Public Opinion About the Adoption of New Technology

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This work is a quantitative analysis of the data in a survey to understand the general factors in the mind of the people who form the public opinion about the adoption of new technology. This survey was designed as a precursor in the exploratory stage to gain understanding the tendency in the thinking of the people before designing another survey in details so that it can be applied to a subset of people who have authority to decide about an adoption of the new technology for their organizations. Due to the general nature of the desired information, a factor analysis was done to identify groups of variables that are related and relevant so that the important factors can be emphasized in the development of the second survey with more appropriate details. Data mining was applied to the data to identify the groups of participants who responded with similar data in the survey for the extraction of demographic information.

Keywords: public opinion, quantitative analysis, factor analysis, technology adoption

INTRODUCTION

Public opinion is the collective mind of the majority of the population that can affect the policy, tactic, strategy, or action of an organization (Glynn et al, 2018). In this sense, the public opinion is important to direct the marketing efforts of a company that has to sell their products to the population. However, it is expected that the opinion of the population is not unanimously uniform due to the individualistic nature of human beings and their thinking. Furthermore, the public opinion might not necessarily be reflected in the decision making process of a subset of the population that has authority to make important decisions (Sengupta & Gupta, 2016) that affect the marketing effort for a product (West, Ford & Ibrahim, 2015).

Delivering a product of new technology to the consumers sometimes is considered a challenge to the manufacturer of said product because there exists no knowledge of the product in the mind of the people (Capaldo, Lavie & Petruzzelli, 2014; Shane, 2000). In this aspect, it is important to classify the products into two general categories: products that are sold directly to the consumers for their use immediately, and products that are sold to other manufacturers for them to integrate into their own products before selling them to the consumers. In the first case of selling directly to the consumers, the public opinion might be valuable for a manufacturer of the products. In the second case of selling to other manufacturers for integration, the opinion of the decision makers can be more valuable than that of the public.

This work is focused on the information for the marketing of the products of new technology that are integrated into other products. Specifically, the product is an integratable device in a bottle for authenticating the wine inside that bottle. Due to the unknown nature of a completely new product, the entrance to the market is a challenge (Padilla-Pérez & Gaudin, 2013) for the inventor of the product. Since the product will be sold to wine producers instead of consumers, it is important to understand what the vineyard managers think in their decision making process about adopting a new technology and incorporating it into their products. This need can be satisfied through an extensive survey administered to the vineyard managers. Due to their busy schedules, it is important that the survey was designed efficiently to require the minimum time for managers to participate but to reveal sufficient information for the marketing purpose.

With the requirement that a survey must be efficient and sufficient, it is important to design it correctly (Blair, Czaja & Blair, 2013). For this reason, it is proposed that the survey be designed in two stages: exploratory stage, and discovery stage. This approach uses deductive logic (Hahn, 2015) that begins with a first survey with general questions in the exploratory stage to understand what the general public thinks about adopting a new technology, and continues with the development of a second survey with specific questions based on the results of the survey of the exploratory stage to administer in the discovery stage. This work focuses on the exploratory stage where people who are part of the public are asked with a general survey about their thoughts on the adoption of new technology.

BACKGROUND

The adoption of new technology (Andriole, Cox & Khin, 2018) is an interesting topic in Chile because it is known to be necessary and important to obtain a competitive advantage, but the action (or lack of action) sometimes speaks differently. Informal conversations with some managers in the Maule Region suggested that there is a lack of communications between the universities where new technologies are developed and the industry where these new technologies should be implemented. As a result, the industry may not be aware of the new technologies that are strategically useful to them, and therefore did not even plan any adoption.

At the University of Talca, two FONDEF (Fund for the Promotion of Scientific and Technological Development) projects funded by CONICYT (National Commission of Scientific and Technological Research) were awarded to develop a new technology to authenticate Premium wine with the use of electronic information. After the development work in four years, the technology is ready to be deployed into the industry. As part of the communication between universities and industries (Allen & O'Shea, 2014), a talk was organized to introduce wine authentication technology to people and managers working in the vineyards in the region. In addition, the students, who are the employees of the future, were invited to learn about the technology and the introduction routine at the maturity of the technology. After the talk, a general survey was applied to attendees to gauge their opinions on the adoption of new technologies.

An impediment (Garg, Shukla & Kendall, 2015; Baldwin & Lin, 2002) commonly found in the adoption of new technologies to integrate it into other products is the initial cost and the variable cost that increase the total cost of a product (Naor, Bernardes, Druehl & Shiftan, 2015). In the context of wine authentication, the initial cost is eliminated due to the careful design of the researchers so that new equipment is not required. In addition, the variable cost (cost of an NFC/RFID tag per wine bottle) is absorbed by the provider according to their strategy in exchange for the use of the information created in the authentication activities by the consumers. This strategy is similar to the concept of free software (free software) in which the software is provided free of charge in exchange for the service or information needed as a result of using the software.

In some cultures, people can be skeptical (Novella, 2018), especially when they are offered products for free. Usually, a skeptical person would ask, why is the product free? or is there a hidden cost or hidden agenda that is associated with this offer? Otherwise, this person would think that a free product is not good because it cannot be sold easily. These questions and thinking serve as causes of hesitation in the minds of skeptics when they are faced with a decision to adopt new technology offered as a free product. For this reason, the concept of free software (Fogel, 2005) is used as a practical example to illustrate a new paradigm (Foxall, 1997) of offering new technology products at no cost to users.

While the thinking of people when they encounter a decision to adopt a new technology is generally understood (Sharma & Rai, 2017; Nugroho, 2015; Jones *et al*, 2014; Gil-Garcia, Helbig, & Ojo, 2014), it is strategically important to understand what these people think when said technology is offered without cost in analogous relation to the concept of free software. This objective can be developed in the research questions: (i) what are the general factors that are in the minds of people about the adoption of new technology?, (ii) can the thought be affected when the technology is offered at no cost to users?, and (iii) is it possible to develop a survey in details based on the general factors identified and the understanding of people's thinking about free products?

METHODOLOGY

The methodology used for the factor analysis (Cureton & D'Agostino, 1983) in this work is the methodology of quantitative analysis (Render, Stair, Hanna & Hale, 2014). The factor analysis is an exploratory study that reduces the number of the variables to a smaller number of groups of related variables to identify factors.

Instrument

A brief survey serves as the instrument of this work. The survey should be short because the sample consists of the attendees of the talk that introduces the new technology and the free product concept. This survey asked the general opinion of the adoption potential of the new technology, with 7 questions about the connection between innovation and competitive advantages, the industry in which a participant works, consideration of adopting, initial cost limitation, cost of training, transfer of technology without cost, and time to achieve the expected result. The survey was designed to require a very short time to complete to capture the voluntary participation of the people who attended the talk. In addition, the survey was designed to reinforce the extension of the concept of free innovative products that were explained in the presentation. The validity of the questions is based on previous research. It has been observed that there is a strong relationship between the use of the innovative product and the competitive advantage (Cantwell, 2005; Carayannis & Gonzalez, 2003). However, this relationship could vary between different industries (Bobillo, Rodriguez-Sanz, & Tejerina-Gaite, 2006, Smallbone, 1993), and it is therefore important to identify the relationship for each vertical industry. In addition, the enthusiasm of the leader in the adoption of the innovative product is also important for the success of the adoption (Lloréns-Montes, Ruiz-Moreno, & Morales, 2005, Turnbull & Meenaghan, 1980). However, an important impediment to the adoption of innovation is the initial cost, and this issue must be resolved before the adoption is made (Ceschin, 2013; Kirkland & Thompson, 1999). For this reason, it is important to know how much money is a reasonable amount to invest in an innovative product. In addition, adoption often requires user training (Choi & Chang, 2009; Edmondson, Bohmer, & Pisano, 2001) which may be another impediment. When there is initial investment, results are expected within a specific time duration (Muller, Välikangas, & Merlyn, 2005; Tidd, 2002), and therefore it is important to know this length of time so that adoption can be prepared.

Sample

A sample can be selected to represent a specific portion of the population. For this reason, several demographic groups of this specific portion must be included proportionally in the sample and the participants should be randomly selected from the population. In this scenario, it is said that the sample represents that specific portion of the population. However, sometimes the representation cannot be achieved due to the availability of the participants, and in this case the result cannot be generalized to any part of the population. In addition, it is often that the demographic groups in the sample cannot be arbitrarily identified. The common practice is to segment the sample into clusters through the data mining process, in which each cluster contains similar data so that features of that cluster can be extracted and its demographic information analyzed.

The size of a sample can show the statistical power of its data in terms of sufficiency in representation and reliability in the statistical result. Based on the Cohen d value (Kelley & Preacher, 2012), the size of a sample can be selected for the appropriate statistical power as shown in Table 1.

TABLE 1
SIZE OF A SAMPLE ACCORDING TO THE COHEN *D* VALUE*

Statistical Power	Cohen *d* Value		
	0.2	**0.5**	**0.8**
0.25	84	14	6
0.50	193	32	13
0.60	246	40	16
0.70	310	50	20
0.80	393	64	26
0.90	526	85	34
0.95	651	105	42
0.99	920	148	58

*source: https://en.wikipedia.org/wiki/Sample_size_determination#Tables

Quantitative Analysis

Quantitative analysis is used to reduce the dimension of data into a smaller number of (important) factors. This task consists of a sequence of sub-tasks that are described below.

KMO Test. The adequacy of the data for the analysis of factors is a condition for the data to be appropriate and suitable for the factorial analysis. According to this definition, before performing the factor analysis, a KMO (Kaiser-Meyer-Olkin) measure of sampling adequacy is applied (Cureton & D'Agostino, 1983). This measure produces a constant index with a value between 0 and 1. This constant index indicates the proportion of variance in the variables that can be caused by underlying factors, and therefore factor analysis is necessary to identify such factors when the value of the index is high (between 0.5 and 1.0). Table 2 shows how to interpret the value of the KMO index.

TABLE 2
INTERPRETATION OF THE VALUES OF KMO INDEX*

KMO Index	Interpretation
0.0 - 0.5	Data not appropriate for factor analysis
0.5 - 0.6	Data acceptable for factor analysis
0.6 - 0.8	Data recommended for factor analysis
0.8 - 1.0	Data excellent for factor analysis

*source: https://www.projectguru.in/publications/interpretation-of-factor-analysis-using-spss/

It is common to perform the Barlett test together with the KMO test to determine if the factor analysis is appropriate with the data set. While the KMO test measures a level of correlation between the variables, the Barlett test measures a level of lack of correlation between the variables by comparing the correlation matrix with the identity matrix that represents the completely independent variables. Due to the availability of the correlation matrix and the KMO index in a factor analysis, it is common not to perform the Barlett test.

Factor Analysis. Factor analysis is based on the matrix of correlations between the variables of the survey. The calculation of this matrix is the first step in the analysis of factors, and therefore all the steps that follow it depend on the correct characteristic of the calculation. There are two methods to calculate the correlation matrix: (i) Pearson method (Shevlyakov & Oja, 2016) that is more specific (and therefore more accurate) because it is based on the assumption that the data are of normal distribution, and (ii) Spearman method (Kendall, 1976) that is more general (and therefore, less precise) because it does not require the assumption that the data are of normal distribution.

Normality Data Test. To determine if a series of data has normal distribution, there are two tests: (i) Shapiro-Wilk test (Shapiro & Wilk, 1965) for a sample size of less than 2000 respondents, and (ii) Kolmogorov-Smirnov test (Kolmogorov, 1933; Smirnov, 1948) for a sample size of more than 2000 respondents. The Shapiro-Wilk test is a test that examines the null hypothesis that a sample $x_1, ..., x_n$ comes from a population with normal distribution through test statistics consisting of the order statistic, the sample mean, the mean values of the ordered statistic, and the covariance matrix of that order statistic. The Kolmogorov-Smirnov test is a test that accumulates the difference of the reference probability distribution function and the empirical probability distribution function of data in a sample.

Correlation Matrix. The Pearson method (Shevlyakov & Oja, 2016) is used to calculate a correlation coefficient between two variables based on the values of the covariance between these two variables, and the standard deviation of each variable. This method requires that each variable under consideration must be of normal distribution. A special property of the Pearson correlation is that it is invariable to changes in the location of the data in the series and to any scaling in the data. The Spearman method (Kendall, 1976) is used to calculate a correlation coefficient between two variables based on the ranking of the data values. This method does not require that each variable under consideration must be of normal distribution. In fact, the calculation of the Spearman correlation coefficient can be done by replacing the data with their rankings and using the Pearson method to approximate the coefficient.

Identification of Factors. In a set of variables, sometimes a variable can be represented by other variables. In this case, it is better to identify the representable variables and eliminate them to reduce the size of the set of variables. The identification of the variables that can be represented by other variables is done through the examination of the determinant value of the correlation matrix. If the value of the determinant of the correlation matrix is numerically zero, it is said that there are variables that can be represented by other variables and these representable variables can be eliminated through the analysis of principal components (Hotelling, 1933).

The rotation of variables is an action to avoid assigning many variables to a factor (component) during the early stage of iterations towards a final solution due to the mathematical nature of the algorithm that requires the factors to be orthogonal (independent). To balance the variables among the factors in a more equitable manner, the rotation step is performed. However, the calculation in this rotation can result in a numerical error of dividing a number by zero. To avoid this error, the correlation matrix is required to be invertible. This requirement can be verified with the examination of the determinant value of the correlation matrix: if the value of the determinant is numerically zero, the correlation matrix is not invertible; and if the value of the determinant is not numerically zero, the correlation matrix is invertible and therefore the rotation is numerically possible. For this reason, to avoid numerical error, the value of the determinant of the correlation matrix must be verified to be non-zero in the numerical sense before performing the rotation of variables.

Segmentation of Clusters With Similar Data

Segmentation (Aggarwal, 2015) is the process of separating a data set into several subsets in which each subset of data only contains data of a similar nature. Therefore, the subsets of data resulting from the segmentation process are called clusters. Segmentation is the first step in data mining to identify clusters used in the discovery of information associated with these clusters. In a quantitative analysis, when it is not easy to identify the demographic groups for a more specific analysis of each of these groups, it is common to use segmentation to identify clusters of data that may represent some demographic groups. In this case of segmentation, there are two methods: deterministic method and statistical method. The test to determine if a data set is of normal distribution can provide information to select the segmentation method. If the data are of normal distribution, the statistical method is used; and if the data are not of normal distribution, the deterministic method is used.

NUMERICAL RESULTS

A sample of 55 participants was collected. The size of 55 participants corresponds to the power level of 75% shown in Table 1 for the Cohen *d* value of 0.5 which means a sufficiently visible effect of the results. Therefore, this size is considered acceptable for the analysis of factors in the quantitative sense. There are 7 questions, as was described in the previous subsection "Instrument," and the variables corresponding to these questions are named in Table 3.

KMO Test. Before performing the factor analysis, a KMO test was performed to determine if the data is appropriate for this type of analysis. Table 4 shows that the KMO indicator value is 0.576, and according to Table 2, it means that the data is acceptable for factor analysis.

Normality Data Test. Table 5 shows both the Shapiro-Wilk test and the Kolmogorov-Smirnova test. Due to the small size of 55 respondents in the sample, the result of the recommended Shapiro-Wilk test is used for sample sizes of less than 2000 respondents. In all the variables P1, P2, ..., P7, the *p*-value is numerically zero for each variable, meaning that the null hypothesis that the variable is of normal distribution is rejected (the rejection threshold is $p \leq 0.05$). Therefore, the Pearson method cannot be used to calculate the correlation matrix, and instead, the Spearman method must be used to calculate the correlation matrix.

TABLE 3
VARIABLE NAMES AND THEIR CORRESPONDING TOPICS

Variables	Questions in the Survey
P1	the connection between innovation and competitive advantages
P2	the industry in which the participant works
P3	consideration of adopting
P4	limitation of initial cost
P5	cost of training
P6	technology transfer without cost
P7	time to achieve the expected results

TABLE 4
QUALIFICATION OF DATA FOR FACTOR ANALYSIS

Indicador	Value
KMO Measure of Sampling Adequacy	0.576

TABLE 5
NORMALITY TEST OF DATA

	Kolmogorov-Smirnova			Shapiro-Wilk		
	Statistic	df	Sig	Statistic	df	Sig
P1	0.540	55	0.000	0.186	55	**0.000**
P2	0.299	55	0.000	0.846	55	**0.000**
P3	0.535	55	0.000	0.117	55	**0.000**
P4	0.331	55	0.000	0.738	55	**0.000**
P5	0.336	55	0.000	0.746	55	**0.000**
P6	0.511	55	0.000	0.348	55	**0.000**
P7	0.320	55	0.000	0.773	55	**0.000**

Correlation Matrix. The correlation matrix that is shown in Table 6 was calculated with the Spearman method that uses the ranking of the data because the Shapiro-Wilk test showed that the data do not have normal distribution and therefore the Pearson method cannot be used. The determinant of the correlation matrix is 0.664, which means that the rotation of variables to balance them more evenly is numerically possible.

Factor Analysis. In the first analysis, the factors are identified without rotation as shown in Table 7. In this table, the variables P4 (initial cost limitation) and P7 (time to achieve expected result) are grouped in factor F1; the variables P5 (training cost), P2 (the industry in which a participant works), and P1 (the connection between innovation and competitive advantages) are grouped in Factor F2; and the variables P6 (technology transfer without cost) and P3 (consideration of adopting) are grouped in Factor F3. Table 8 shows the commonality values between variables, and any value over 0.4 is considered a good extraction of variable to assign it to a factor. Here in this Table, all values are more than 0.5, indicating that the result in Table 7 is acceptably good. In this result, the variables are divided somewhat equally among the three factors. In general, it is not necessary to rotate the variables because of this fairly equal distribution. However, to satisfy the intellectual curiosity, the analysis of factors was carried out again, this time with rotation of the variables, given that the condition for avoiding numerical error during the rotation has been satisfied (determinant of the correlation matrix is non-zero).

TABLE 6
CORRELATION MATRIX *

	P1	P2	P3	P4	P5	P6	P7
P1	1,000	0,120	–0,026	–0,183	–0,184	–0,067	0,102
P2	0,120	1,000	0,084	0,155	–0,130	0,056	–0,072
P3	–0,026	0,084	1,000	0,131	0,042	–0,047	–0,220
P4	–0,183	0,155	0,131	1,000	0,014	0,201	–0,384
P5	–0,184	–0,130	0,042	0,014	1,000	–0,072	–0,079
P6	–0,067	0,056	–0,047	0,201	–0,072	1,000	–0,096
P7	0,102	–0,072	–0,220	–0,384	–0,079	–0,096	1,000

determinant = **0.664**
*obtained through the Spearman method with ranking data

TABLE 7
ANALYSIS OF PRINCIPAL COMPONENTS
(WITHOUT ROTATION)

variables	Components (Factors)		
	F1	F2	F3
P4	**0.774**	0.098	–0.150
P7	**–0.737**	0.007	–0.165
P5	0.148	**–0.693**	0.176
P2	0.246	**0.645**	0.160
P1	–0.373	**0.584**	0.278
P6	0.351	0.217	**–0.697**
P3	0.425	0.036	**0.653**

TABLE 8
COMMONALITY IN THE EXTRACTION
(WITHOUT ROTATION)

variables	Initial	Extraction
P4	1.000	**0.632**
P7	1.000	**0.570**
P5	1.000	**0.533**
P2	1.000	**0.502**
P1	1.000	**0.558**
P6	1.000	**0.656**
P3	1.000	**0.608**

TABLE 9
ANALYSIS OF PRINCIPAL COMPONENTS (WITH ROTATION*)

variables	Components (Factors)		
	F1	F2	F3
P7	**–0.750**	0.083	–0.027
P4	**0.711**	–0.030	0.355
P3	**0.587**	0.072	–0.509
P5	0.125	**0.674**	–0.251
P1	–0.228	**0.663**	–0.257
P2	0.339	**0.622**	0.022
P6	0.168	0.065	**0.790**

*Varimax method of rotation

TABLE 10
COMMONALITY IN THE EXTRACTION (WITH ROTATION*)

variables	Initial	Extraction
P7	1.000	**0.570**
P4	1.000	**0.632**
P3	1.000	**0.608**
P5	1.000	**0.533**
P1	1.000	**0.558**
P2	1.000	**0.502**
P6	1.000	**0.656**

*Varimax method of rotation

Table 9 shows the result of the factors identified when the variables are rotated. In this table, the variables P7 (time to achieve expected result), P4 (initial cost limitation), and P3 (consideration of adopting) are grouped into factor F1; the variables P5 (training cost), P2 (the industry in which a participant works), and P1 (the connection between innovation and competitive advantages) are grouped into Factor F2; and variable P6 (technology transfer without cost) is assigned in Factor F3. Table 10 shows the commonality values between variables, and these values, being more than 0.4, are considered a good extraction of variable to assign to a factor. Here, the factor F1 is the resulting factor F1 done without rotation plus the variable P3, the factor F2 is the same the resulting factor F2 done without rotation, and the factor F3 is the resulting factor F3 done without rotation minus the variable P3. For this comparison, the result without rotation and the result with rotation are similar.

Segmentation of Clusters with Similar Data. The segmentation of the entire data set, through the K-means clustering method selected because of the lack of knowledge of the distribution of the data, results in three clusters: Cluster C1 contains 35 participants, Cluster C2 contains 18 participants, and Cluster C3 contains 2 two participants. Due to the very small size of cluster 3, it is considered an outlier. Table 11 shows the centers of these three clusters, with each center representing the average data of the participants assigned in the cluster.

TABLE 11
CENTERS OF THE CLUSTERS IDENTIFIED IN THE SEGMENTATION STEP*

		Clusters		
		C1	C2	C3
Variables	P1	1	1	1
	P2	2	3	3
	P3	1	1	1
	P4	2	3	4
	P5	2	2	2
	P6	1	1	4
	P7	2	2	1

*K-means clustering method is used

Considering Cluster C1 of 35 participants, the analysis of factors is shown in Tables 12 to 15. Again, the normal distribution condition is not satisfied, causing the use of data from the rankings for the Spearman method in the calculation of the Correlation matrix. Here, the determinant value of the correlation matrix is numerically non-zero, allowing the rotation of variables for a more equitable distribution of variables between the factors. In Table 12 (without rotation), the variables P7 (time to achieve expected result), P4 (initial cost limitation), and P3 (consideration of adopting) are grouped into factor F1; the variables P5 (training cost), and P2 (the industry in which a participant works) are grouped into Factor F2; and the variables P1 (the connection between innovation and competitive advantages) and P6 (technology transfer without cost) are grouped in Factor F3. Table 13 shows the commonalities of the variables, and their values indicate that the extraction was good for all variables with the exception of the variable P3 that is bad (commonality value of 0.310, less than the threshold of 0.4).

TABLE 12
ANALYSIS OF PRINCIPAL COMPONENTS OF CLUSTER C1 (WITHOUT ROTATION)

variables	Components (Factors)		
	F1	F2	F3
P7	**–0.862**	0.029	0.000
P4	**0.761**	–0.110	0.271
P3	**0.533**	0.159	–0.034
P5	–0.054	**0.720**	0.329
P2	0.367	**0.661**	–0.335
P1	–0.170	0.341	**–0.714**
P6	–0.279	0.435	**0.605**

TABLE 13
COMMONALITY IN THE EXTRACTION OF C1 (WITHOUT ROTATION)

variables	Initial	Extraction
P7	1.000	**0.743**
P4	1.000	**0.665**
P3	1.000	**0.310**
P5	1.000	**0.629**
P2	1.000	**0.684**
P1	1.000	**0.655**
P6	1.000	**0.633**

TABLE 14
ANALYSIS OF PRINCIPAL COMPONENTS OF CLUSTER C1 (WITH ROTATION*)

variables	Components (Factors)		
	F1	F2	F3
P7	**–0.849**	0.146	–0.020
P4	**0.777**	–0.026	–0.245
P3	**0.536**	0.025	0.150
P5	0.048	0.767	0.195
P6	–0.164	0.750	–0.208
P1	–0.229	–0.154	**0.761**
P2	0.376	0.251	**0.692**

*Varimax method of rotation

Table 15
COMMONALITY IN THE EXTRACTION OF C1 (WITH ROTATION*)

variables	Initial	Extraction
P7	1.000	**0.743**
P4	1.000	**0.665**
P3	1.000	**0.310**
P5	1.000	**0.629**
P6	1.000	**0.633**
P1	1.000	**0.655**
P2	1.000	**0.684**

*Varimax method of rotation

Tables 14 and 15 show the result of the factor analysis for Cluster C1, this time with rotation in the variables. In Table 14 (with rotation), the variables P7 (time to achieve expected result), P4 (initial cost limitation), and P3 (consideration of adopting) are grouped into factor F1; the variables P5 (cost of training), and P2 (the industry in which a participant works) are grouped into factor F2; and the variables P1 (the connection between innovation and competitive advantages) and P6 (technology transfer without cost) are grouped into factor F3. Table 15 shows the communities of the variables, and their values indicate that the extraction was good for all variables with the exception of the variable P3 that is bad (commonality value of 0.310, less than the threshold of 0.4).

Considering the Cluster C2 of 18 participants, the factor analysis results in a numerical error because variable P3 shows variance of the value zero (all data contain the same value). When excluding this variable from the analysis, Table 16 (without rotation) shows that variables P5 (training cost), and P4 (initial cost limitation) are grouped into factor F1; the variables P6 (technology transfer without cost), P1 (the connection between innovation and competitive advantages) and P2 (the industry in which a participant works) are grouped into factor F2; and variable P7 (time to achieve expected result) is assigned to factor F3. Table 17 shows the commonalities of the variables, and their values indicate that the extraction was good for all variables (commonality value is more than the threshold of 0.4).

TABLE 16
ANALYSIS OF PRINCIPAL COMPONENTS OF CLUSTER C2 (WITHOUT ROTATION)

variables	Components (Factors)		
	F1	F2	F3
P5	**–0.848**	0.021	0.032
P4	**–0.627**	0.455	0.030
P6	0.455	**0.727**	0.289
P1	0.471	**–0.635**	0.064
P2	0.465	**0.545**	–0.531
P7	0.145	0.116	**0.907**

TABLE 17
COMMONALITY IN THE EXTRACTION OF C2 (WITHOUT ROTATION)

variables	Initial	Extraction
P5	1.000	**0.720**
P4	1.000	**0.601**
P6	1.000	**0.820**
P1	1.000	**0.629**
P2	1.000	**0.796**
P7	1.000	**0.857**

TABLE 18
ANALYSIS OF PRINCIPAL COMPONENTS OF CLUSTER C2 (WITH ROTATION*)

variables	Components (Factors)		
	F1	F2	F3
P4	**0.773**	–0.048	0.022
P1	**–0.766**	–0.205	0.007
P5	**0.672**	–0.509	–0.101
P2	–0.016	**0.830**	–0.327
P6	0.103	**0.747**	0.501
P7	–0.044	–0.060	**0.922**

*Varimax method of rotation

TABLE 19
COMMONALITY IN THE EXTRACTION OF C2 (WITH ROTATION*)

variables	Initial	Extraction
P4	1.000	**0.601**
P1	1.000	**0.629**
P5	1.000	**0.720**
P2	1.000	**0.796**
P6	1.000	**0.820**
P7	1.000	**0.857**

*Varimax method of rotation

When considering the Cluster C2 of 18 participants again, this time with rotation, the factor analysis also results in a numerical error because variable P3 shows variance of the value zero (all data contain the same value). By excluding this variable from the analysis, Table 18 (with rotation) shows that variables P5 (training cost), P4 (initial cost limitation), and P1 (the connection between innovation and competitive advantages) are grouped into factor F1; the variables P6 (technology transfer without cost) and P2 (the industry in which a participant works) are grouped into factor F2; and variable P7 (time to achieve expected result) is assigned in factor F3. Table 19 shows the commonalities of the variables, and their values indicate that the extraction was good for all variables (commonality value is more than the threshold of 0.4).

DISCUSSION AND FUTURE DIRECTION

The results of the factor analysis in the previous section are summarized in the following Tables 20 and 21. In each table, the results (the variables contained in a factor) are shown in three rows: the first row shows the results of the entire set of data, the second row shows the results of Cluster C1, and the third row shows the results of Cluster C2. Cluster C3 contains only two participants and therefore will not be analyzed.

TABLE 20
FACTORS WITHOUT ROTATION*

	data	F1	F2	F3
no	all	P4, P7	P1, P2, P5	P3, P6
	C1	P3, P4, P7	P2, P5	P1, P6
	C2	P4, P5	P1, P2, P6	P7

*Spearman method of correlation

TABLE 21
FACTORS WITH ROTATION*

	data	F1	F2	F3
rotation	all	P3, P4, P7	P1, P2, P5	P6
	C1	P3, P4, P7	P5, P6	P1, P2
	C2	P1, P4, P5	P2, P6	P7

*Spearman method of correlation, Varimax rotation

In the first result of the factor analysis without rotation, the factor F1 contains the variables P4 (limitation of initial cost) and P7 (time to achieve expected result). It is easy to understand that when a person has concerns about the initial cost, he also expects to achieve the positive result after having to pay for the adoption of a new technology. Therefore, these two variables are combined to form a factor, and this factor can be named *Financial Factor* that dictates that the initial investment of money comes with the expectation of the positive results promised by the provider of the new technology. Factor F2 contains the variables P1 (the connection between innovation and competitive advantages), P2 (the industry in which a participant works), and P5 (training cost). Here, the industry in which a participant works can define the specific cost of training for the use of a technology. In addition, the level of the connection between innovation and competitive advantages probably depends on the type of vertical industry, for example the information industry is highly dependent on innovation to achieve competitive advantages, and the construction industry is less dependent on innovation. Therefore, these three variables are combined to form a factor, and this factor can be called an *Industrial Factor*. Factor F3 contains the variables P3 (consideration of adopting) and P6 (transfer of technology without cost). In this aspect, when considering adoption, the transfer of technology without cost probably offers the minimum risk that favors the positive decision. Therefore, these two variables are combined to form a factor, and this factor can be called a *Minimum Risk Factor*.

Cluster 1 has results (without rotation) very similar to those of the entire data set. The Factor F1 has the same variables P4 (initial cost limitation) and P7 (time to achieve expected result) of the factor F1 of the whole data set, plus the variable P3 (consideration of adopting). Of course, when considering adoption, it is common sense to consider the initial cost and time to achieve the benefit. While the adoption consideration is related to the option with minimum risk in the whole data set, the Factor F1 relates the consideration to the initial cost and the time to the benefit. The factor F2 has the same variables of the whole set of data minus the variable P1 (the connection between innovation and competitive advantages). Instead, this variable P1 is related to variable P6 (technology transfer without cost) in factor F3.

Cluster 2 has results (without rotation) that are more different from those of the entire data set. The Factor F1 has the variables P4 (initial cost limitation) and P5 (training cost). The Factor F2 has the same variables P1 (the connection between innovation and competitive advantages), P2 (the industry in which a participant works) of the case of the whole data set, plus the variable P6 (technology transfer without cost). The Factor F3 only contains the variable P7 (time to achieve expected result) that is not possible to analyze.

In the second result of the analysis with rotation, the factor F1 contains the same variables P4 (limitation of initial cost) and P7 (time to achieve expected result) of the case without rotation, plus the variable P3 (consideration of adopting). This factor is exactly the same F1 factor of Cluster C1 without rotation. The factor F2 contains the same variables of the factor F2 of the case without rotation. However, factor F3 only contains a variable P6 (technology transfer without cost) and it is not practical to consider a single variable as a factor.

Cluster 1 has results (with rotation) similar to those of the case of Cluster 1 without rotation. Factor F1 has the same variables P3 (consideration of adopting), P4 (limitation of initial cost) and P7 (time to achieve expected result) of the case without rotation. Factor F2 has the same variable P5 (training cost) of the factor F2 of the case without rotation, plus the variable P6 (transfer of technology without cost). This factor can be named *Awareness of Costs*. Factor F3 has the same variable P1 (the connection between innovation and competitive advantages) of the factor F3 of the case without rotation, plus the variable P2 (the industry in which a participant works). This factor can be named *Dependent on the Vertical Industry*.

Cluster 2 has results (with rotation) somewhat different from those of the case of Cluster 2 without rotation. Factor F1 has the same variables P4 (initial cost limitation) and P5 (training cost) of the case without rotation, plus variable P1 (the connection between innovation and competitive advantages). The factor can be named *Cost vs. Benefit*. Factor F2 has the same variables P2 (the industry in which a participant works), and P6 (technology transfer without cost) of the case without rotation. Factor F3 only has one variable P7 (time to achieve expected result) and should not be considered as a factor.

In general, the case of rotation produces two factors that cannot be analyzed in comparison to the case of non-rotation. For this reason, it is said that the case of non-rotation distributes the variables more equally among the factors, and therefore, it is preferable over the case of with rotation. Thus, in this case there are three general factors: financial factor, industrial factor, and minimum risk factor. Two clusters are identified from the entire data set: a larger cluster that is very similar to the results of the entire data set, and a smaller cluster that is very different from the results of the entire data set. Based on the size of each cluster and the composition of the participants (more technology developers than technology users), it is speculated that Cluster C1 represents technology developers, and Cluster C2 represents technology users.

In reviewing the research questions proposed at the beginning of this work, the first research question, what are the general factors that are in the minds of people about the adoption of new technology?, was answered with the analysis of factors that found the financial factor, industrial factor, and minimum risk factor existing in the mind of the people surveyed on the adoption of new technology. The second research question, can the thought be affected when the technology is offered without cost to the users?, was answered with the minimum risk factor that links the variable P3 (consideration of adopting) to the variable P6 (transfer of technology without cost), indicating a positive effect of free technology on the thinking of decision makers of adoption. The third research question, is it possible to develop a survey in details based on the general factors identified and the understanding of people's thinking about free products?, will be answered positively in the next paragraph on the discussion of future work with the development of a survey in more detail in the next stage of discovery.

The work for the immediate future is to develop a survey in more detail based on the three factors: financial, industries, and minimum risk. This next survey should be designed with interviews of carefully selected managers in the industry who have the authority to make decisions about the adoption of technology. In this interview, it is important to identify the educational background of a manager so that more consideration of their focus is emphasized in the conversation regarding the profile of Cluster C1 or Cluster C2. The result of the interview is condensed into a list of specific questions in a survey to all managers of the relevant vineyards so that an understanding of the mentality of the managers when considering the adoption of new technology can be achieved.

CONCLUSION

In the exploratory stage, a survey was applied for a quantitative study of factor analysis on the topic of adopting new technology, especially in the context of free distribution (at no cost). In general, three factors were identified in the public opinion: financial factor (cost vs benefit), vertical industry factor (type of industry vs. the level of expected benefit), and minimum risk factor (zero cost for consideration). In addition, two clusters of participants were identified: one cluster with profile of technology developers, and another cluster with profile of technology users. Each cluster offers some variation in the three factors already identified. This finding will be used in the second stage of exploration, where a detailed survey based on these results can be designed to obtain an understanding of managers' thinking when considering the adoption of new technology.

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