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### An evaluation of competitive and technological intelligence tools: A cluster analysis of users' perceptions

Fatma Fourati-Jamoussi<sup>a\*</sup>, Claude-Narcisse Niamba<sup>a</sup> and Julien Duquennoy<sup>a</sup>

<sup>a</sup>INTERACT Research Unit UP 2018.C102, UniLaSalle, Beauvais Mont-Saint-Aignan, France; \*fatma.fourati@unilasalle.fr

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## An evaluation of competitive and technological intelligence tools: A cluster analysis of users' perceptions

Fatma Fourati-Jamoussi<sup>a\*</sup>, Claude-Narcisse Niamba<sup>a</sup> and Julien Duquennoy<sup>a</sup>

<sup>a</sup> *INTERACT Research Unit UP 2018.C102, UniLaSalle, Beauvais Mont-Saint-Aignan, France*

Corresponding author (\*): [fatma.fourati@unilasalle.fr](mailto:fatma.fourati@unilasalle.fr)

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**ABSTRACT** The purpose of this article 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 article introduces an application of the cluster analysis method and 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 the Technology Acceptance Model (TAM). A survey was 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 the 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 of future engineers for monitoring and management of strategic information. That's why practical courses in CTI are taught to the students in order to take into account the companies' needs.

**KEYWORDS** Competitive and technological intelligence, cluster analysis, TTF model, TAM model, user perception

### 1. INTRODUCTION

Generation Y students need to understand why we use information gathering tools and how these tools have evolved since their emergence. 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 do they need today in an engineering school?

These questions prompted us to think about 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 (Fourati-Jamoussi, 2015). We have applied these types of surveillance (French *veille*) to a problem related to the fields of study 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 a choice between different monitoring tools to collect, process and disseminate information?

## 2. What are the different perceptions between students 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 processes of “competitive intelligence” and “technological intelligence”. In a third section, we propose the approach of our study and the research method. In the fourth section, we present our results on the monitoring tools developed within UniLaSalle and cluster users’ perceptions of these tools. Conclusions are drawn in the fifth section.

## 2. CONCEPTUAL BACKGROUND

### 2.1 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. He discussed the conceptual problems in cluster analysis and presented many major areas of application. These are:

- The life sciences: the object of the analysis method is to develop complete taxonomies to delimit the subspecies of a distinct but varied species (for example, plants or 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 soils, countries, or regions of the world;
- The engineering sciences: the application has been relatively unused in this field.
- The information, policy and decision sciences: the applications to documents,

the political units, products, markets, sales, programs, research and development projects.” (p. 5-6)

A cluster analysis is considered to be a tool of classification, most frequently used in marketing research (Punj and Stewart, 1983).

### 2.2 Cluster analysis methodology

“Cluster analysis is the art of findings groups in data” (p. 1), the classification of similar objects or perceptions into groups is an important human activity (Kaufman and Rousseeuw, 2009). Berkhin (2006) defined clustering as 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 deal 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 individual 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.

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 as a dendrogram. The dendrogram illustrates the mergers or divisions that have been made at successive level and looks like a tree” (Johnson and Wichern, 1998). 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, it’s necessary to find, at each step, the pair of individuals or clusters that leads to a 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” (Johnson and Wichern, 1998).

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 (Johnson and Wichern, 1998).

### 2.3 Cluster analysis with SPAD v.8

SPAD is a useful statistical software used to deal with multivariate data analysis techniques such as hierarchical clustering. 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 that will be classified into groups by using the 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. 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 the 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 good to have an idea of the best groupings even if those groupings are not necessarily stable. In practice, there are two or three possible cuttings. It is up to the user to choose one of 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 (Johnson and Wichern, 1998).

SPAD also offers the opportunity to work with 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 the “ $K$ -means” technique (Everitt, 1998), is applied to the dataset prior to the hierarchical clustering technique.

### 2.4 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

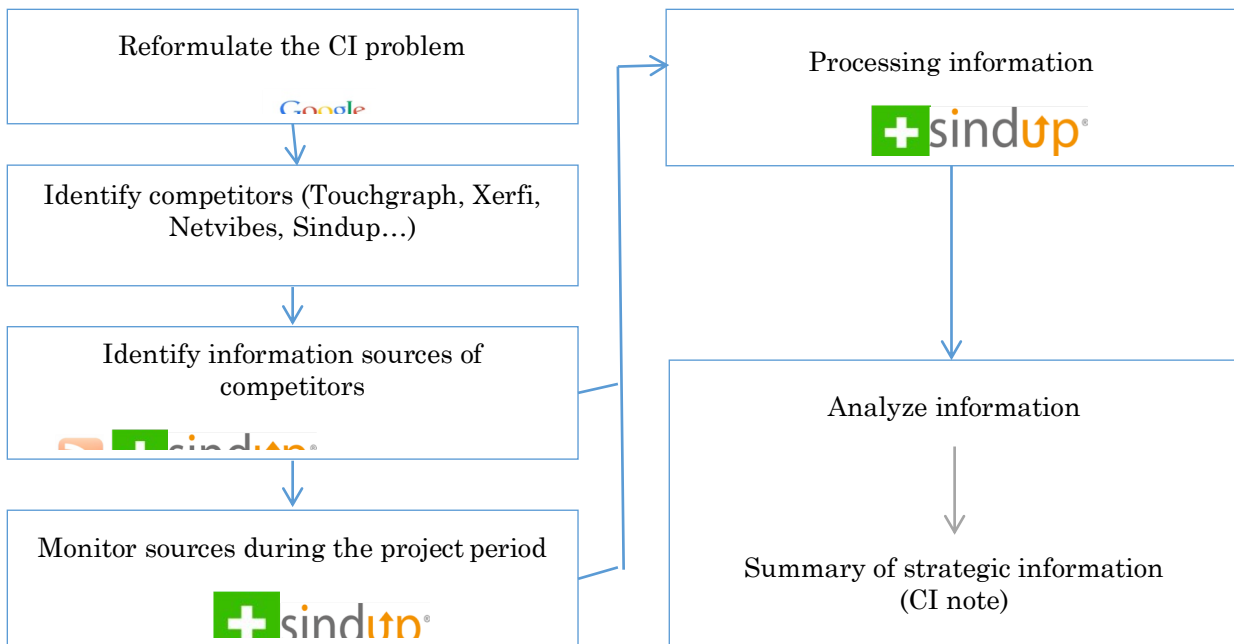


Figure 1 Teaching the Competitive Intelligence (CI) Methodology

of “business intelligence” (Giald and Giald, 1988; Sakys and Butleris, 2011). Solberg Soilen (2015) proposed the classification of intelligence studies to help place different forms of intelligence and 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 between 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 serves to identify, monitor competitors and decrypt their strategy. Technological intelligence is to follow a technical and scientific domain in time and to monitor developments ([www.ie.bercy.gouv.fr](http://www.ie.bercy.gouv.fr)). 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 traits, 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 problems have emerged: to study the differentiation of business intelligence vendors (Solberg Soilen and Hasslinger, 2012), to

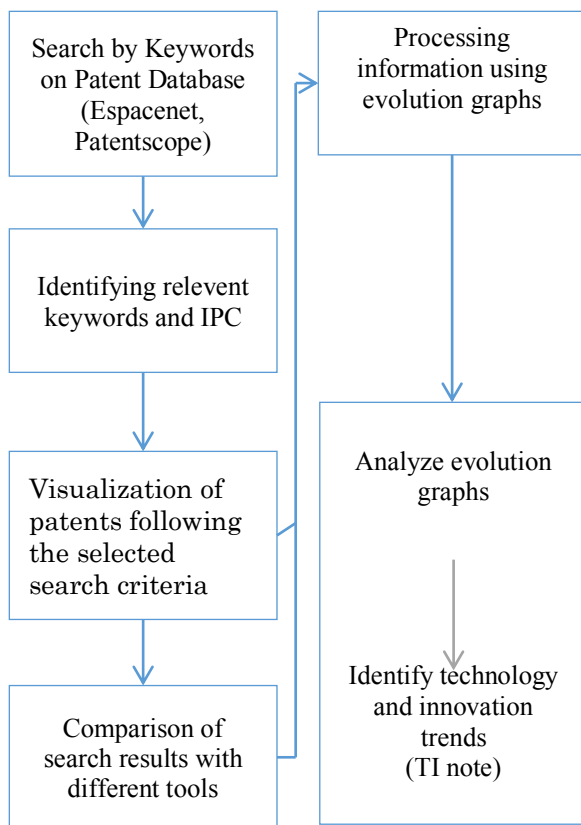


Figure 2 Teaching the technology intelligence (TI) methodology

classify business intelligence software based on their functionalities and performance (Amara et al. 2012; Nyblom et al. 2012; Abzaltynova and Williams, 2013), and 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 definition 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 problems (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 collected 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 organized and analyzed all information treated to understand the strategic development of all competitors.

The TI methodology consists of establishing the goal of the project, then organizing 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, and inventors. To exploit and analyze all pertinent patents, 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).

### 3. THE METHODOLOGY AND THE RESEARCH MODEL

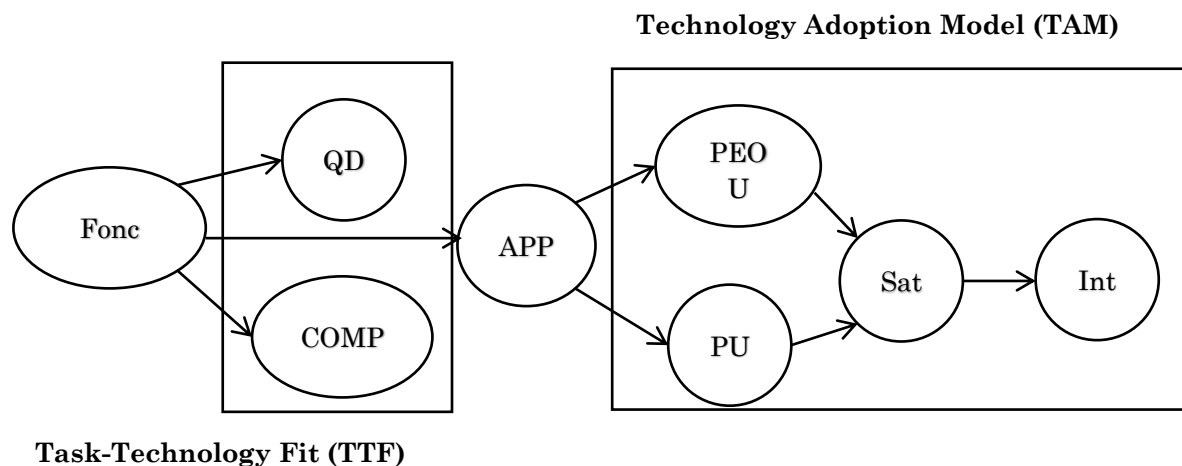
#### 3.1 Data collection

The study concentrated on a 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 strategic intelligence. A survey 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 answered this survey. It was designed and diffused to UniLaSalle students after applying CTI methodologies presented above. Our database is composed of 265 responses for clustering the users' monitoring tools. These respondents were from three specialties: i) agriculture; ii) food and health; iii) geology.

#### 3.2 Logic of the study

To evaluate and compare the user profiles, the selected criteria were taken from the theoretical fusion of these two models: technology / task fit (Goodhue and Thompson, 1995) and 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):



Legend:

Fonc: Functionalities of monitoring tools

QD: Quality of Data

COMP: Compatibility of Sources

APP: Capacity of learning

PEOU: Perceived Ease of Use

PU: Perceived Utility

Sat: User satisfaction

Int: Intention of use

Figure 3 Research Model of CTI tools used

a. CTI tools used: is not shown 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 a 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 in the degree of use. The intensity depended on the integration of the business intelligence system (Grublješić 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 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 plans 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.

**4. RESULTS ANALYSIS**

Descriptive statistics have been used in order to show population characteristics. We have used the 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 of 20-25 years, 1.5% were between the ages 26-30 years. Finally, our sample of users comes from three fields of studies: 50.2% from agriculture and 23% from food and health and 26.8% from geology (Table 1).

Table 1 Demographic profile of respondents (n=265)

Characteristic	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 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, Touchgraph, Xerfi, Espacenet, Patentscope), 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.

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.

Table 2 Respondents' tools usage and characteristics

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

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

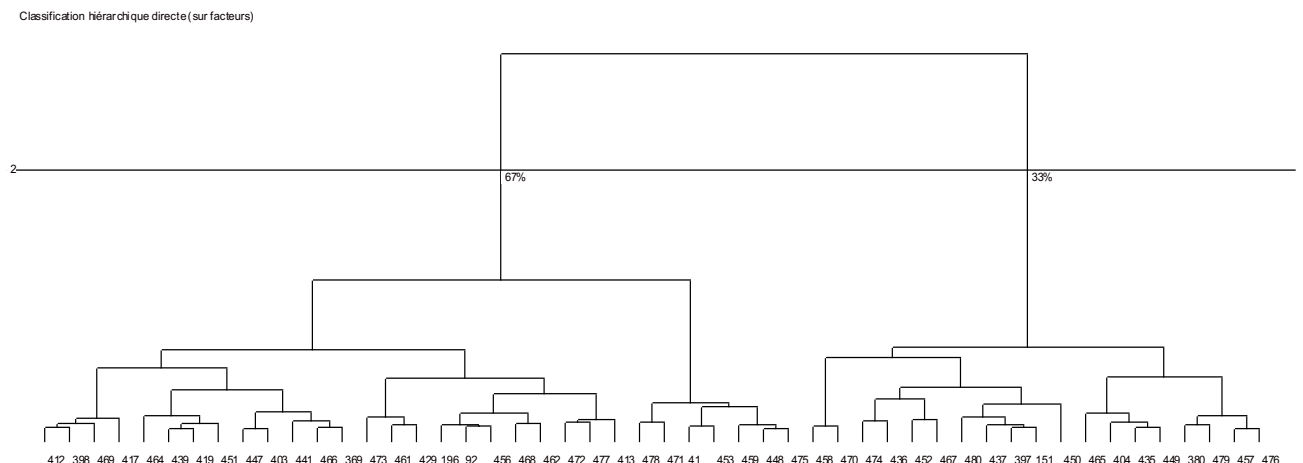


Figure 4 Dendrogram of similarities between 265 students according to the TTF model



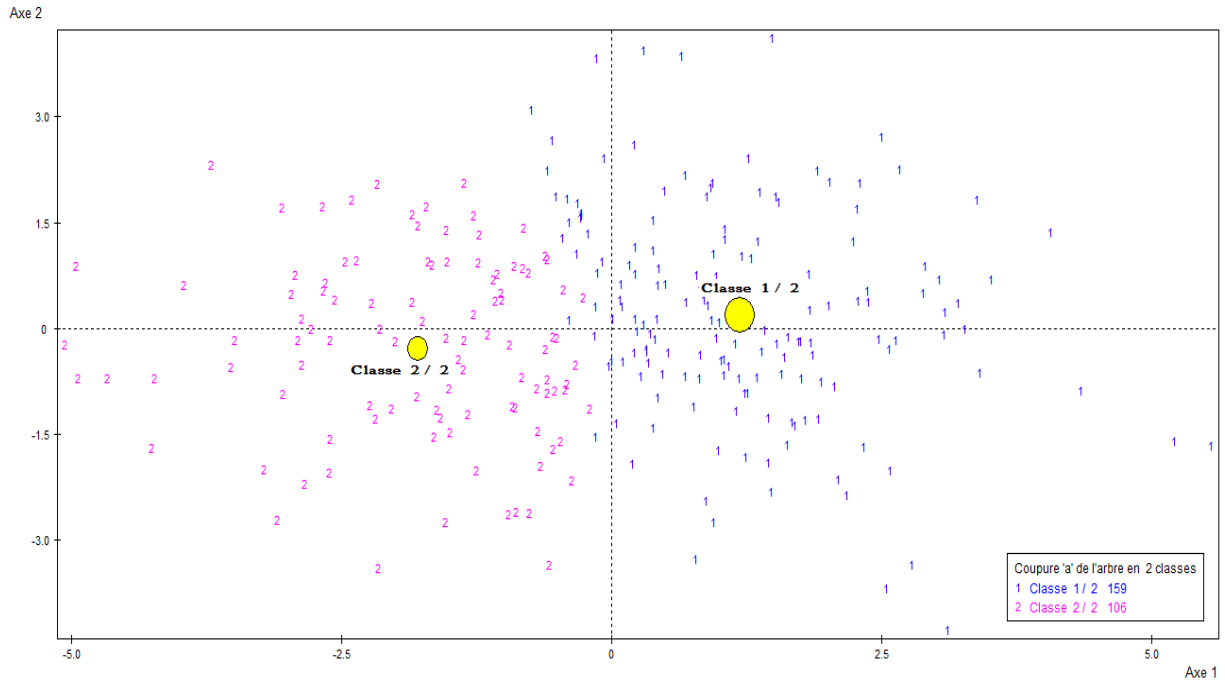


Figure 5 Positioning of the two clusters in a scatter plot of principal component scores.

represented by a point whose size indicates the proportion of individuals in the cluster.

The categorical data (gender, field of studies, tools, usage frequency) used in the description of the groups show otherwise that the first group of 60% of respondents is mainly composed of 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 claim to have greater capacities of learning by using CTI tools;
- They mostly agree with the functionalities of monitoring tools;

Classification hiérarchique directe (sur facteurs)

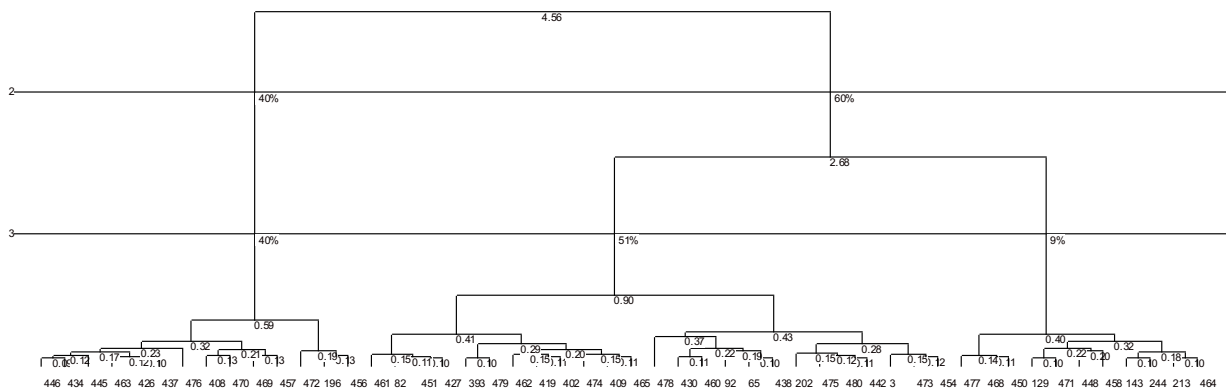


Figure 6 Dendrogram of similarities between 265 students according to the TAM model.

On the other hand, it is not easy for them to find useful tools for their daily work.

The characteristics of the students from group 2, according to the 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.

The 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 cluster 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

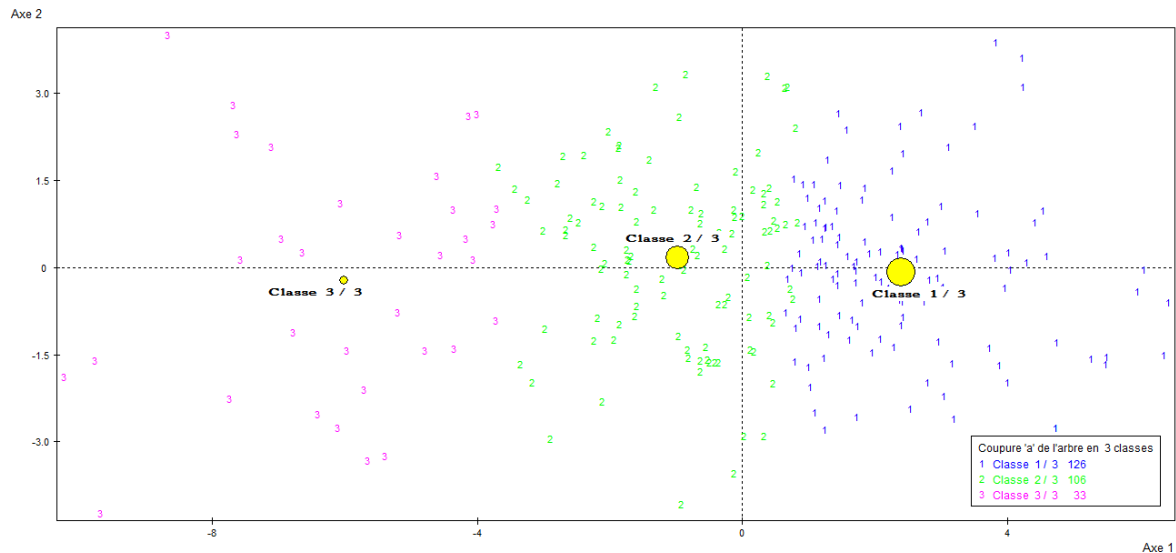


Figure 7 Positioning of the three clusters in a scatter plot of principal component scores.

step for the grouping stability search indicates three clusters whose observed frequencies are 126, 106 and 33. Categorical data are also used in the description of these clusters. General statements and characteristics of respondents in each group are:

Group 1: often use 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 general tools, little interest.

Group 3: Never use 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.

## 5. CONCLUSIONS

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 dissatisfaction 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/agents/analysts 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 article provides evidence that competitive and technological intelligence (*e-veille*: 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<sup>ème</sup> édition, Dunod, 2016.) 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.

This study ensures the furthering of existing models to classify business intelligence software based on their functionalities and performance (Amara et al. 2012; Nyblom et al. 2012; Abzaltynova and Williams, 2013) and to show the perception of business intelligence tools by professionals and students using two models of information systems literature (Fourati-Jamoussi and Niamba, 2016). We have focused our attention on the perception of future engineering students coming from different specialties to meet several objectives: i) observe the learning and discovery process of CTI tools by students; ii) adapt our teaching to the needs of student profiles, and iii) help these students to understand and develop individual and collective skills (able to implement a competitive and technological intelligence system).

We will increase the number of respondents for future studies to prove the significance of all variables.

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