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**Contemporary advanced statistical methods for the science of marketing:
Principal Components Analysis vs Analyse Factorielle des Correspondances**

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Introduction: There is substantial growth and employment of patterning methods in statistics, although a direct comparison of multivariate methods in group/cluster identification in the field of Consumer Behavior in relation to Perceived Risk of e-Services Adoption Intentions has not yet been undertaken.

Objective: This study analyses two different statistical techniques: i.e Principal Components Analysis (PCA) and Analyse Factorielle des Correspondances (AFC). The main objective is to compare patterns derived from Principal Components Analysis (PCA) and Analyse Factorielle des Correspondances (AFC) procedures with respect to the Perceived Risk relating to the e-Services Adoption Intentions.

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 and Responsible Behavior subscales are related to the Perceived Risk of e-Services Adoption Intentions. These subscales were measured by 25 items, rated on a seven-point Likert scale.

Methods: The study focuses on the presentation of the two main types of clustering methods, Principal Components Analysis (PCA) and Analyse Factorielle des Correspondances (AFC).

Results: PCA's results verified the construct validity of Perceived Risk of e-Services Adoption Intentions multidimensional and hierarchical scale (Featherman & Pavlou, 2003). It demonstrated the existence of seven Components, amongst which are the *Financial Risk*, *Performance Risk*, *Privacy Risk*, *Psychological Risk*, *Social Risk*, *Time Risk* and *Overall Risk*. Analyse Factorielle des Correspondances (AFC) revealed the first factorial axis which expresses a negative attitude with respect to *Privacy Risk*, *Performance Risk*, *Overall Risk*

and *Financial Risk* on its left side and a positive attitude with respect to *Privacy Risk*, *Performance Risk* and part of *Overall Risk* on its right side. Analyse Factorielle des Correspondances (AFC) revealed the second factorial axis a neutral attitude to a part of the conceptual construct *Overall Risk*, a neutral attitude to part of the conceptual construct *Financial Risk*, to part of conceptual construct *Performance Risk* and to conceptual construct named *Privacy Risk*. In addition, the second factorial axis detects those respondents who did not have a crystal clear view as to whether they get Overall Service Quality also with respect to their Purchase Intentions. The first factorial axis juxtaposes the extreme cases while the second one, those in-between of the extreme ones.

On the first factorial level, at the first quadrant (e_1^+, e_2^+) the group of respondents may be distinguished by their positive attitude with respect to *Privacy Risk*, *Performance Risk* and part of *Overall Risk*.

On the first factorial level, at the second quadrant (e_1^-, e_2^+) the group of respondents may be distinguished by their negative attitude with respect to *Privacy Risk*, *Performance Risk*, *Overall Risk* and *Financial Risk*.

Finally, on the fourth factorial level and at the second quadrant (e_1^-, e_2^-) the group of respondents may be distinguished by their neutral attitude with respect to a part of the conceptual construct *Overall Risk*, to a part of conceptual construct *Financial Risk*, to a part of conceptual construct *Performance Risk* and to conceptual constructs *Privacy Risk*, *Overall Service Quality* and their *Purchase Intentions*.

Psychological Risk and *Social Risk* seemed to be unimportant factors - their role in determination of customers' behavior is insignificant.

AFC's results related to the customers psychological aspects regarding the specific scale dimensions that determined their behaviour.

Key words: Principal Components Analysis, Analyse Factorielle des Correspondances, Perceived Risk, e-Services Adoption Intention

Theoretical Framework

E-services are interactive software-based information systems received via the Internet which provide on-demand solutions while on the provider end they are seen as a means of driving new revenue streams and creating efficiencies. Unlike decisions for one-time purchases over the Internet, the adoption of an e-Service is a more complex decision on the part of the consumer, since it initiates a long-term relationship with a distant and faceless service provider to purchase what essentially is the functionality offered by a web-portal. Thus, the decision to adopt an e-Service is typically more complex and involves the evaluation of the perceived risks, or adoption barriers. As Koller (1988) puts it, the degree of importance of the situation determines the potential effect of risk. Given that the adoption of e-Services is an important decision for most consumers with long-term implications, the role of risk is likely to become prominent.

Discussions and analyses of the barriers to technological adoption in an on-line context usually utilize the Technology Acceptance Model (TAM, Davis, 1989) to gauge user perceptions of system use and the probability of adopting an on-line system (Teo et al., 1999; Gefen and Straub, 2000; Moon and Kim, 2001; Pavlou, 2001). The variable relating to perceived risk is initially modeled as a singular one within TAM and afterwards, following Cunningham's theorization, it is decomposed into its sub-facets, so as to offer insight as to the salient risk facets for potential consumers of e-Services. It is common to think of perceived risk (PR) as the uncertainty with respect to possible negative effects from using a service or product. Bauer (1967) defines it as "a combination of uncertainty plus seriousness of outcome involved", while Peter and Ryan (1976) augment this definition by including "the expectation of losses associated with purchase and acts as an inhibitor to purchase behavior".

The Instruments/ Measures

Perceived Risk of e-Services Adoption Intention multidimensional and hierarchical scale by Featherman & Pavlou (2003) consisting of 25 items, rated on a seven-point Likert format. Perceived Risk of e-Services Adoption Intentions, in particular, contains the following constructs: *Financial Risk*, *Performance Risk*, *Privacy Risk*, *Psychological Risk*, *Social Risk*, *Time Risk* and *Overall Risk*.

The first group regards conceptual construct Financial Risk, and is comprised of 4 items (PRFi) (e.g. PRF1: There are chances that I stand to lose money if I use the e-shop?), while

the second group regards conceptual construct *Performance Risk* and comprises of 5 items (PRPi) (e.g. PRP1: The e-shop might not perform well and create problems with my credit). The third group regards conceptual construct *Privacy Risk* and includes 3 items (PRVi) (e.g. PRV1: What are the chances that using an e-shop will cause me to lose control over the privacy of your payment information), and the fourth group regards conceptual construct *Psychological Risk* and contains 2 items (PRCi) (e.g. PRC1: The e-shop will not fit in well with my self-image or self-concept). The fifth group relates to conceptual construct *Social Risk* and includes 2 items (PRSi) (e.g. PRS1: There are chances that using the e-shop will negatively affect the way others think of me?), and the sixth group regards conceptual construct *Time Risk* and is comprised of 4 items (PRTi) (e.g. PRT2: My signing up for and using an e-shop would lead to a loss of convenience for me because I would have to waste a lot of time fixing errors in payments). Finally, the seventh group regards conceptual construct *Overall Risk* and contains 5 items (PRAi) (e.g. PRA5: Using e-shop exposes me to an overall risk). These seven conceptual constructs contribute to the creation of latent Variable Perceived Risk of e-Services Adoption Intention.

E-service quality was measured through the use of a scale developed expressly for this purpose by Lee and Lin (2005). Lee and Lin's (2005) model, contains a one-item scale developed to measure overall service quality, and a one-item scale for customer satisfaction. The assessment of the overall quality of the e-shop's service is evaluated through another statement investigating the extent by which the overall view of the respondent on the services extended by the e-shop is very positive (GPO).

The assessment of the customer's satisfaction degree is evaluated based on another seven-step on the Likert scale statement, investigating the extent by which the respondent is satisfied from the purchasing experience he had with the e-shop (CSF).

Finally, two further statements of a seven-step Likert scale constitute conceptual construct *Purchase Intentions* (ITBi) (eg. ITB1: If I proceed with the purchase of some product in the coming 30 days, then I shall realize such purchase from this particular e-shop).

Methodology

Analyse Factorielle des Correspondances or AFC: In the course of the research, absolute and relative frequencies were recorded for the 29 statement variables, using classic statistics methods. The 29 statement variables were then classified into three classes each, resulting in all of the data to be described by 87 classes, namely by a logical table (0-1). By means of the categorization of the variables a double entry table was created for the relative and absolute frequencies with dimensions 87x87. This table is a Burt table and each column in this Burt table is considered a vector with a dimension of 105. The Burt table allowed for each class and each variable to be surveyed individually and then for the classes of variables to be cross-examined.

The objective being to determine these relations employed were the $n \times n$ double entry tables, the Burt tables containing all the classes, to which variables have been divided, in their columns and lines. Consequently, each element in the Burt table exclusively depends on two variables, thus revealing the relationship that connects them. Data Analysis techniques were employed for the processing of the data, since this paper necessitated that no a priori hypotheses be made. This convention was totally covered by Data Analysis methods or, more precisely, by Multivariate/Multidimensional Statistical Analysis without models. The selection of the methods rests on the fact that traditional statistical hypotheses as to the behavior of the phenomenon described by the table under analysis were not employed, but a more specific determination of their structure is attempted. The detection of the characteristics of the variables affecting the behavior and attitudes of respondents makes it possible to approach the real dimensions that customers' attitudes take with respect to e-shop services.

The approach consisting of an a posteriori categorization of e-shop customers' attitudes, as such is presented via the questionnaires, is expedited with the help of factorial axes, namely the complex variables, and the factorial levels providing a more complete supervisory view. It is through these that the qualitative relationships between all variables are accentuated and designated.

From the Data Analysis methods, cited above, Analyse Factorielle des Correspondances (Correspondence Factor Analysis) (AFC) technique was employed to analyse the data.

Analyse Factorielle des Correspondances (Correspondence Factor Analysis) (AFC) technique allows for the simultaneous statistical processing of categorized qualitative and quantitative variables (Benzecri, 1973; Karapistolis, 2015; Papadimitriou, 2007;

Anastasiadou, 2016). The grouping of dominant observation groups is effected through this and thus attained is an almost universal description of the phenomenon which is expressed by the table analysed with the help of a smaller number of new complex variables-factors (Papadimitriou, 1994). These factors, independent per couple between them, are created from the synthesis of groups of the initial variables, fact that simplifies the process for probing the relations between the variables, thus offering a full and more complex image of the phenomenon under examination. The factors can assume the form of axes and form the factorial levels in pairs, which will allow the graphic representation of the variables.

The contribution and cohesion of the indexes are then presented, constituting the criteria for the selection of the variables for constructing and interpreting the axes and, consequently, the factorial levels.

1. The contribution of a point, line and column, towards the construction of a factorial axis. If λ_k is the total inertia along axis k and if λ_k is the total inertia along part of axis k and $f_i F_k^2(i)$ is the inertia of point i in cloud N_j on each axis k , then contribution, which is symbolized as $Ctr_k(i)$ is given from relation (4), $Ctr_k(i) = \frac{f_i F_k^2(i)}{\lambda_k}$ (4) where

$$\sum_{i=1}^n Ctr_k(i) = 1 \quad (5) \text{ for each axis } k.$$

The contribution of points j in cloud N_j is correspondingly defined.

As defined, contribution gives the inertia percentage of the point with respect to the inertia explained by the factorial axis.

Since the contribution index reveals the points that principally contribute towards the construction of the axis, we seek points with high $Ctr_k(i)$ and on which the interpretation of the axis may possibly rest, a fact that is significant for the interpretation of the phenomenon (Drosos, 2004; Papadimitriou, 2007).

2. The square of cosine $\cos_{k,2}(i)$ (or relevant contribution) signifies the representation quality of a point by the factorial axis and essentially depicts a form of correlation

between point i and factorial axis k , while it is symbolized as $Cor_k(i)$ and given from

relation (6), $Cor_k(i) = \frac{F_{k^2}(i)}{d^2(G,i)} = \cos^2 \omega$ (6), where $d^2(G,i)$ is the distance of i from

the centroid (center of gravity) (Drosos, 2004).

High value for $Cor_k(i)$ means a small angle ω namely high correlation of point i with the axis, that is good quality for the projection of i with the axis, namely good projection quality of i axis. Pursuant to the above, index $Cor_k(i)$ expresses the percentage of inertia at point i which is interpreted by axis k .

Points with very high Cor also exhibit high Ctr . In the case where they exhibit high values for Cor and low values for Ctr this means that they have good projection quality on the axis but do not participate in the construction thereof (Papadimitriou, 2007).

In the case where they exhibit low values for Cor and high values for Ctr , this means that they contribute towards the construction of the axis but are better projected on some other axis towards the construction of which they may potentially contribute more (Drosos, 2004; Papadimitriou 2007; Anastasiadou, 2016).

Principal component analysis or PCA is a method for the analysis of multivariate data, considered as constituting a part of factor Analysis.

The principal objectives of PCA are:

- 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. This process explains 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), converts them to measurable ones.

Each component has the form: $\text{Component}_i = b_1X_1 + b_2X_2 + \dots + b_nX_m$. It is evident that PCA forecasts components based on measured variables. It is rendered clear that PCA breaks 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, 1974) or equal or greater than 0.70 (Jolliffe, 1972, 1986).

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 Eastern 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, 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 55 to 64. 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 that he has completed 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.

Findings

Analyse Factorielle des Correspondances (AFC) results: The indexes employed to interpret the results of this particular correspondence factor analysis are the well-known indexes “inertial” and “contribution” (Benzécri, 1980; Papadimitriou, 2007). These indexes allow one to immediately distinguish the most important and determinative variables or objects that contribute to the creation of factorial axes. The results of this factorial analysis were interpreted with the help of inertia, which is explained by each factorial axis, of correlation and of the contribution.

The data table analysis using AFC initially produces Table 1, which presents the eigenvalues of the Burt table as well as the inertia percentages for each factorial axis. Table 1 offers the capacity to distinguish the number of the most significant factorial axes, which are the most appropriate in order to interpret the results. The inertia percentage of each factorial axis denotes the significance percentage expressed by each one.

According to the values complemented by the histogram (Table 1), the significance percentage of the first factorial axis is 52.92%, while that of the second amounts to 9.08%, the third 4.37%, the fourth 3.72% etc. The total information offered by the 12 factorial axes amounts to 83.27%, as can be seen from the table below (Table 1).

Table 2: Inertia – Eigenvalues

TOTAL INERTIA 0.16572				
AXIS	INERTIA	%INTERPRETATION	SUM	EIGENVALUES HISTOGRAM
01	0.0876958	52.92	52.92	*****
02	0.0150499	9.08	62.00	*****
03	0.0072446	4.37	66.37	****
04	0.0061599	3.72	70.09	***
05	0.0043896	2.65	72.74	***

06	0.0036697	2.21	74.95	***
07	0.0029736	1.79	76.75	***
08	0.0025851	1.56	78.31	***
09	0.0023805	1.44	79.74	***
10	0.0021107	1.27	81.02	*
11	0.0019320	1.17	82.18	*
12	0.0017978	1.08	83.27	*

Based on cumulative frequency, the first three factorial axes interpret 66.37% of the total data variance (Table 1). This percentage is deemed satisfactory to interpret the data (Karapistolis, 2015). Moving on and from the table of the results of the factorial analysis of correspondences, pursuant to the aforementioned criteria that were chosen (inertia, correlation and contribution), the variables contributing to the shaping of the two first factorial axes were detected, using MAD software (Karapistolis, 2000). The aforementioned variables are deduced in compliance with two criteria, correlation ($Cor \geq 200$, criterion 2) and contribution ($Ctr \geq \frac{1000}{87} \approx 11.4 \approx 12$, criterion 3) (Karapistolis, 2015).

Interpretation of the first factorial axis e_1 : More specifically, based on the responses by the respondents and as follows from factor analysis, the first axis – factor e_1 , with eigenvalue 0.0876958 explaining 52.92% of the total variance is constructed from classes PRV11, PRV31, PRV21, PRP11, PRP21, PRP31, PRP51, PRP41, PRA41, PRA21, PRA41, PRA31, PRA11, PRF11, PRF41, PRF21, PRF31, PRV33, PRV23, PRV13, PRP13, PRF13, PRP23, PRP53, PRP33, PRP43, PRA43, PRA53, PRA13.

More specifically, the factorial axis e_1 is constructed from those variable classes, that project a negative attitude with respect to *Privacy Risk*, *Performance Risk*, *Overall Risk* and *Financial Risk* and which are quoted on its left side and the positive attitude with respect to *Privacy Risk*, *Performance Risk* and part of *Overall Risk* on its right side (Figure 1).

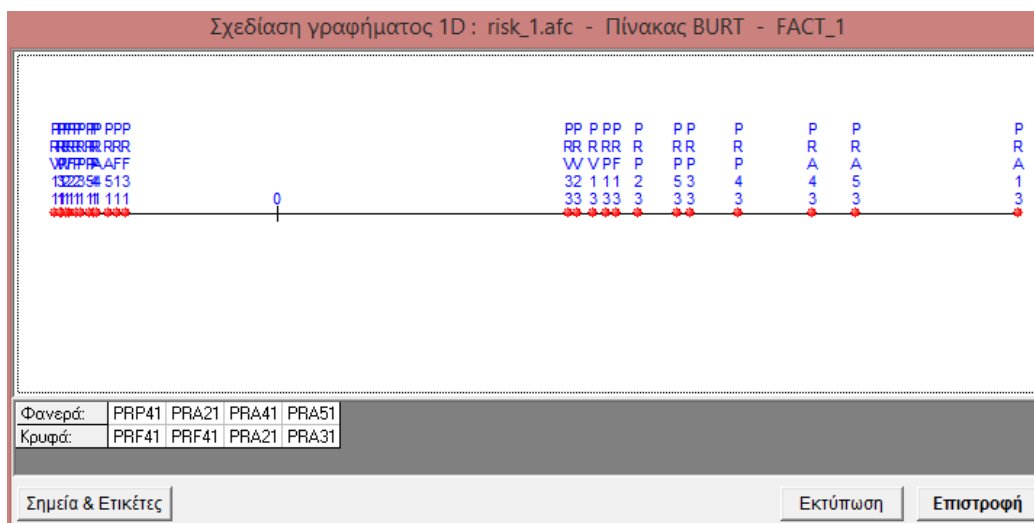


Figure 1: First factorial axis e_1

We initially come across the respondents' views with respect to conceptual construct *Privacy*, which support that the chances of them losing control of the privacy of their payment information when using an e-shop are probable (PRV11), (Cor=863, Ctr=18), Internet hackers (criminals) might assume control of their checking account if they use an e-shop (PRV31) (Cor=847, Ctr=16) and finally that it is probable for their signing up and using an e-shop to lead them to lose their privacy because their personal information would be used without their knowledge (PRV21) (Cor=821, Ctr=16).

We then come across the respondents' views with respect to conceptual construct *Performance Risk*. It supports that The e-shop might not perform well and lead to problems with their credit card (PRP11) (Cor=832, Ctr=16), due to the fact that the security systems built into the E-SHOP are not strong enough to protect their checking account (PRP21) (Cor=821, Ctr=15) and the risk of the likelihood that there will be something wrong with the performance of the e-shop or that it will not work properly (PRP31) (Cor=815, Ctr=15) is a high functional risk. Considering the expected level of service performance of the e-shop, it would be risky for them to sign up for and use it (PRP41) (Cor=879, Ctr=14). Additionally, the respondents claimed that e-shop servers may not perform well and process payments incorrectly (PRP51) (Cor=899, Ctr=15). We then come across the respondents' views on conceptual construct *Overall Risk*. The respondents supported that Using thje e-shop would

add great uncertainty to their bill paying (PRA41) (Cor=940, Ctr=16) and using e-shop to pay their bills would be risky (PRA21) (Cor=891, Ctr=14) and, finally, that using the e-shop exposes them to an overall risk (PRA51) (Cor=940, Ctr=15). Furthermore they claimed that e-shops are perilous to use (PRA31) (Cor=918, Ctr=14). On the whole and considering all sorts of factors combined, about how risky they would say using an e-shop is, they suggested that it is very risky to sign up for and use the services of an e-shop (PRA11) (Cor=940, Ctr=16).

Lastly, classes of variables quoted on its left side express views with respect to conceptual construct named *Financial Risk*. Responders considered that there are high chances of losing money if they use the e-shop (PRF11) (Cor=783, Ctr=12) and thus Using an Internet bill-payment service subjects their checking account to financial risk (PRF41) (Cor=771, Ctr=13) and to potential fraud (PRF21) (Cor=757, Ctr=15). Accordingly, their signing up for and using an e-shop would lead to a financial loss for them (PRF31) (Cor=904, Ctr=12).

The variables projecting a positive attitude with respect to *Privacy Risk*, *Performance Risk* and part of *Overall Risk* are quoted to the right of the factorial axis. We initially come across the views by respondents expressing a positive attitude with respect to the conceptual construct *Privacy Risk* and more specifically claiming that Internet hackers (criminals) might not take control of their checking accounts if they used an e-shop (PRV33) (Cor=795, Ctr=19); that their signing up for and using an e-shop would probably not lead to a loss of privacy for them due to their personal information being used without their knowledge and permission (PRV23) (Cor=749, Ctr=18) and that there are no chances that using an e-shop will cause them to lose control over the privacy of their payment information (PRV13) (Cor=776, Ctr=21) because the e-shop might perform well and not create problems with their credit card (PRP13) (Cor=743, Ctr=19) and thus their signing up for and using an e-shop would not lead to a financial loss for them (PRF13) (Cor=704, Ctr=18).

In addition, variables that are quoted on its right side express views with respect to the conceptual construct *Performance Risk*. Respondents claimed that the security systems built into the e-shop are strong enough to protect their checking account (PRP23) (Cor=755, Ctr=20), e-shop servers may perform well and process payments correctly (PRP53) (Cor=778, Ctr=22), that there is low functional risk that there will be something wrong with the performance of the e-shop or that it will not work properly (PRP33) (Cor=879, Ctr=14)

and thus that there is no risk at all involved in the expected level of service performance of the e-shop, for them to sign up for and use it (PRP43) (Cor=805, Ctr=25), while this is then followed by a positive attitude to part of the conceptual construct *Overall Risk*. More specifically, respondents considered that using e-shop would not encumber their bill paying with great uncertainty (PRA43) (Cor=725, Ctr=26); using the e-shop will probably not expose them to an overall risk (PRA53) (Cor=737, Ctr=27). On the whole and considering the combination of factors relevant to risk, these respondents would claim that it is not risky to sign up and use the e-shop (PRA13) (Cor=801, Ctr=34).

It is, therefore, relatively easy to draw the conclusion that in the first factorial axis e_3 and to its left one comes across those variable classes expressed by a group of respondents that project a negative attitude with respect to *Privacy Risk*, *Performance Risk*, *Overall Risk* and *Financial Risk*, while variable classes quoted to the right of the first factorial axis that represent a group of respondents who have a positive attitude with respect to construct *Privacy Risk*, the construct *Performance Risk* and part of the construct *Overall Risk*.

Interpretation of the second factorial axis e_2 : Based on the answers given by the respondents and as follows from factor analysis, the second axis – factor e_2 , with an eigenvalue of 0.0150499 and explaining 9.08% of total variance, is constructed from classes GPO2, PRA12, PRA42, PRV32, PRF22, PRV12, PRA22, PRF42, PRP22, ITB22, PRF12, PRP32, PRP52, PRV22 and PRP12 (Figure 2).

To the left of the second factorial axis e_2 one finds those respondents who did not have a crystal clear view with respect as to whether they get Overall Service Quality (GPO2) (Cor=272, Ctr=37); with regards to their Purchase Intentions (Cor=209, Ctr=19); and, taking into account all combinations of factors, about how risky they would say it is to sign up and use the e-shop (PRA12) (Cor=292, Ctr=33). Their views were also unclear as to whether by using the e-shop they would add great uncertainty to their bill paying (PRA42) (Cor=212, Ctr=30) and as to how risky it would be for them to use the e-shop to pay their bills (PRA22) (Cor=243, Ctr=27). Thus we came across a neutral attitude to part of the conceptual construct *Overall Risk*.

In addition, variables that are quoted on its left side express views with respect to conceptual construct *Privacy Risk*. Respondents did not seem to have a crystal clear view with respect to whether Internet hackers (criminals) might take control of their checking accounts if they

used an e-shop (PRV32) (Cor=386, Ctr=29); what are the chances that using an e-shop will result in them losing control over the privacy of their payment information (PRV12) (Cor=322, Ctr=27) and whether their signing up for and using an e-shop would lead to a loss of privacy for them because their personal information would be processed and shared without their knowledge PRV22 (Cor=206, Ctr=15). Moving forward, to the left side of the second factorial axis e_2 we came across a neutral attitude to part of conceptual construct *Financial Risk*. Respondents exhibited a neutral attitude with respect to whether using an Internet-bill-payment service subjects their checking account to potential fraud (PRF22) (Cor=261, Ctr=19); whether using an Internet bill-payment service subjects their checking account to financial risk (PRF42) (Cor=313, Ctr=31) and, finally, whether the chances for them to lose money because they used the services of an e-shop are low or high (PRF12) (Cor=235, Ctr=19).

Finally, variables classes PRP22, PRP32, PRP52 and PRP12 that are quoted on its left side relate to part of conceptual construct *Performance Risk*. Respondents had a neutral attitude as to whether the security systems built into the e-shop are strong enough to protect their checking account (PRP22) (Cor=397, Ctr=34); if there is a low or high functional risk for something to go wrong with the performance of the e-shop, i.e. that it will not work properly (PRP32) (Cor=331, Ctr=26); whether the e-shop servers may not perform well and, thus, incorrectly process payments (PRP52) (Cor=253, Ctr=27) and finally whether the e-shop as a whole may not perform well and, thus, create problems with their credit cards (PRP12) (Cor=220, Ctr=15).

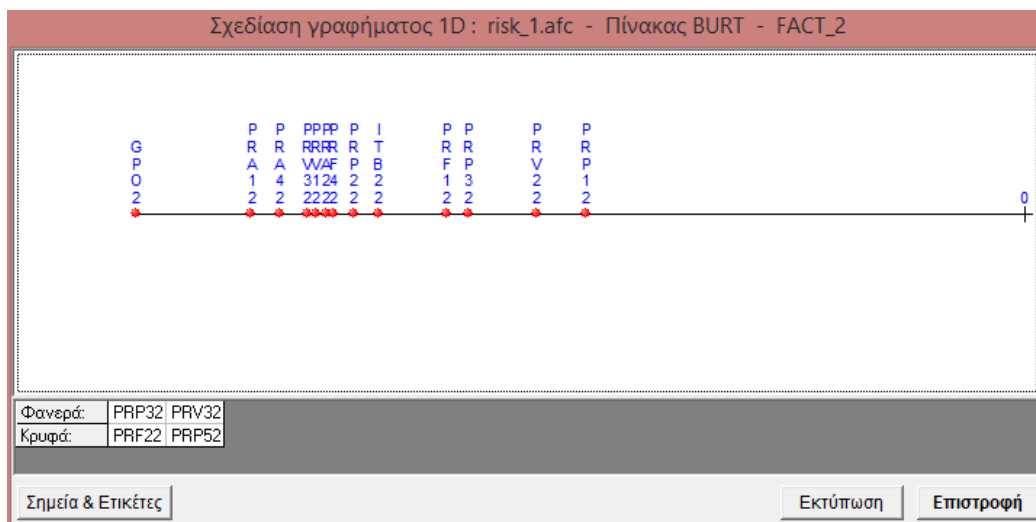


Figure 2: Second factorial axis e_2

The first factorial level $e_1 \times e_2$: The variables which are most significant for the first factorial level $e_1 \times e_2$ and pursuant to the criteria of inertia, contribution and correlation are analysed in what follows.

The first factorial level $e_1 \times e_2$ (Figure 3) interprets 62% of total inertia– information, a satisfactory percentage. The first factorial axis juxtaposes the extreme cases and the second those in-between of the extreme ones.

On the first factorial level and at the first quadrant (e_1+, e_2+) the group of respondents may be distinguished vis-a-vis their positive attitude with respect to *Privacy Risk*, *Performance Risk* and part of *Overall Risk*.

On the first factorial level and at the second quadrant (e_1-, e_2+) the group of respondents may be distinguished as to their negative attitude with respect to *Privacy Risk*, *Performance Risk*, *Overall Risk* and *Financial Risk*.

Finally, on the fourth factorial level and at the second quadrant (e_1-, e_2-) the group of respondents may be distinguished by reference to their neutral attitude with respect to part of conceptual construct *Overall Risk*, to part of conceptual construct *Financial Risk*, to part of

conceptual construct *Performance Risk* and to conceptual constructs *Privacy Risk*, *Overall Service Quality* and their *Purchase Intentions*.

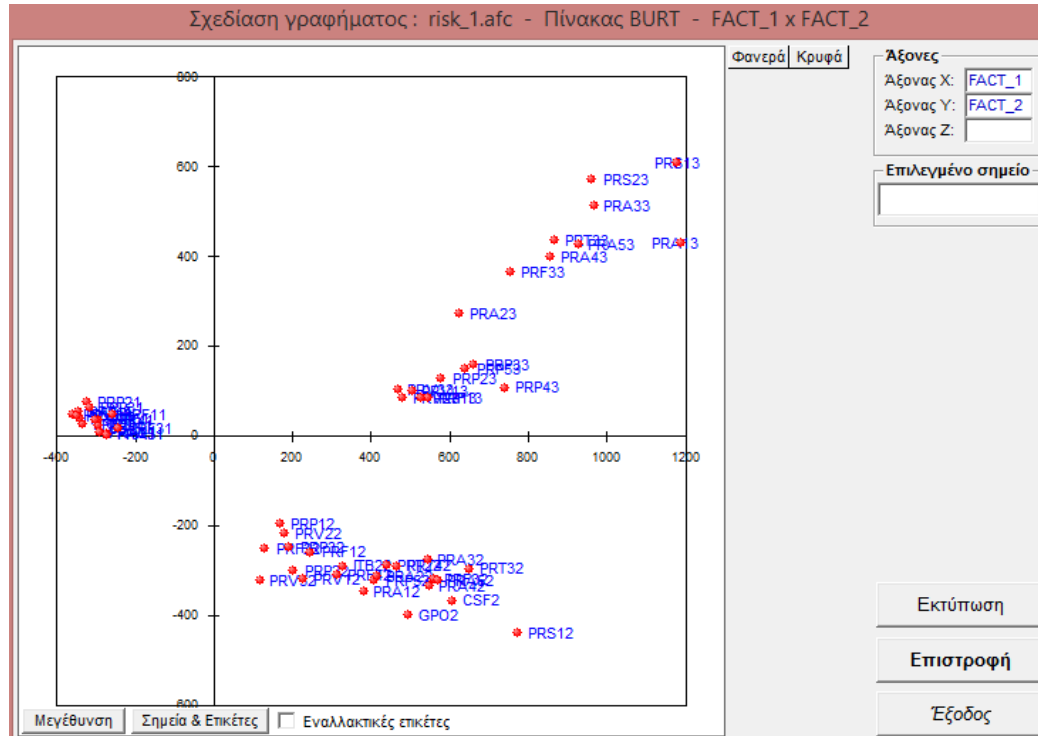


Figure 3: First factorial level $e_1 \times e_2$

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 0.929 and deemed very satisfactory, as it exceeds the acceptable value of 0.60, and Bartlett's Test of Sphericity ($\chi^2=5739.637$, $df=300$, $p<0.001$) have shown that the application of the Principal Component Analysis with varimax rotation method is permitted (Kaiser, 1974).

Table 2: KMO and Bartlett's Test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.929
Bartlett's Test of	Approx. Chi-Square	5739.637

Sphericity	df	300
	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 8 Components. These specific factors explained 75.462% of the variance. Similarly, according to the Scree Plot criterion, the steep descending trend of eigenvalues begins after the 8th Principal Components (PC8) (Cattel, 1996). Consequently, the existence of the 8 Components was verified.

The first Principal Component (PC1), with an eigenvalue equal to 11.852, interprets 11.773% of the total variance of data, a percentage deemed satisfactory (Hair, 2005) and gathers values for variables PRT2, PRT3, PRT4 and PRT1 with very high loadings. These gathered values amount to 0.827, 0.772, 0.743 and 0.728, respectively (Table 3).

The values of the Communalities of items PRT2, PRT3, PRT4 and PRT1, take on values 0.739, 0.790, 0.753, 0.728 and 0.639, 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). The First Component (PC1) is constructed and interpreted by PRT2, PRT3, PRT4 and PRT1. The First Component (PC1) is shown to essentially be the *Component of Time Risk*.

The Second Component (PC2) refers to PRP3, PRP2, PRP4, PRP5 and PRP1, related to *Information Sharing*. This Component has an eigenvalue of 2.545 and interprets 11.305% of total data variance. The eigenvalue criterion, eigenvalue over one, verifies that the 5 variables/items PRP3, PRP2, PRP4, PRP5 and PRP1 which exhibit very high loadings 0.790, 0.698, 0.653, 0.595 and 0.572 correspondingly, are represented by the same conceptual construct (Table 3). The values for the Communalities of PRP3, PRP2, PRP4, PRP5 and PRP1 take on prices 0.796, 0.668, 0.711, 0.608 and 0.599 respectively, and exceed the 0.40 value criterion posed as the verification limit for the satisfactory quality of statements of Second Component (PC2) named *Performance Risk*.

The Third Component (PC3) (Table 3) refers to *Information Seeking*, which is represented by items PRA2, PRA3, PRA, PRA4 and PRA1 and exhibit high loadings of 0.745, 0.733, 0.709, 0.697 and 0.494 respectively, with an eigenvalue of 2.188, that interprets 11.167% of total

data variance, a percentage deemed satisfactory (Hair et al., 2005), while falling under it are, in order, elements PRA2, PRA3, PRA, PRA4 and PRA1. The values of the Communalities of PRA2, PRA3, PRA, PRA4 and PRA1 take on prices 0.796, 0.841, 0.802, 0.800 and 0.709 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 Overall Risk*.

The Fourth Component (PC4) (Table 3) refers to *Information Seeking*, which is represented by items ITB2, Customer Satisfaction, Overall Service Quality and ITB1 and exhibit high loadings of 0.850, 0.832, 0.766 and 0.705 respectively, with an eigenvalue of 1.344, that interprets 9.953% of total data variance, a percentage deemed satisfactory (Hair et al., 2005), while falling under it are, in order, elements ITB2, Customer Satisfaction, Overall Service Quality and ITB1. The values of the Communalities of ITB2, Customer Satisfaction, Overall Service Quality and ITB1 take on prices 0.0.792, 0.799, 0.736 and 0.633 exceeding the 0.40 value criterion posed as the limit for the verification of the satisfactory quality of Fourth Component (PC4). The Fourth Component (PC4) is essentially shown to be the *Component of Overall Service Quality Customer, Satisfaction and Purchase Intentions*.

The Fifth Component (PC5) (Table 3) refers to *Information Seeking*, which is represented by items PRF2, PRF4, PRF1 and PRF3 and exhibit high loadings of 0.807, 0.769, 0.661 and 0.607 respectively, with an eigenvalue of 1.167, that interprets 9.892% of total data variance, a percentage deemed satisfactory (Hair et al., 2005), while falling under it are, in order, elements PRF2, PRF4, PRF1 and PRF3. The values of the Communalities of PRF2, PRF4, PRF1 and PRF3 take on prices 0.809, 0.792, 0.682 and 0.682 exceeding the 0.40 value criterion posed as the limit for the verification of the satisfactory quality of Fifth Component (PC5). The Fifth Component (PC5) is essentially shown to be the *Component of Perceived Risk*.

The Sixth Component (PC6) (Table 3) refers to *Information Seeking*, which is represented by items PRV2, PRV1 and PRV3 and exhibit high loadings of 0.834, 0.762 and 0.644 respectively, with an eigenvalue of 1.077, that interprets 8.303% of total data variance, a percentage deemed satisfactory (Hair et al., 2005), while falling under it are, in order, elements PRV2, PRV1 and PRV3. The values of the Communalities of PRV2, PRV1 and PRV3 take on prices 0.847, 0.887 and 0.634 exceeding the 0.40 value criterion posed as the

limit for the verification of the satisfactory quality of Sixth Component (PC6). The Sixth Component (PC6) is essentially shown to be the *Component of Privacy Risk*.

The Seventh Component (PC7) (Table 3) refers to *Information Seeking*, which is represented by items PRS2 and PRS1 and exhibit high loadings of 0.848 and 0.817 respectively, with an eigenvalue of 1.046, that interprets 6.987% of total data variance, a percentage deemed satisfactory (Hair et al., 2005), while falling under it are, in order, elements PRS2 and PRS1. The values of the Communalities of PRS2 and PRS1 take on prices 0.874 and 0.846 exceeding the 0.40 value criterion posed as the limit for the verification of the satisfactory quality of Seventh Component (PC7). The Seventh Component (PC7) is essentially shown to be the *Component of Social Risk*.

The Seventh Component (PC7) (Table 3) refers to *Information Seeking*, which is represented by items PRS2 and PRS1 and exhibit high loadings of 0.848 and 0.817 respectively, with an eigenvalue of 1.046, that interprets 6.987% of total data variance, a percentage deemed satisfactory (Hair et al., 2005), while falling under it are, in order, elements PRS2 and PRS1. The values of the Communalities of PRS2 and PRS1 take on prices 0.874 and 0.846 exceeding the 0.40 value criterion posed as the limit for the verification of the satisfactory quality of Seventh Component (PC7). The Seventh Component (PC7) is essentially shown to be the *Component of Social Risk*.

The Seventh Component (PC8) (Table 3) refers to *Information Seeking*, which is represented by items PRC1 and PRC2 and exhibit high loadings of 0.865 and 0.749 respectively, with an eigenvalue of 1.016, that interprets 6.082% of total data variance, a percentage deemed satisfactory (Hair et al., 2005), while falling under it are, in order, elements PRC1 and PRC2. The values of the Communalities of PRC1 and PRC2 take on prices 0.890 and 0.843 exceeding the 0.40 value criterion posed as the limit for the verification of the satisfactory quality of eighth Component (PC8). The eighth Component (PC8) is essentially shown to be the *Component of Psychological Risk*.

Financial Risk, Performance Risk, Privacy Risk, Psychological Risk, Social Risk, Time Risk and Overall Risk constructs constitute the latent variable named Perceived Risk of e-Services Adoption Intentions. The construct validity of the scale is evident from this fact. Additionally, variables related to Overall Service Quality Customer, Satisfaction and Purchase Intentions contribute to another independent construct.

PRC1	,865
PRC2	,749

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 7 iterations.

Conclusion

The current study presents two different statistical techniques: i.e the Analyse Factorielle des Correspondances (AFC) and the Principal Components Analysis (PCA). The main objective is to compare the outcomes derived from Analyse Factorielle des Correspondances (AFC), Principal Components Analysis (PCA) procedures with respect to Consumer Behavior and specifically with respect to the Perceived Risk of the Adoption Intention of e-Services.

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 of Marketing Scientists.

Analyse Factorielle des Correspondances (AFC) application unveils factors, independent per couple between them, which are created from the synthesis of groups of the initial variables, simplifying the process for probing the relations between the variables and thus offering a full and more complex image of the phenomenon under examination. The factors can assume the form of axes and form factorial levels in pairs, which will then allow for the graphic representation of the variables. Analyse Factorielle des Correspondances (AFC) is a method where no a priori hypothesis is made.

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

Perceived Risk of e-Services Adoption Intentions multidimensional and hierarchical scale by Featherman & Pavlou (2003) consists of seven constructs: *Financial Risk*, *Performance Risk*, *Privacy Risk*, *Psychological Risk*, *Social Risk*, *Time Risk* and *Overall Risk*. The application of Analyse Factorielle des Correspondances (AFC) made it evident that only *Financial Risk*,

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Performance Risk, Privacy Risk, Time Risk and *Overall Risk* constructs are shaped attitudes. *Psychological Risk* and *Social Risk* constructs seem to be unimportant because none of their dimensions play a role to respondents mind. The application of Analyse Factorielle des Correspondances (AFC) based on the three criteria, inertia (criterion 1) correlation (*Cor*, criterion 2) and contribution (*Ctr2*, criterion 3) reveal the latent dimension of respondents psychological attributes towards Perceived Risk of e-Services Adoption Intentions.

The application of Principal Components Analysis (PCA) creates patterns for Perceived Risk of e-Services Adoption Intentions scale and made it evident that the specific scale constitutes a seven dimension scale containing the constructs *Financial Risk, Performance Risk, Privacy Risk, Psychological Risk, Social Risk, Time Risk* and *Overall Risk*.

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