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An evaluation of Competitive and Technological Intelligence tools: A cluster analysis of users' perception

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ABSTRACT

The purpose of this chapter is to discuss and evaluate the use of Competitive and Technological Intelligence (CTI) tools by students to help designers of these tools get the best efficiency out of a monitoring process. This chapter introduces an application of cluster analysis method and explores the Competitive and Technological Intelligence literature. In order to evaluate the use of CTI tools, we deal with two evaluation models: Task-Technology Fit (TTF) and Technology Acceptance Model (TAM). A survey is sent to users of CTI tools addressed to engineering students and the most pertinent replies were examined. The responses were analyzed by using the statistical software SPAD. Results showed a typology from the various profiles of users of this technology by using the method of classification. We note different perceptions between student users. Although this study remains focused on individual perspective, it requires more examination about the organizational impact of the use of CTI tools. The identification of the different user profiles was done by using a cluster analysis. For the designers of CTI tools these results highlight the importance of user perception, suggesting designers take into account the perception of all user types. As these tools develop, more and more companies will be looking for skills for monitoring and management of strategic information.

Keywords: Competitive and Technological Intelligence, cluster analysis, TTF model, TAM model, User Perception.

INTRODUCTION

Generation Y students need to understand why we use gathering information tools and how has it evolved since their birth? What sense can be given to the quality of information found on the web? Are they able to judge the quality of the monitoring tools used and the information found? What they need today in an engineering school even if they are supposed to know the classical research methods?

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All these questions prompted us to think about the method of teaching a module entitled Economic and Strategic Intelligence at UniLaSalle where we present the tools of Competitive Intelligence, Technological Intelligence, Marketing Intelligence and E-reputation. We have applied these types of watch on a problem related to the fields of studies of our students. We have three specialties in engineering training: Agriculture, Food and Health and Geology.

Our approach seeks to answer two key research questions:

1. How can engineering students make their choice between different monitoring tools to collect, to process and to disseminate information?
2. What are the different perceptions between students by using monitoring tools?

To answer these questions, we propose in the second section the conceptual background about some cluster analysis applications, cluster analysis methodology, cluster analysis with SPAD and we define the two process of “Competitive Intelligence” and “Technological Intelligence”. In a third section, we propose the approach of our study and the research method. In a fourth section, we present our results on the monitoring tools developed within the higher education institution UniLaSalle and clustering user’s perception of these tools. Conclusion is drawn in a fifth section.

CONCEPTUAL BACKGROUND

Cluster analysis applications

Anderberg (1973, 2014) presented all various applications of cluster analysis, the topics covered from variables and scales to measures of association among variables and data units. They discussed the conceptual problems in cluster analysis. This book presented many major areas of applications, so we summarize them:

- The life sciences: the object of the analysis method is to develop complete taxonomies to delimiting the subspecies of a distinct but varied species (plants, animals...)
- The medical sciences: the cluster may be a disease, patient (or their disease profiles) and laboratory tests...
- The behavioral and social sciences: the objects of analysis covered training method, factors of human performance, organizations, students, courses in school, teaching methodologies or techniques,...Factor analysis is a competitor to cluster analysis in these applications.
- The earth sciences: the object of these applications is to land soils, countries, regions of the world...
- The Engineering sciences: the application have been relatively few in this field.
- The information, policy and decision sciences: the applications to documents, the political units, products, markets, sales, programs, research and development projects.

A cluster analysis is considered as a tool of classification mostly used in marketing research (Punj and Stewart, 1983).

Cluster analysis methodology

« Cluster analysis is the art of findings groups in data », the classification of similar objects or perceptions into groups is an important human activity (Kaufman and Rousseeuw,

2009). Berkhin (2006) defined clustering like a division of data into groups of similar objects, it is related to many disciplines and plays an important role in a broad range of applications that deals with large database with many attributes.

Clustering must not be confused with classification. In clustering, we must first develop a quantitative scale on which to measure the similarity between objects and secondly an algorithm for sorting objects into groups (Johnson and Wichern, 1998). In classification, we first separate a known number of groups and then assign new observations to one of these group according to the measurements.

To carry out a cluster analysis, a wide variety of clustering algorithms is available: hierarchical techniques and nonhierarchical techniques.

Hierarchical clustering techniques proceed by either a series of successive mergers (agglomerative hierarchical methods) or a series of successive divisions (divisive hierarchical methods).

“Agglomerative hierarchical methods start with the individuals objects. Thus, there are initially as many clusters as objects. The most similar objects are first grouped, and these initial groups are merged according to their similarities” (Johnson and Wichern, 1998).

“Divisive hierarchical methods work in the opposite direction. An initial single group of objects is divided into subgroups such that the objects in one subgroup are “far from” the objects in the other. These subgroups are then further divided into similar subgroups; the process continues until there are many subgroups as objects – that is, until each object forms a group”. (Johnson and Wichern, 1998).

The results of both agglomerative and divisive methods may be displayed in the form of a two-dimensional diagram known a dendrogram. The dendrogram illustrates the mergers or divisions that have been made at successive level and looks like a tree. This is why it’s sometimes called the “hierarchical tree”.

Nonhierarchical clustering techniques are design to group items into a collection of k clusters. The number of clusters, k , is specified before starting the clustering procedure.

However, hierarchical clustering techniques are the most popular. In the following sections, we will deal with one particular agglomerative hierarchical procedure, say the Ward’s hierarchical clustering method. In this method, a variance criterion is used to decide on which individuals or which clusters should be fused at each stage in the procedure. To implement this method, at each step find the pair of individuals or clusters that leads to minimum decrease in total between-cluster variance after merging. In other words, two items whose merging results in the smallest decrease in between-cluster variance are joined. The results of Ward’s method can be displayed as a dendrogram which is often used to identify the best groups of clusters: those in which the between-cluster variance is high whereas the within-cluster variance is low. The vertical axis of the dendrogram gives the values of the between-cluster variance decrease at which the mergers occur.

Beyond the identification of the best groups of clusters, it is important to know how the clusters could be described, in other words which variables are concerned by the observed similarities.

Cluster analysis with SPAD v.8

The SPAD software is a useful statistical software to deal with multivariate data analysis techniques such as hierarchical clustering techniques. An exploratory factor analysis

(principal component analysis or multiple correspondence analysis) is always conducted prior to a cluster analysis. The aim is to extract the meaningful dimensions in the dataset and then describe the objects which will be classified into groups by using such dimensions which are also called factors. In fact, there are two types of attributes involved in the data to be clustered: metric and nonmetric. If the data are metric then a principal component analysis is used, if not, a multiple correspondence analysis is used. The SPAD offers the opportunity to reduce the dimensions in the data and then use the scores from the suitable exploratory factor analysis to perform the Ward's hierarchical clustering method. After performing the clustering, the analyst is involved in two main steps:

- Step 1: Choosing the best groupings of individuals by using a visual cutting of the dendrogram. The "branches" of dendrogram are cut with horizontal lines where the consecutive nodes are distant. In other words, the dendrogram is cut where its branches are very long. It's a good way to have an idea of the best groupings even if that groupings are not necessary stable. In practice, there are two or three possible cuttings. It is up to the user to choose one them.

- Step 2: Description of the clusters from a chosen grouping. The significant variables are used to characterize the individuals from each cluster. That description is done when the groupings are "consolidated". For instance, each individual is assigned to the cluster whose centroid is nearest.

SPAD also offers the opportunity to work with by using a hybrid clustering technique when the size of the dataset, especially the number of individuals, is very important (more than several thousand individuals). A nonhierarchical clustering technique, such as "K-means" technique (Everitt, 1998), is applied to the dataset prior to a hierarchical clustering technique.

The process of Competitive and Technological Intelligence

"Competitive Intelligence" (Jakobiak, 1998; Herring, 1998; Kahaner, 1998; Ruach and Santi, 2001) is regarded as a specialized branch of "Business Intelligence" (Giald and Giald, 1988; Sakys and Butleris, 2011). Solberg Soilen (2015) proposed the classification of intelligence studies to help us to place different forms of intelligence and to show how they related to each other. The first concept aims to collect and analyze data on specific and generic competitive environments, it is also defined by Bel Hadj et al. (2016) as « a voluntary process whereby a company can begin to scan and absorb information from its socioeconomic environment in order to minimize the risks associated with the uncertainty and locate available opportunities » (Pateyron, 1998). While the second focuses on the current competitors and can analyze areas such as potential acquisitions-mergers and evaluate specific country risks (Lesca and Caron Fasan, 2006). Bel Hadj et al. (2016) highlighted the literature that examines competitive intelligence in relation to its integration with company strategy (Porter, 1999); knowledge management (Jacob and Patriat, 2002); collective learning and cooperation (Salles, 2006); business opportunities (Marmuse, 1996); and entrepreneurial orientation (Bel Hadj et al., 2014).

Du Toit (2015) listed the terms and the number of articles selected for the period 1995 and 2014 to show the evolution of terms using the database ABI/Inform: Competitive Intelligence (75%), Business Intelligence (13%), Marketing Intelligence (8%), Strategic Intelligence (1%), Technological Intelligence (1%) and Competitor Intelligence (1%). He showed also the main

journals that published a high percentage of competitive intelligence articles and only two journals: Journal of Intelligence Studies in Business and Marketing Intelligence & Planning that focused exclusively on the publication of intelligence types.

Competitive Intelligence serve to identify, monitor competitors and decrypt their strategy. Technological Intelligence is to follow a technical and scientific domain in the time and to monitor developments¹. Salvador et al. (2014) presented a patent analysis on additive manufacturing and showed the work of Calof and Smith (2010) that “consider that competitive technical intelligence (CTI) and strategic technological foresight (STF) are fields with similar objectives and techniques. While the authors define CTI as a practice that provides business sensitive information on external scientific or technological treats, opportunities or developments that have the potential to affect a company’s competitive position. STF according to them is a collaborative tool that draws upon the talents of many individuals (not only from the technology domain) and is an important source for technical and business intelligence.”

The articles published in the Journal of Intelligence Studies in Business since 2011 were focused on developing and testing models to evaluate Business Intelligence systems and software. Following these studies, new problematics have emerged: to study the differentiation of Business Intelligence vendors (Solberg Soilen and Hasslinger, 2012); to classify Business Intelligence software based on their functionalities and performance (Amara et al. 2012; Nyblom et al. 2012; Abzaltynova and Williams, 2013); to show the perception of Business Intelligence tools by professionals and students using two models of Information systems literature (Fourati-Jamoussi and Niamba, 2016).

This literature review has enabled the construction of a Competitive and Technological Intelligence plan (Figure 1 and 2). These two methodologies of CTI were applied by all students when they reformulated and responded to their watch problematics (for example: extraction of pea protein; create new food products such as ice cream and energy cake; future of renewable energies and rare metals ;...)

To apply this CI methodology, the students collect information from the competitive environment of the firm selected, they used general and monitoring tools to identify information sources of competitors, then monitor them over time (period of the watch project). Finally, they organised and analyse all informations treated to understand the strategic development of all competitors.

¹ www.ie.bercy.gouv.fr

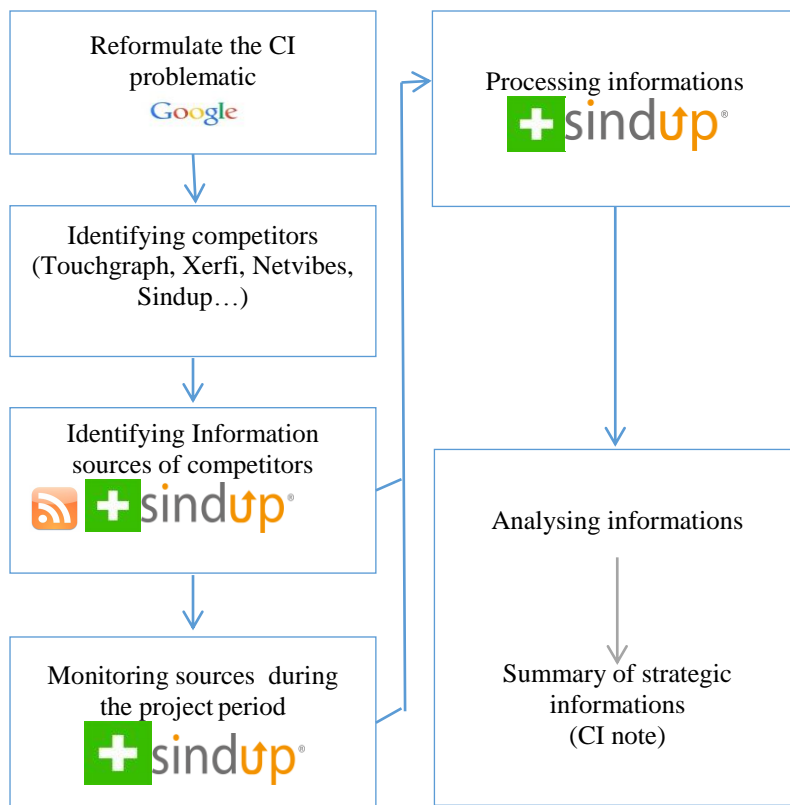


Figure 1. The teaching Competitive Intelligence (CI) Methodology

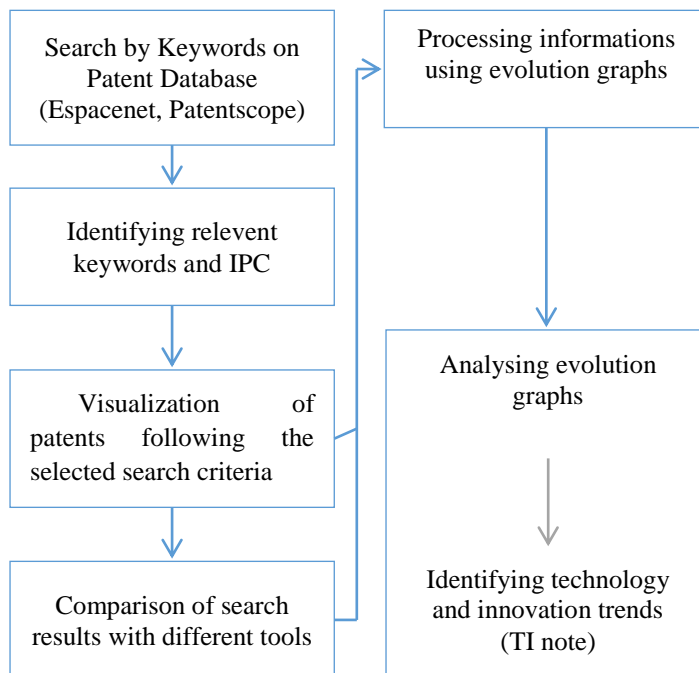


Figure 2. The teaching Technology Intelligence (TI) Methodology

The TI methodology consist to establish the goal of the project then to organize a collection of patent information by using Databases : Espacenet and Patentscope designed by the INPI (Institut National de la Propriété Intellectuelle) and the WIPO (World Intellectual Property Organization). The students need to identify the main countries, International Patent Classifications (IPCs), applicants, inventors. To exploit and analyse all pertinent patent, they used the keyword-based patent analysis (Salvador et al. 2014) that represents an important method used to determine technology trends, discover technological opportunities and predict new technological advances. This method is based on patent keyword frequencies between them (Choi et al. 2012).

THE METHODOLOGY AND THE RESEARCH MODEL

Data collection

The study concentrated on certain number of variables stemming from the literature in information systems, which join the problem of the evaluation of the CTI tools used within the framework of the process of the strategic intelligence. A questionnaire was built in the field of the conception of the CTI tools (Fourati-Jamoussi, 2014). Through this study, we tried to show the use of the watch tools and their applications. The survey was built with the aim to operationalize the variables of the theoretical model as well as to profile the users who can answer this survey. It was designed and diffused to the UniLaSalle students after applying the CTI methodologies presented in section II. Our database is composed by 265 responses for clustering the user's monitoring tools (these respondents were from three specialties: i) Agriculture; ii) Food and Health; iii) Geology).

Logic of the study

To evaluate and compare the user profiles, the selected criteria were from the theoretical fusion of these two models: Technology / Task Fit (Goodhue and Thompson, 1995) and the Technology Acceptance (Davis, 1989; Venkatesh et al., 2003) as part of the literature on the evaluation of information systems (Figure 3):

Model I: "Task/Technology Fit" aims to evaluate the user perception towards the used system. It is defined by the degree of correspondence between the functional needs relative to the task and the technical features offered by the information technology. It was explained by four criteria (b, c, d, e):

a. CTI tools used: is not showed in the model but in the survey. These tools are classified into three categories (presented in Table 2).

b. Functionalities of CTI tools: were the capacities of the system to help individuals or group determined by the type of system used (Benbasat and Nault, 1990; Wierenga and Van Bruggen, 2000). The tasks presented in the questionnaire were: search information, store, process and extract a large quantity of information, resolve the semantic and syntactic problems.

c. Data Quality: measured the correspondence between needs and the available data, it also measured the exactness of these available data by using CTI tools and the quality of data at a level of detail suitable for the tasks?

d. Data Compatibility: between the various sources of data.

e. Capacity of learning: the ability of students to use these watch tools.

f. The intensity or frequency of use: it was a subjective appreciation of the increase or the decrease of the degree of use. The intensity depended on the integration of the Business Intelligence system (Grublješič and Jaklič, 2014) and on the strategy adopted by the company (Presented in the survey).

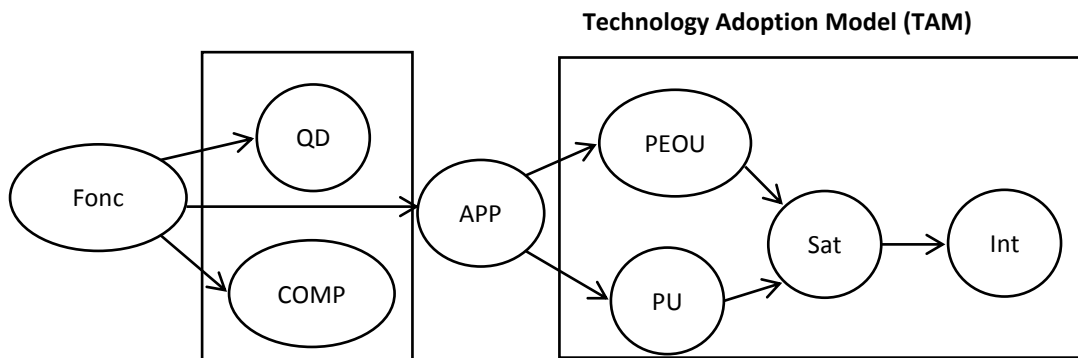
Model II: The acceptance of CTI tools is inspired from the “Technology Acceptance Model” of Davis’86, this model was explained by:

a. Ease of use of the CTI tools (Davis, 1989): measured the degree of faith of a user in the effort to supply in order to use the system. To measure the ease of use, we referred to the measuring instrument of Davis (1989) which consists of six items, proven valid and reliable by Doll and Torkzadeh (1998).

b. Perceived Utility of the CTI tools: this element was not directly measurable. This notion came from microeconomic analysis: it was the measure of the use value of hardware or software for a user. It measured at the same time the impact of CTI tools on the productivity and quality. The perceived utility was defined by the degree of improvement of the performances expected from the use of the system (Davis, 1989).

c. Satisfaction of the CTI tools user: it was the degree of continuity of use by the individual. It was a positive faith of the individual perception which showed the value of CTI tools. This variable was considered as a dimension of success of CTI tools (Seddon, 1997). It could influence the intention, but it was also a consequence of the use (Delone and McLean, 2003) of the utility and the ease of use perceived.

d. Intention of CTI tools use: the manager can accept a system but decides when he uses it or plan to use it in the process of decision-making. The intention of a user to use a system adopted by the organization as well as its satisfaction by this use depended on the utility and on the ease of use perceived from the system.



Task-Technology Fit (TTF)

Legend:

Fonc: Fonctionnalités of monitoring tools

QD: Quality of Data

COMP: Compatibility of Sources

APP: Capacity of learning

PEOU: Percieved Ease of Use

PU: Percieved Utility

Sat: User satisfaction

Int: Intention of use

Figure 3. Research Model of CTI tools used

RESULTS ANALYSIS

Descriptive statistics have been used in order to show population characteristics. We have used statistical software SPAD v.8 to treat the data. 35.8% of respondents were male and 64.2% were female. 98.5% of respondents were between the ages 20-25 years, 1.5% were between the ages 26-30 years. Finally, our sample of users is composed for three fields of studies: 50.2% of Agriculture and 23% of Food and Health and 26.8% of Geology. (Table 1)

Table 1. Demographic profile of respondents (n = 265)

Characteristics	Descriptor	Distribution (%)
Gender	Male	35.8
	Female	64.2
Age	20-25 years	98.5
	26-30 years	1.5
Field of studies	Agriculture	50.2
	Food and Health	23.0
	Geology	26.8

According to Table 2, about 42.6% of respondents used general tools such as the search engines and other free tools (Google search, Google alert, Websites,...), while 35.8% used monitoring tools like databases of patents or sector studies (Search engines, Touchgaph, Xerfi, Espacenet, Patenscope,...), and finally 21.5% used platforms to monitor the competitive environment, the E-reputation brands and social networks (Geological Databases, Netvibes, Sindup, Alerti, Mention, Talkwalker...).

Around 50.5% of respondents didn't frequently use monitoring tools, 48.3% used them sometimes or often, and 1.1% always used them.

Table 2. Respondents' tools usage and characteristics

Characteristics	Descriptor	Distribution (%)
Tools	Search Engines and Websites	42.6
	Search Engines and Patent Databases	35.8
	Specialized monitoring tools	21.5
Usages' Frequencies	Never	6.0
	Rarely	44.5
	Sometimes	35.5
	Often	12.8
	Always	1.1

Results 1. Using the Task-Technology Fit (TTF) model leads to 14 variables with scale values. The Ward's hierarchical clustering technique shows that the sample of students could be split in two opposite groups before the research of the stable groupings (Figure 4): the first one with 67% of students and the second one with 33% of them.

The search for *stability* of groupings leads to two clusters whose frequencies are respectively 60% and 40%, instead of 67% and 33%. Each individual is represented in a scatter plot of principal component scores by a point which is the number of the cluster it belongs to (Figure 5). Each cluster mean (centroid) is also represented by a point whose size indicates the proportion of individuals in the cluster.

The categorical data (gender, field of studies, tools, usages' frequencies) used in the description of the groups show otherwise that the first group of 60% of respondents is mainly composed by students from the specialty "Geology" who often used CTI specialized tools. The characteristics of these students from group 1, according to CTI tools' perception, are shown below:

- The available data are either suitable for their needs or helpful for their tasks;
 - They stated to have greater capacities of learning by using CTI tools;
 - They mostly agree with the functionalities of monitoring tools;
- On the other hand, it is not easy for them to find useful tools for their daily works.

The characteristics of the students from group 2, according to CTI tools' perception are certainly antagonistic, but it can be noted that the individuals who belong this second group are students from the specialty "Agriculture" who never used search Engines and Websites.

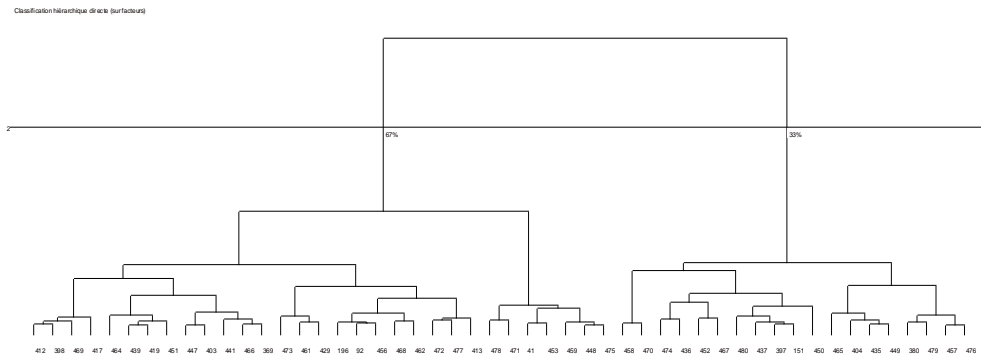


Figure 4. Dendrogram form similarities between 265 students according to the TTF model

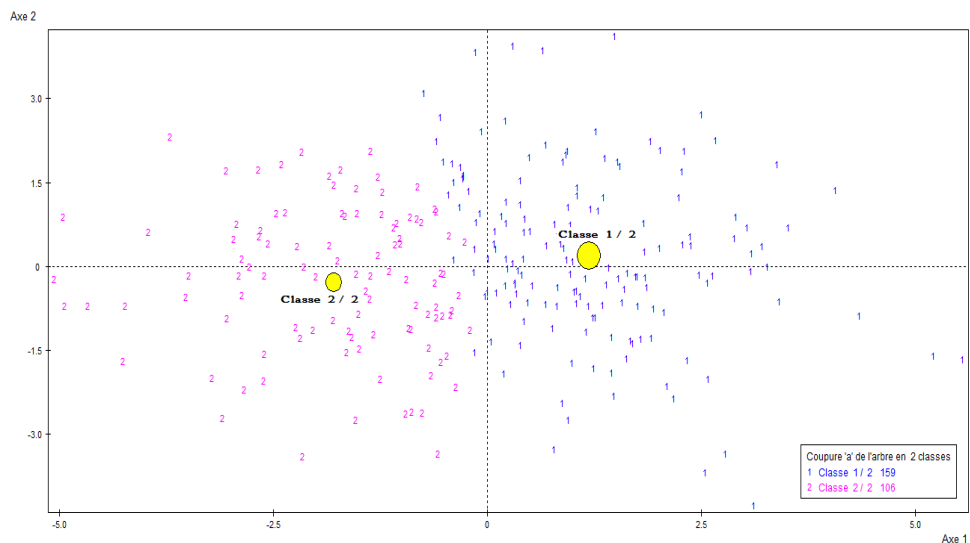


Figure 5. Positioning of the two clusters in a scatter plot of principal component scores

Results 2. Technology Adoption Model (TAM) leads to 25 variables with scale values. Two groups of students or three groups are highlight by the cuttings of the displayed dendrogram (Figure 6). In the following paragraph, the clusters description in three groups is made in order to take into account the presence of a small group of 33 students with particular characteristics. The reallocation step for the grouping stability search indicates three clusters whose observed frequencies are 126, 106 and 33. Categorical data are also used in that description of these clusters. General statements and characteristics of respondents in the each group are describe as following:

Group 1: often use of CTI specialized tools, interest shown for CTI tools (utility, ease of use, ease of learning, satisfaction and intention to use in the future).

Group 2: rarely use of general tools, little interest.

Group 3: Never use of general CTI tools, rare interest in monitoring tools.

The dispersion of classes described above can be visualized on the scatter plot of principal component scores (Figure 7). It shows how differentiated the clusters are. The individuals are represented on the plane by identifying them by their group number. The centroids are also represented by points whose size is proportional to the size of the clusters.

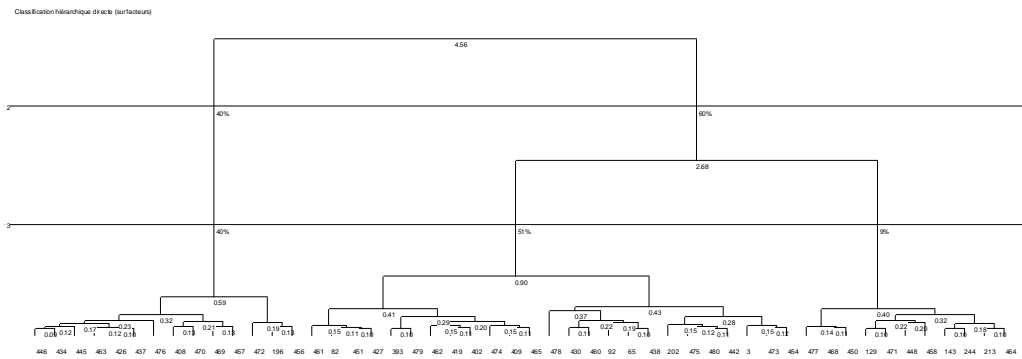


Figure 6. Dendrogram form similarities between 265 students according to the TAM model

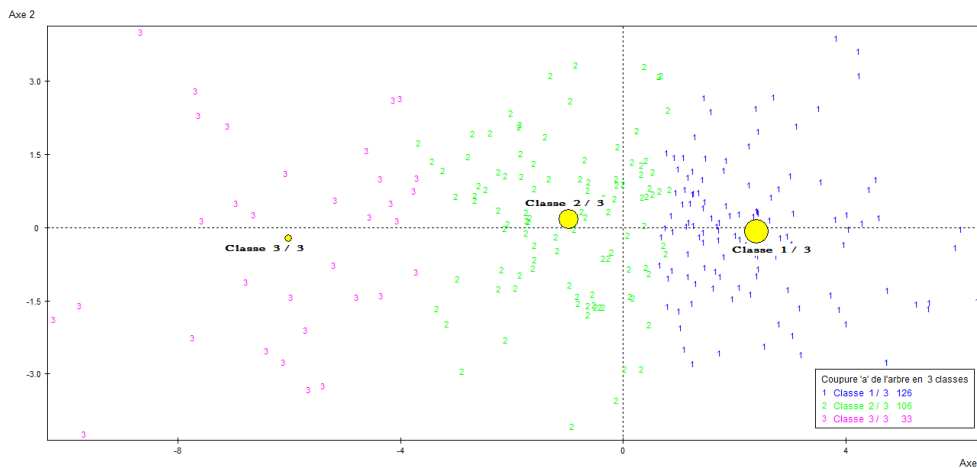


Figure 7. Positioning of the three clusters in a scatter plot of principal component scores

CONCLUSION

Regarding the managerial implication, the first Technology-Task Fit model showed two groups from those who used CTI tools, ranging from source identification to the dissemination of information. We can see that the profile of the first group of users can be part of an advance monitoring unit. The second group of users were latecomers in adopting this technology. Finding the monitoring tools not flexible, this implies the un-satisfaction with the quality of service offered by this technology may be due to limited use.

Three groups were identified in the second Technology Adoption Model, the first group is aware of the perceived usefulness of these monitoring tools and the second is considered as intermediate because they used general tools that showed their limits to achieve a watch type. The third is not satisfied completely as first users of a watch platform as part of a monitoring project. The difficulty lies in the appropriation of these tools by students and their adaptation to the selected CTI projects.

We deduced that a CTI tool implementation in a company is accompanied by organizational change, sometimes cultural, which task-technology fit and tools adoption impact were not negligible. This would explain, in part, why these tools can have both success and failure in the watch projects.

The implementation of this monitoring system has shown the pervasive role of students/watchers in the organization and coordination of steps in this process, from receipt of the request to the dissemination of results using different monitoring tools according to their needs of information and watch types (competitive, technological, marketing,...).

Our chapter provides evidence that the Competitive and Technological Intelligence (e-veille²) was most taught to be applied to business cases for purely pedagogic education using the free and commercial watch tools (Netvibes, Touchgraph, Google, Xerfi, Espacenet, Patentscope, Sindup,...) to achieve these methodologies. Finally the monitoring of open and closed data can be a full search. This study showed us how to use a cluster analysis method to identify the groups of students who differ in attitude, perception and utility of the monitoring tools by putting them in situations of watching problematic. All these indicators are important to measure in subsequent works the adequacy between the functionalities of these tools and the quality of the data and the compatibility of the sources, as well as the acceptance of the monitoring tools by engineering students.

² See the definition of "e-veille" in Lexique de Gestion et de Management sous la direction de J.P. Denis, A.C. Martinet et A. Silem, 9^{ème} édition, Dunod, 2016.

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