2, pp.412-419. Tokyo, Berlin, Heidelberg, New York : Springer-Verlag.

Gras, R., & Bodin, A. (2017 ). L'A.S.I., Analyseur et révélateur de la complexité cognitive taxonomique. 9ème Colloque International sur Analyse Statistique Implicative, Belfort – France, In Jean-Claude Régnier, Régis Gras, Raphaël Coutourier, Antoine Bodin (edus) pp. 128-142.

International Journal of Entrepreneurship and Innovative Competitiveness

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Gras, R. (1996). The statistical implication-A new method for data esploration (in french). La Pensse Sauvage, editor.

Gras, R & Kuntz, P. (2008). An overview of the Statitical Implicative Analysis (ASI) development, In Gras, R., Suzuki, E., Guillet,F and Spanolo, F. (2008). Statistical Analysis: Theory and Applications, Studies in Computational Intelligence Volumr No. 127, Berlin & Heidelberg: Springer- Verlag.

Gras, R. (1979). Contribution étude expérimental et l'analyse de certaines acquisitions cognitives et de certains objectifs en didactique des mathématiques, Thèse de doctorat, l'Université de Rennes 1.

Gras, R., & Couturier, R. (2013). Spécificités de l'Analyse Statistique Implicative par rapport à d'autres mesures de qualité de règles d'association. *Educação Matemática Pesquisa, 15*(2).

Gras, R., Couturier, R., Blanchard, J., Briand, H., Kuntz, P., & Peter, P. (2004), Quelques critères pour une mesure de qualité de règles d'association. *Revue des nouvelles technologies de l'information RNTI E-1,* 3-30

Gras, R., Regnier, J. C., & Guillet, F., (2009). *Analyse statistique implicative : Une* méthode d'analyse de données pour la recherche de causalités (p. 510). Cépaduès Editions.

Gras, R., Régnier, J. C., Marinica, C., & Guillet, F., (2013). L'analyse statistique implicative Méthode exploratoire et confirmatoire à la recherche de causalités (p. 522). Cépaduès Editions

Gras R., Suzuki E., Guillet F. and Spagnolo F. (Eds) (2008). *Statistical Implicative Analysis.* Springer-Verlag, Berlin-Heidelberg.

Jollife, I. T (1972). Discarding variables in the principal components analysis, I: Artificial data. *Applied Statistics,* 1, 57-93.

Jollife, I. T (1986). *Principal components analysis,* New York: Springer.

Kaiser, H. F. (1960). The application of electronic computers to factor analysis. *Educational and Psychological Measurements*, 20, 141-151.

Kaiser, H. F. (1974). In order of factorial simplicity, *Psychometrika,* 39, 31-36.

Lerman, I. C. (1981). Classification et Analyse Ordinale des Données, Dunod, Paris.

Lerman, I. C. (1978). Formes d' aptitude et taxinomie d' objectifs en mathematiques. In: Revue française de pédagogie, Vol. 44, pp. 5-53.

International Journal of Entrepreneurship and Innovative Competitiveness

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Lerman, C. (1993). Likelihood linkage analysis (LLA) classification method: An example treated by hand. Biochimie. Vol. 75, Issue 5, pp.379-397.

Yi, Y. and Gong, T., 2013. Customer value co-creation behavior: Scale development and validation. *Journal of Business Research*, 66(9), pp.1279-1284.