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**QUESTIONNAIRES ADAPTATIFS POUR IDENTIFICATION AUTOMATIQUE  
DES STYLES D'APPRENTISSAGE**

PAR  
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THÈSE PRÉSENTÉE À LA FACULTÉ DES ÉTUDES SUPÉRIEURES ET  
DE LA RECHERCHE EN VUE DE L'OBTENTION DE LA MAITRISE  
ÈS SCIENCES EN INFORMATIQUE

JANVIER 2015

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## **REMERCIEMENTS**

Mes premiers remerciements s'adressent aux professeurs Chadia Moghrabi et Philippe Fournier-Viger pour leur soutien, conseils et encadrement tout au long de ce travail.

Je remercie également les membres du jury d'avoir accepté d'évaluer mon travail, l'Agence Canadienne de Développement International (ACDI) d'avoir financé mes études ainsi que tous les agents de l'Université de Moncton pour l'accueil et la gentillesse qu'ils n'ont cessé de me témoigner.

Un grand merci aussi à Emmanuel, mon fiancé, pour ses encouragements et son Amour constants,

Merci à toute personne qui, de près ou de loin, a participé à la réalisation du présent travail.

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**N.B.** : Les titres des figures apparaissent en anglais, car ils ont été publiés dans des articles en anglais.

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## **LISTE DES ACRONYMES**

**DT:** Decision Tree

**EI:** Extraverted-Introverted dimension

**IRT:** Item Response Theory

**JP:** Judging-Perceiving dimension

**MBTI:** Myers-Briggs Types Indicator

**NN:** Neural Network

**SN:** Sensing-iNtuitive dimension

**TF:** Thinking-Feeling dimension



## RÉSUMÉ

Connaître le style d'apprentissage d'un apprenant permet d'une part de lui prodiguer une assistance adaptée à ses besoins et à ses préférences et d'autre part de rendre son apprentissage plus facile et captivant. Une des principales approches pour identifier le style d'apprentissage d'un apprenant est de lui demander de répondre à un questionnaire spécialement conçu à cette fin, puis de faire appel à un spécialiste pour analyser les réponses et déterminer son style d'apprentissage. Cette approche présente cependant plusieurs problèmes. Tout d'abord, les questionnaires d'évaluation comportent généralement un très grand nombre de questions, ce qui peut démotiver l'apprenant, le menant à l'abandon ou bien à répondre insouciamment. Par ailleurs, il peut être difficile d'accéder à un spécialiste pour l'analyse des réponses. Finalement, l'analyse par un spécialiste requiert un certain temps avant d'obtenir les résultats. Pour répondre à ces problèmes, une solution prometteuse est de concevoir des questionnaires électroniques adaptatifs, capables de (1) réduire le nombre de questions de façon dynamique en fonction des réponses de l'apprenant, (2) de prédire le type psychologique instantanément, sans avoir recours à un spécialiste humain, et (3) tout en minimisant le taux d'erreur qui en découlerait.

Dans cette thèse, nous proposons deux questionnaires adaptatifs répondant à ces objectifs pour le questionnaire de Myers-Briggs (MBTI). Le premier, Q-SELECT, emploie les règles d'association et les réseaux de neurones pour prédire les réponses aux questions et pour détecter de manière automatique les types psychologiques des apprenants. Les résultats expérimentaux obtenus avec un jeu de données de 1,931 questionnaires remplis majoritairement par des étudiants montrent que Q-SELECT permet d'éliminer 30% des questions tout en prédisant les types psychologiques avec un taux d'erreur inférieur ou égal à 12%. Le second, nommé T-PREDICT analyse la capacité de chaque question à différencier les types psychologiques pour ainsi réordonner les questions et ensuite tenter de prédire le type de chaque apprenant en utilisant le moins de questions possible. L'expérimentation montre que T-PREDICT pose en moyenne 81% moins de questions que Q-SELECT tout en offrant un taux d'erreur similaire.

**Mot clés :** MBTI, questionnaires adaptatifs, classification, types psychologiques, réseaux de neurones, règles d'association, arbres de décisions.

## ABSTRACT

Knowing the learning style of a student allows providing assistance tailored to his needs and preferences. This can make the learning activities easier and more exciting. A popular approach to identify the learning style of a learner is to fill out a questionnaire that has been specifically designed for this purpose, and then to ask a specialist to analyze the provided answers and determine the corresponding learning style. However, this approach suffers from several limitations. First, assessment questionnaires are generally very long, which can demotivate the learner leading him to quit or to respond carelessly. Furthermore, it can be difficult to find a specialist to analyse the answers. Finally, asking a specialist to analyze answers can take some time before getting the results. To address these problems, a promising solution is to design adaptive electronic questionnaires, capable of (1) reducing the number of questions dynamically based on answers provided by the learner, and (2) predicting automatically the psychological type, without relying on a human expert, while maintaining a minimal error rate.

In this thesis, we propose two adaptive questionnaires that meet these objectives for the Myers-Briggs Type Indicator questionnaire (MBTI). The first one, Q-SELECT uses Association Rules and Neural Networks to predict answers to questions and automatically recognize psychological types of learners. Experimental results obtained with a dataset of 1,931 filled questionnaires show that Q-SELECT can eliminate 30% of the questions while predicting psychological types with an error rate less than or equal to 12%. The second one, named T-PREDICT analyzes the capacity of each question to discriminate among psychological types with the intention to reorder questions and therefore predict the type of each student using as few questions as possible. The experimentation shows that T-PREDICT asks, on average, 81% less questions than Q-SELECT while providing a similar error rate.

**Keywords:** MBTI, adaptive questionnaires, classification, psychological types, neural networks, association rules, decision trees.

## INTRODUCTION GÉNÉRALE

La *formation en ligne* désigne l'ensemble des procédés d'enseignement utilisant les technologies informatiques et permettant à des apprenants d'effectuer des activités d'apprentissage sans avoir à se rendre en un lieu physique [1]. La formation en ligne peut prendre plusieurs formes. Par exemple, une classe traditionnelle peut être donnée en ligne par un système de vidéoconférence. Il existe également des activités d'apprentissage offertes sur le Web et des logiciels d'autoformation ou associés aux cours formels, que nous appellerons par la suite, *systèmes d'apprentissage en ligne*.

La formation en ligne peut offrir plusieurs avantages par rapport à une formation traditionnelle telle que permettre l'apprentissage en temps et lieu différé, favoriser la réutilisation du matériel pédagogique, des facteurs qui tendent à augmenter l'accessibilité à l'éducation. De surcroît, l'apprenant a généralement plus de liberté et d'autonomie, ce qui lui permet de bien gérer son temps [2].

Bien que ce genre de formations soit pratique et avantageux, il soulève aussi certains défis [1, 3, 4]. Le principal obstacle pour l'apprenant est de préserver sa motivation. En effet, il est très facile de se décourager et de procrastiner lorsqu'on est davantage maître de son temps. En cas de difficultés, il peut n'y avoir personne pour éclaircir nos idées et il peut être difficile d'échanger des idées. Ainsi, une forte motivation, une bonne gestion du temps et une grande implication sont nécessaires, pour bien réussir une formation en ligne.

Il existe diverses solutions pour engager davantage l'apprenant et favoriser l'apprentissage. Une solution proéminente est d'offrir un apprentissage personnalisé [5, 6]. La personnalisation peut être plus ou moins complexe et faite à différents niveaux [7, 8, 9, 10]. Par exemple, certains systèmes tentent d'évaluer les connaissances de l'apprenant pour proposer des problèmes, conseils, indices et instructions personnalisés [6, 11]. D'autres sont conçus pour détecter et réagir aux émotions des apprenants [12], leurs habiletés spatiales [13], leur motivation et leurs traits culturels [14]. Dans cette thèse, nous sommes intéressés par l'adaptation aux styles d'apprentissage, aussi appelés préférences ou types psychologiques.

Pour déterminer le style d'apprentissage d'un apprenant, deux approches sont principalement utilisées. La première approche consiste à intégrer au système d'apprentissage en ligne un module d'*apprentissage machine* pour examiner l'interaction de l'apprenant et inférer son type [7, 15]. Toutefois, cette approche pose problème, car un style initial aléatoire doit être assigné à l'utilisateur. Si cette attribution est incorrecte, le système offrira une interaction inappropriée, ce qui pourra avoir un impact négatif sur l'apprentissage. Ce problème perdurera tant que le système n'aura pas recueilli suffisamment de données pour identifier correctement le style d'apprentissage [15].

La seconde approche consiste à soumettre l'apprenant à un questionnaire standardisé pour l'évaluation des styles d'apprentissage, puis à recourir à un spécialiste pour examiner les réponses et attribuer le style correspondant. Bien que cette approche procure de meilleurs résultats que la première, elle présente cependant plusieurs problèmes. Tout d'abord, les questionnaires d'évaluation comportent généralement un très grand nombre de questions, ce qui peut démotiver l'apprenant, le mener à l'abandon ou bien à répondre insouciamment. Par exemple, le questionnaire de Myers-Briggs qui est l'objet de notre travail contient plus de 90 questions. Par ailleurs, il peut être difficile d'accéder à un spécialiste pour l'analyse des réponses. Finalement, cette analyse requiert un temps qui peut être considérable avant l'obtention des résultats.

Comme suite aux constats des problèmes de la seconde approche, une question de recherche importante émerge : peut-on développer un logiciel pour (1) réduire automatiquement le nombre de questions d'un questionnaire d'évaluation des styles psychologiques et (2) prédire automatiquement le type psychologique d'un apprenant tout en gardant une haute exactitude, sans faire appel à un spécialiste?

Un certain nombre de recherches ont été effectuées pour tenter de répondre à cette question. Par exemple, les arbres de décision ont été utilisés [15] pour réduire dynamiquement le nombre de questions d'un questionnaire et prédire le type d'un apprenant pour le modèle de Felder-Silverman. Pour le questionnaire de Myers-Briggs, les réseaux de neurones et les arbres de décision ont été appliqués pour déterminer un ensemble de questions à éliminer et prédire le type d'une personne [17].

Dans cette thèse, nous sommes intéressés par le développement d'une nouvelle approche visant à mieux répondre à la question de recherche citée plus haut, spécifiquement pour le questionnaire de Myers-Briggs.

## **1 Hypothèses**

Les hypothèses de cette recherche sont au nombre de quatre :

- Un questionnaire adaptatif, c.-à-d. posant des questions différentes à chaque répondant et pouvant changer l'ordre des questions dynamiquement, permettrait-il de réduire davantage le nombre de questions posées par le questionnaire de Myers-Briggs qu'une méthode éliminant le même nombre et un ordre fixe de questions pour tous les répondants?
- Une approche basée sur l'analyse des associations entre les réponses d'un ensemble de répondants pourrait-elle permettre d'inférer les réponses probables futures d'un répondant, ce qui serait une information utile pour réduire le nombre de questions et prédire le type du répondant.
- Poser en premier les questions plus pertinentes dont les réponses départagent mieux l'appartenance aux différents types psychologiques permettrait de réduire le nombre de questions posées,
- Recalculer l'appartenance probable d'un répondant à chaque type selon ses réponses après chaque question posée et cesser de poser des questions lorsqu'une certitude suffisante est atteinte, permettrait de réduire le nombre de questions posées tout en permettant de prédire son type avec une exactitude élevée.

## **2 Objectifs du travail**

Le but principal de cette recherche est de proposer un questionnaire électronique capable de réduire davantage le nombre de questions du questionnaire de Myers-Briggs (MBTI), tout en proposant un taux d'exactitude élevé quant à la prédiction automatique du type du répondant.

### 3 Organisation de la thèse

Cette thèse suit le format d'une thèse par articles. Les chapitres 2 et 3 comportent des articles arbitrés publiés dans des conférences internationales. Chacun présente une solution alternative au développement d'un questionnaire électronique adaptatif pour le questionnaire de Myers-Briggs:

- a. Mwamikazi, E., Fournier-Viger, P., Moghrabi, C., Barhoumi, A. & Baudouin, B., 2014. An Adaptive Questionnaire for Automatic Identification of Learning Styles. In: *Proceedings of the 27th International Conference on Industrial, Engineering and Other Applications of Applied Intelligent Systems*. Springer, Heidelberg, pp. 399-409.
- b. Mwamikazi, E., Fournier-Viger, P., Moghrabi, C. & Baudouin, B., 2014. A Dynamic Questionnaire to Further Reduce Questions in Learning Style Assessment. In: *Proceedings of the 10th International Conference on Artificial Intelligence Applications and Innovations*. Springer, Heidelberg, pp. 224-235.

Il est à noter que ces chapitres ajoutent certains détails qui avaient été omis dans les versions publiées par manque d'espace.

Finalement, la section 4 présente la conclusion de la thèse, incluant une discussion des limites du travail et des travaux futurs envisagés.

# CHAPITRE I. AN ADAPTIVE SIMPLIFIED QUESTIONNAIRE FOR AUTOMATIC IDENTIFICATION OF LEARNING STYLES

**Abstract.** Learning styles refer to how a person acquires and processes information. Identifying the learning styles of students is important because it allows more personalized teaching. The most popular method for learning style recognition is through the use of a questionnaire. Although such an approach can correctly identify the learning style of a student, it suffers from three important limitations: (1) filling a questionnaire is time-consuming since questionnaires usually contain numerous questions, (2) learners may lack time and motivation to fill long questionnaires and (3) a specialist needs to analyze the answers. In this paper, we address these limitations by presenting an adaptive electronic questionnaire that dynamically selects subsequent questions based on previous answers, thus reducing the number of questions, while predicting learning styles with a minimum error rate. Experimental results with 1,931 questionnaires for the Myers Briggs Type Indicators show that our approach (*Q-SELECT*) considerably reduces the number of questions asked (by a median of 30%) and predicts learning styles with a low error rate.

**Keywords:** adaptive questionnaire, association rules, neural networks, learning styles, Myers Briggs Type Indicator.

## I.1 Introduction

Learning styles refer to how people acquire and process information [7, 18]. In education, knowing the learning styles of students is important because it allows to further personalize interaction between teachers and students. It was shown in several studies that presenting information in a way that is adapted to the learning style of a learner facilitates learning [9].

Although several studies have been presented on how to perform learning style assessment, there are still several important limitations to current approaches. The first approach is used by e-learning systems that can provide adaptation according to the learning style of a learner. The approach consists of designing a software module that analyzes the learner's interactions with the system to detect the learning style [7, 15].

This approach has the benefit of being seamless for the learner. However, it suffers from a major drawback, namely that a random learning type is assigned initially to the learner and thus the system will initially guide and assist the learner according to that type. If the initial guess is incorrect, the system will thus interact with the learner according to the wrong learning style, which may have negative effect on learning. Furthermore, this interaction will continue until enough data is recorded to find the correct learning style [7].

The other main method for learning style assessment is to use a standardized questionnaire that a person has to fill out. A specialist then analyzes the answers to determine the correct learning style. The advantage of this approach is that the learning style of a person can be identified immediately. However, this approach suffers also from important limitations. First, questionnaires are usually very long. For example, the Myers-Briggs Type Indicator questionnaire discussed in this paper consists of more than 90 questions. This means that it is very time-consuming for a person to fill out the questionnaire. Second, long questionnaires have a negative effect on a person's motivation [15], which may lead to abandoning the test, skipping questions or answering falsely. This can furthermore provoke an incorrect learning style assessment, which may have undesirable consequences in future interactions [19]. For example, in the case of an e-learning system, if a learner does not answer the questionnaire correctly, the ensuing interactions with the system may be done according to a wrong learning style, which may have detrimental effect on learning. Third, using a questionnaire usually requires a specialist to analyze the learner answers and to determine the learning style.

In this paper, we address all the above limitations by presenting a novel learning style identification approach, which takes the form of an adaptive electronic questionnaire. Our contributions are fourfold. First, the electronic questionnaire relies on an efficient algorithm PREDICT for predicting answers to questions based on associations between questions already answered and answers from previous users<sup>1</sup>. Predicting answers allows skipping questions from the standardized questionnaire, thus reducing the number of questions to be answered by the learner. Second, the electronic

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<sup>1</sup> We assume that the learner population and their learning styles are homogeneous in order to generate association rules and predict possible answers.



questionnaire incorporates an efficient question selection algorithm *Q-SELECT* that analyzes associations between question answers to determine which questions should be asked first to minimize the number of questions asked when the aforementioned prediction algorithm is used. Third, once all questions have been answered or predicted, the electronic questionnaire uses a novel prediction algorithm to accurately predict a person learning style based on the answers and predicted answers. Fourth, we performed an extensive experimental study with 1,931 questionnaires for the assessment of the Myers-Briggs Type Indicator (MBTI). Results show that our approach reduces the number of questions presented to the user by a median of 30% while maintaining a low error rate in identifying the learning styles. In other words, the adaptive electronic questionnaire allows the identification of learning styles with the maximum possible reduction of the number of questions asked.

The rest of the paper is organized as follows. The Myers-Briggs Type Indicator model is presented in section 2. Section 3 discusses related work on adaptive questionnaires. In section 4 and 5, we respectively present the proposed electronic questionnaire and the experimental results. Finally, section 6 draws the final conclusions.

## **I.2 Myers-Briggs Type Indicator (MBTI)**

A popular personality inventory that has been used for more than 30 years is the Myers-Briggs Type Indicator (MBTI). This is a self-report questionnaire that identifies personality types using Carl Jung's personality type theory. A four-letter code is used to describe each individual's personality. It uses choice items to classify individuals into dichotomous preferences. One can either be extraverted (E) or introverted (I); sensing (S) or intuitive (N); thinking (T) or feeling (F) and finally be either judging (J) or perceiving (P). Personality types are thus determined by the combination of these four dimensions. There are 16 four-letter codes that are possible (cf. Table 1.1). Descriptive outcomes of these codes or personality types help in one's classification [18 - 20].

Table 1.1: The sixteen Myers-Briggs Indicators

ISTJ	ISFJ	INFJ	INTJ
ISTP	ISFP	INFP	INTP
ESTP	ESFP	ENFP	ENTP
ESTJ	ESFJ	ENFJ	ENTJ

Each type describes tendencies and reflects variations in individual attitudes and styles of decision-making. The E-I dimension (extraverted-introverted) focuses on whether an individual's world attitude is outwardly-oriented to other objects and individuals, or it is internally-oriented. The S-N dimension (sensing-intuitive), on the other hand, describes the perceptual style of an individual. Sensing refers to attendance to sensory stimuli while intuition entails analyzing stimuli and events. Based on the T-F dimension, thinking encompasses logical reasoning together with decision processes. This dimension further shows that feeling has to do with a personal, subjective, and value oriented approach [20- 22]. The J-P dimension involves either a judging attitude and quick decision-making or perception that demonstrates more patience and information gathering prior to decision-making.

Some of the preferences are dominant and others are auxiliary and can be influenced by other dimensions. For example, the J-P dimension influences the two function preferences: S or N versus T or F [20].

The MBTI has its limitations. Its theoretical and statistical imports are limited by the application of dichotomous choice items [22]. The large number of questions to be answered can discourage users and cause them to fill out the questionnaire without much attention. Reducing the number of questions in a questionnaire has been a way to increase its efficiency [15, 22].

### **I.3 Related Work**

One major challenge in building a system that can adapt itself to a learner is giving it the capability to reduce the number of questions presented to the student [15, 19, 24]. For instance, McSherry [23] reports that reducing the number of questions asked by

an informal case-based reasoning system minimized frustration, made learning easier and increased efficiency.

Numerous researches on adaptive educational hypermedia systems have been conducted to minimize the number of questions asked to learners based on their capabilities and knowledge level [25 - 28] by using methods such as Item Response Theory [8, 25, 26]. Questions are initially categorized by their difficulty. The score that a learner obtains for each completed section determines the difficulty level of the next questions that would be asked and whether some questions should be skipped. Nevertheless, few researches have attempted to measure the impact of reducing the number of questions on the correct identification of the learner profile. The AH questionnaire in [15] relies on decision trees to reduce the number of questions and to classify students according to the Felder-Silverman model of learning styles. Its experimental results with 330 students show that it effectively predicts the learning styles with high accuracy and limited number of questions.

Petri et al. [29] proposed EDUFORM, a software module for the adaptation and dynamic optimization of questionnaire propositions for profiling learners online. This tool, based on probabilistic Bayesian modeling and on Abductive reasoning, reduced the number of questionnaire propositions (items) by 30 to 50 percent, while maintaining an error rate between 10 to 15 percent. Experimental results have shown that a significant reduction in the numbers of proposition in the questionnaires was often accompanied by a correct classification of individuals.

Even though these studies have shown that it was possible to reduce the length of questionnaire using adaptive mechanisms, and in the case of [15] to apply it to learning styles, none of these studies have been done with the MBTI model of learning styles. Furthermore, our work differs from [15] in two important ways. First, our approach allows computing likely answers to unanswered questions and those are also taken into account to predict the learning style of a learner. Second, our proposal is based on the novel idea of exploiting associations between answers and questions to predict answers and skip questions (by mining association rules and using neural networks).

## I.4 The Electronic Questionnaire

In this section, we present our proposed electronic questionnaire for the automatic assessment of learning style. It comprises three components: (1) an answer prediction algorithm, (2) a dynamic question selection algorithm and (3) an algorithm to accurately predict a person's learning style based on both user supplied and predicted answers.

### I.4.1 The answer prediction algorithm

Let there be a questionnaire such as that of the MBTI. Let  $Q = \{q_1, q_2, \dots, q_n\}$  be the set of multiple-choice questions from the questionnaire. Let  $A(q_i) = \{a_i, l \dots a_{i,m}\}$  denote the finite set of possible answers to a given question  $q_i$  ( $1 \leq i \leq n$ ). Let  $R = \bigcup_{i=1}^n A(q_i)$  be the set of all possible answers to all questions  $q_i$  ( $1 \leq i \leq n$ ). A set of answers  $U = \{u_1, u_2, \dots, u_k\}$  is a set  $U \subseteq R$  where there do not exist integers  $a, b, x$  such that  $u_a, u_b \in A(q_x)$  and such that  $a$  is different from  $b$ . A completed set of answers is a set of answers  $U$  such that  $|U| = n$ . A partial set of answers is a set of answers  $U$  such that  $|U| < n$ . An empty set of answers is a set of answers  $U$  such that  $|U| = 0$ . Given a set of answers  $U$ , a question  $q_x$  is an unanswered question if  $A(q_x) \cap U = \emptyset$ . Otherwise,  $q_x$  is an answered question. For a set of answers  $U$  and a set of questions  $Q$ ,  $Unanswered(U, Q)$  denotes the set of unanswered questions, defined as  $Unanswered(U, Q) = \{q_i \mid q_i \in Q \wedge A(q_i) \cap U = \emptyset\}$ . Intuitively, a "set of answers" would be the filled-out answers in a questionnaire that might be supplied by a user. It could be completed, partial, or empty.

**Problem of answer prediction.** Let  $U$  be a partial set of answers. Let  $q_x$  be an unanswered question such that  $A(q_x) \cap U = \emptyset$ . The problem of predicting the answer to  $q_x$  is to determine the answer from  $A(q_x)$  that the user would choose.

To address the above problem, we assume that we have a training set  $T$  of completed sets of answers. This set is used to build a prediction model that is then used to predict answers for any unanswered question. In a set of answers  $U$ , we use the term predicted answer to refer to an answer that was predicted by the prediction model.

**Building the prediction model.** To build the prediction model, we rely on association rule mining, an efficient and popular method to discover associations between

items in sets of symbols, originally proposed for market basket analysis [30]. In our context, the problem of association rule mining can be defined as follows. Given the training set  $T$ , the *support* of a set of answers  $U$  is denoted as  $sup(U)$  and defined as the number of completed sets of answers in  $T$  containing  $U$ , that is  $sup(U) = |\{V \mid V \in T \wedge U \subseteq V\}|$ . An association rule  $X \rightarrow Y$  is a relationship between two sets of answers  $X, Y$  such that  $X \cap Y = \emptyset$ . The *support of a rule*  $X \rightarrow Y$  is defined as  $sup(X \rightarrow Y) = sup(X \cup Y) / |T|$ . The *confidence* of a rule  $X \rightarrow Y$  is defined as  $conf(X \rightarrow Y) = sup(X \cup Y) / sup(X)$ . The *lift* of a rule  $X \rightarrow Y$  is defined as  $lift(X \rightarrow Y) = sup(X \rightarrow Y) / (sup(X) \times sup(Y) / |T|^2)$ . The problem of mining association rules is to find all association rules in  $T$  having a support no less than a user-defined threshold  $0 \leq minsup \leq 1$  and a confidence no less than a user-defined threshold  $0 \leq minconf \leq 1$  [30]. For instance, Figure 1.1 shows a set of completed answers  $T$  (left) and some association rules found in  $T$  for  $minsup = 0.5$ ,  $minconf = 0.5$  (right).

ID	sets of answers
$t_1$	$\{a, b, c, e, f, g\}$
$t_2$	$\{a, b, c, d, e, f\}$
$t_3$	$\{a, b, e, f\}$
$t_4$	$\{b, f, g\}$

→

ID	Rules	Support	Confidence
$r_1$	$\{a\} \rightarrow \{e, f\}$	0.75	1
$r_2$	$\{a\} \rightarrow \{c, e, f\}$	0.5	0.6
$r_3$	$\{a, b\} \rightarrow \{e, f\}$	0.75	1
$r_4$	$\{a\} \rightarrow \{c, f\}$	0.5	0.6

Figure 1.1: (a) A set of answers and (b) some association rules found

To build the prediction model, in our experiments with the MBTI questionnaire, we used  $minsup = 0.15$ , set  $minconf$  in the  $[0.75, 0.99]$  interval (the justification for these values are given in the experimental section), and mines association rules using an implementation provided in the SPMF open-source data mining library [16]. Choosing a high confidence threshold allows discovering only strong associations so that only those are used for prediction. Moreover, we also tuned the association rule mining algorithm to only discover rules of the form  $X \rightarrow Y$  having a single item in the consequent, i.e. where  $|Y| = 1$ . The reason behind such a choice is that we are only interested in predicting one answer at a time rather than multiple answers together.

Performing a prediction. We now describe the algorithm for predicting the answer to an unanswered question  $q_z$  for a set of answers  $U$ , by using a set of association rules  $AR$ . Figure 1.2 shows the pseudocode of the prediction algorithm. It takes as input the

question  $q_z$ , the current set of answers  $U$  and the set of association rules  $AR$ . The algorithm first initializes a variable named *prediction* that will hold the final prediction and a variable *highestMeasure* to zero (line 1 to 2). Then, the algorithm considers each association rule  $X \rightarrow Y$  from  $AR$  such that the antecedent  $X$  appears in  $U$  and that the consequent  $Y$  contains an answer to  $q_z$  (line 3). For each rule, we calculate its usefulness for making a prediction, that we define as  $measure = lift(X \rightarrow Y) * |X| - |Unanswered(U, Q)| / |X|$  (line 4). A larger value of this measure is considered better. In this measure, a lift higher than 1 means a positive correlation between  $X$  and  $Y$ , while a lift lower than 1 means a negative correlation. We multiply the lift by  $|X|$  to give an advantage to rules matching with more answers from  $U$  over rules matching with fewer answers. The term  $|Unanswered(U, Q)| / |X|$  is subtracted from the previous term so that previously predicted answers in  $X$  have a negative influence on the measure (to reduce the risk of accumulating error by performing a prediction based on a previous prediction). The algorithm then selects the answer with the highest measure (line 9) as the prediction and adds it to the set of answers  $U$  (line 9).

---

**PREDICT**(a question  $q_z$ , a partial set of answers  $U$ , a set of association rules  $AR$ )

1. *prediction* := null.
2. *highestMeasure* := 0.
3. **FOR** each rule  $X \rightarrow Y$  such that  $X \rightarrow Y \in AR$ ,  $Y \subseteq A(q_z)$  and  $X \subseteq U$
4.      $measure = lift(X \rightarrow Y) * |X| - |Unanswered(U, Q)| / |X|$ .
5.     **IF**  $measure > highestMeasure$  **THEN**
6.          $highestMeasure := measure$ .
7.     **END IF**
8. **END FOR**
9. **IF** *prediction*  $\neq$  null **THEN**  $U := U \cup \{prediction\}$ .

---

Figure 1.2: The answer prediction algorithm

#### I.4.1 The question selection algorithm

We now describe *Q-SELECT*, the question selection algorithm of our electronic questionnaire that dynamically determines the order of questions. The pseudocode is given in Figure 1.3. The algorithm takes as input the set of association rules  $AR$ , previously extracted from the training set  $T$ . The algorithm first initializes the set of answers  $U$  for the current user to  $\emptyset$ . Then, the algorithm scans in one pass association rules  $AR$  to calculate dependencies of each question from  $Q$ . The *set of dependencies of a*

question  $q_x$  is denoted as  $dependencies(q_x)$  and defined as the set of questions that can be used to predict an answer to  $q_x$ , i.e.  $dependencies(q_x) = \{q_z \mid \exists X \rightarrow Y \in AR \wedge q_z \in X \wedge Y \subseteq A(q)\}$ . A question  $q_x$  is said to be an *independent question* if no answer to that question can ever be predicted by the set of association rules  $AR$ , i.e.  $dependencies(q_x) = \emptyset$ . If there are independent questions, the algorithm starts by asking them to the user (line 3 to 4). The reason behind such a priority is that answers to independent questions cannot be predicted. But, their answers may be used to predict answers for other questions. Then, for each unanswered question  $q$ , the algorithm calls PREDICT (cf. Section 4.1) in an attempt to predict an answer for  $q$  (line 5).

---

**Q-SELECT**(the set of questions  $Q$  from the questionnaire, association rules  $AR$ )

1.  $U := \emptyset$
2. **SCAN** each association rules from  $AR$  to calculate dependencies for each question from  $Q$ .
3. **IF** there are independent questions **THEN**
4.     **ASK** all independent questions to the user. Add answers provided by the user to  $U$ .
5.     **FOR EACH** unanswered question  $q$ , **PREDICT**( $q, U, AR$ ).
6. **END IF**
7. **WHILE**( $|U| \neq |Q|$ )
8.     **FOR EACH** unanswered question  $q$ , **CALCULATE**  $unlockable(q)$ .
9.     **ASK** the question  $q$  such that  $|unlockable(q)|$  is the largest among all unanswered questions.
10.    **FOR EACH** unanswered question  $q$ , **PREDICT**( $q, U, AR$ ).
11. **END WHILE**
12. **RETURN**  $U$

---

Figure 1.3: The question selection algorithm

After this loop, all independent questions and possible predictions have been exhausted. Next, the algorithm has to ask a question among the remaining unanswered questions. This is performed by a loop that continues until all questions have been answered (line 7). In this loop, the algorithm selects which question should be asked next. To make this choice, the algorithm estimates the number of questions that can be unlocked for each unanswered question if it was answered. The set of questions that a question  $q$  can unlock is denoted as  $unlockable(q)$  and defined as  $unlockable(q) = \{q_z \mid \exists X \rightarrow Y \in AR \wedge \exists z \in A(q_z) \wedge z \in Y \wedge X \subseteq U \cup A(q) \wedge A(Q) \cap X \neq \emptyset\}$ . The algorithm calculates this set for each unanswered question. This can be done by scanning the set of association rules once (line 8). Then the algorithm asks the question that can unlock the maximum number of

questions according to the previous definition (line 9). Thereafter, for each unanswered question, the algorithm calls PREDICT to use the answer provided by the user to attempt to make a prediction (line 10). The WHILE loop then continues in the same way until no unanswered questions remain. When the loop terminates, for each question  $q$  in  $Q$ , the set of answers  $U$  contains an answer from  $A(q)$ , which has either been answered by the user or predicted.

#### **I.4.2 The learning style prediction algorithm**

We now describe how the electronic questionnaire automatically identifies the learning style of a user based on supplied and predicted set of answers.

The MBTI questionnaire evaluates each dimension (EI, JP, TF and SN) by a distinct subset of questions. Thus, we split the questionnaire into four sets of questions representing each dimension. A prediction algorithm is applied to each subset (dimension) to identify the individual's preference based on available answers. Finally, preferences in all four dimensions are combined to establish the learning style of the user.

Identifying the preference of a person in each dimension is essentially a classification problem. It is achieved, in our system, by a single layer feed-forward neural network, among the most common neural network architectures (it connects the input and output neurons directly, rather than connecting them through an intermediate layer). Neural networks are generally more accurate than other classifiers [23]. We trained a neural network for each dimension using 1,000 filled questionnaires (cf. experimental section). Thereafter, for each new user, the set of answers produced by the question selection algorithm (cf. Section 4.2) is used as input by the networks. The number of input neurons for each network is the number of questions for the corresponding dimension. The MBTI questionnaire uses 21 questions to assess the EI dimension, 23 questions for TF, 25 questions for SN, and 23 questions for JP. There is a single binary neuron as the output of each network because of the dichotomic nature of each dimension. Neural networks are built in MATLAB with the following parameters: activation function = TANSIG, performance function = MSE, number of iterations =



1000, the algorithm used for the training phase was TRAINLM with Goal = 0, Minimum gradient =  $1e-10$  and Max-fail = 6.

## I.5 Experimental Results

A database of 1,931 MBTI completed questionnaires was provided by Prof. Robert Baudouin, an experienced specialist of the MBTI technique at the Université de Moncton. The questionnaire probes users about their tendencies, variations in their individual attitudes and styles of decision-making. The full questionnaire is supplied in Annex 1. We used 1,000 samples for training and 931 for testing and evaluating the electronic questionnaire. The questionnaire is implemented using Java and MATLAB.

The goal of the experiment was to measure how the elimination of questions influences the error rate for the learning type prediction. Recall that our electronic questionnaire is essentially composed of two modules. One predicts user answers in an effort to reduce the number of questions, using association rules. The other predicts the learning types based on real and predicted answers, using feed-forward neural networks. As mentioned earlier, reducing the number of questions improves the user motivation. However, the result of the first module influences the result of the second one and its error rate. In other words, increasing the number of predicted answers, i.e. reducing the number of questions asked, would increase the error rate in the predicted learning style. The challenge is thus to obtain the best balance between these two results.

Since our questionnaire is dynamic and can eliminate a different number of questions for each questionnaire, the number of questions eliminated was measured using the median. Preliminary experimentation showed that *minsup* values lower than 0.15 did not increase accuracy. The reason is that associations having a low support are less representative than associations with a high support. They are more likely to be noise since they appear in few questionnaires. Moreover, less frequent associations are often special cases of more frequent ones. Associations that are too specialized lead to overfitting. Thus, to vary number of questions eliminated (predicted), we instead varied the *minconf* threshold (in the [0.75, 0.99] interval). The error rate for a dimension is the

number of questionnaires where the predicted preference is incorrect, divided by the total number of questionnaires in the test set.

Experimental results are shown in Table 1.2 and Fig. 1.4. The baseline error rates (when no questions are eliminated) are 3.7%, 4.9%, 6% and 5% for the EI, SN, TF and JP dimensions, respectively. We limited our studies to error rates to no more than 12%. Higher error rates are not shown in the table. The maximum number of questions that can be eliminated within this bound is shown in the last filled row of each column of Table 1.2.

For EI, SN, TF and JP, the median number of questions eliminated is respectively 6, 9, 8, and 5, with error rates of 9.9%, 11.8%, 12% and 11.7%. The combined median number of questions eliminated is 28, which represents 30.4% of the MBTI questionnaire. It is important to note that the above numbers are medians. In many cases, individuals had more questions eliminated than the median. For example, Table 1.3, as well as Fig. 1.5 how the distribution of questions eliminated for the TF dimension. Although the median is eight questions, nine questions were eliminated for 292 individuals, and less than eight questions were eliminated for only 231 individuals.

Table 1.2 : Number of questions eliminated and the corresponding error rate

Median number of questions eliminated (predicted)	Error rate for EI	Error rate for SN	Error rate for TF	Error rate for JP
0	3.7%	4.9%	6.0%	5.0%
1	4.6%	5.3%	7.8%	6.0%
2	5.2%	6.3%	8.4%	7.1%
3	7.5%	6.6%	9.1%	8.6%
4	7.7%	7.5%	10.0%	10.0%
5	7.9%	9.0%	10.7%	<b>11.7%</b>
6	<b>9.9%</b>	10.5%	11.7%	
7		11.1%	11.7%	
8		11.7%	<b>12.0%</b>	
9		<b>11.8%</b>		

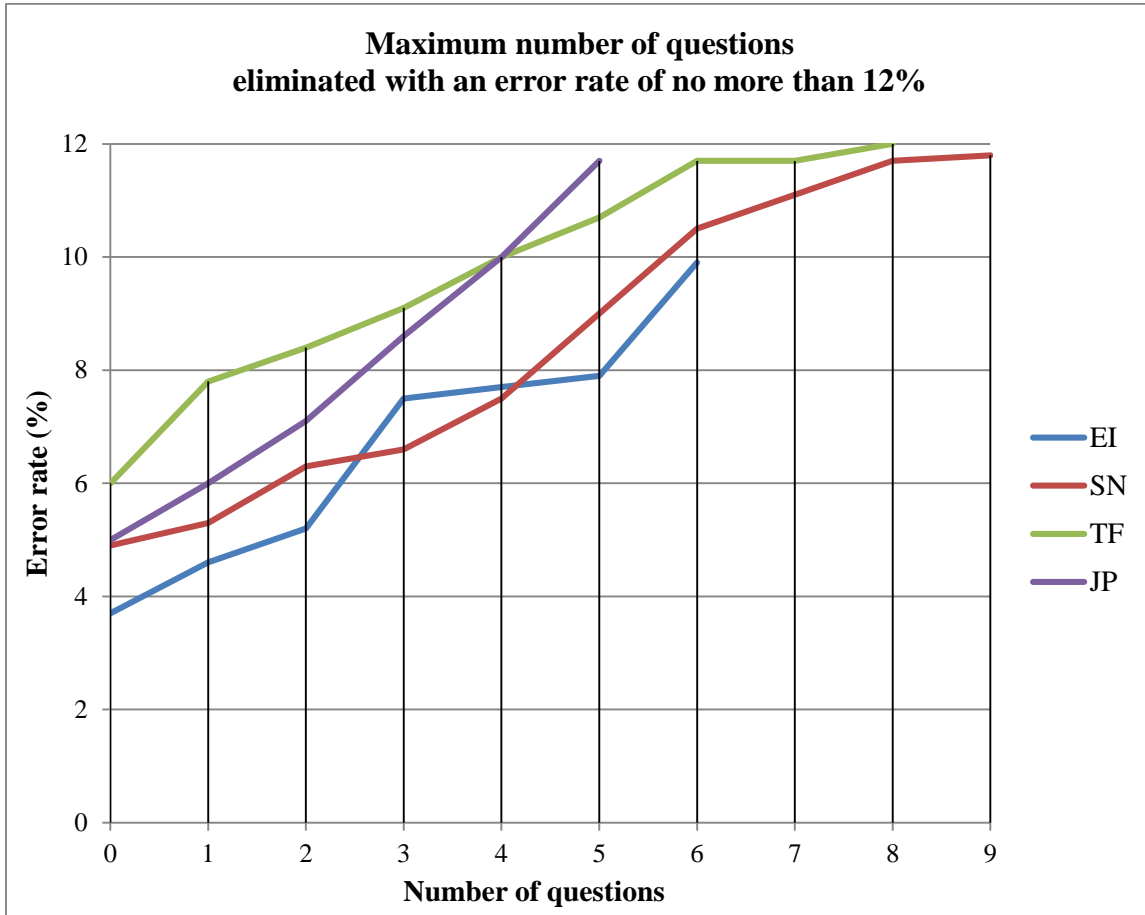


Figure 1.4: Maximum number of questions eliminated with an error rate no more than 12%

Given the error rates from Table 1.2, the probability of predicting incorrectly four preferences for a particular user is only 0.02% ( $9.9\% \times 11.8\% \times 12\% \times 11.7\% = 0.02\%$ ). The probability of predicting three erroneous preferences is 0.6%. The probability of predicting two erroneous preferences is 6.66%, while the probability of predicting one erroneous preference is 33% ( $9.9\% \times (100\% - 11.8\%) \times (100\% - 12\%) \times (100\% - 11.7\%) + (100\% - 9.9\%) \times 11.8\% \times (100\% - 12\%) \times (100\% - 11.7\%) + (100\% - 9.9\%) \times (100\% - 11.8\%) \times 12\% \times (100\% - 11.7\%) + (100\% - 9.9\%) \times (100\% - 11.8\%) \times (100\% - 12\%) \times 11.7\%$ ), and the probability of a perfect prediction is 60%. We note that the combined probability of having no errors or only one error is more than 93%.

Table 1.3 : Number of questions eliminated per questionnaire for the TF dimension

Number of questions eliminated ( $x$ )	Number of questionnaires (individuals)	Number of questionnaires in the $[x, 10]$ interval
1	0	931 (100%)
2	11	931 (100%)
3	7	920 (99%)
4	3	913 (98%)
5	11	910 (98%)
6	14	899 (97%)
7	185	885 (95%)
8 (median)	348	700 (75%)
9	292	352 (38%)
10	60	60 (6%)

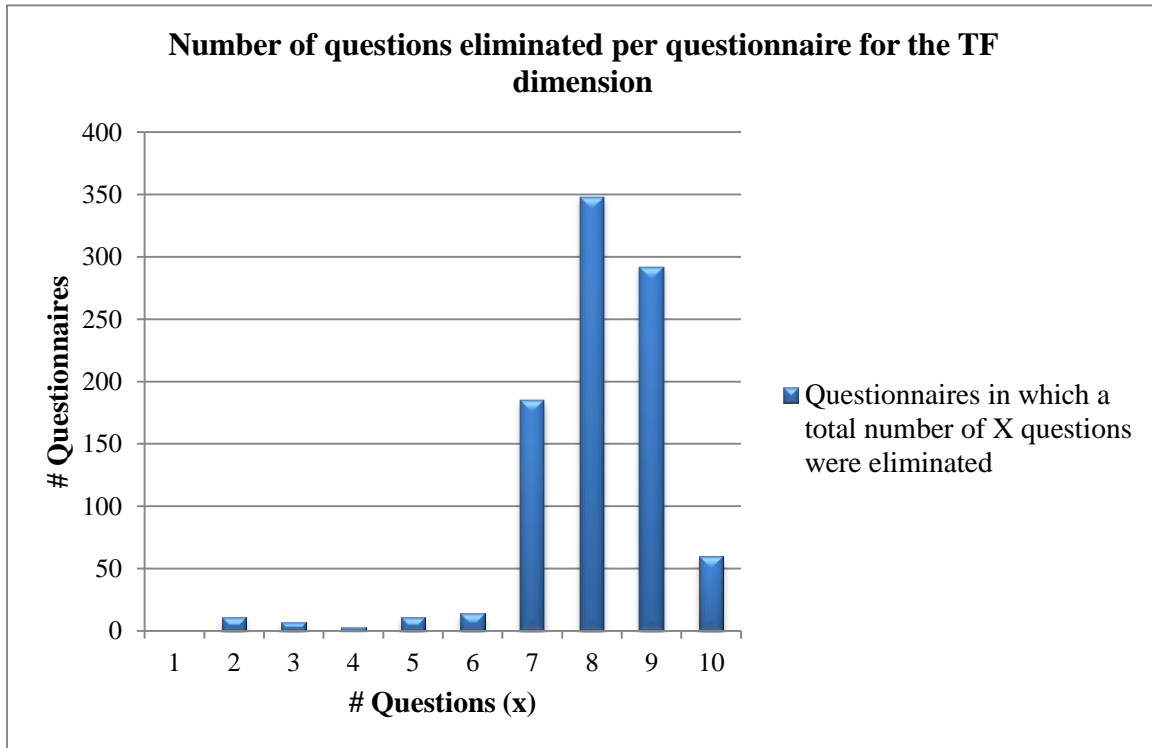


Figure 1.5: Number of questions eliminated per questionnaire for the TF dimension

We compared the *Q-SELECT* algorithm results with those obtained by a *C4.5 decision tree* [16, 33]. Table 1.4 and Fig. 1.6 show the comparable error rates of both methods for the highest number of questions eliminated by the Q-SELECT algorithm. It can be noticed that the error rates generated by the decision tree are two to four percent higher for each of the four preferences.

Table 1.4 : Comparative results for *Q-SELECT* and Decision Tree

	Error rate for EI (6 questions)	Error rate for SN (9 questions)	Error rate for TF (8 questions)	Error rate for JP (5 questions)
Q-SELECT	9.9%	11.8%	12.0%	11.7%
Decision Tree	12.3%	13.2%	16.5%	13.7%

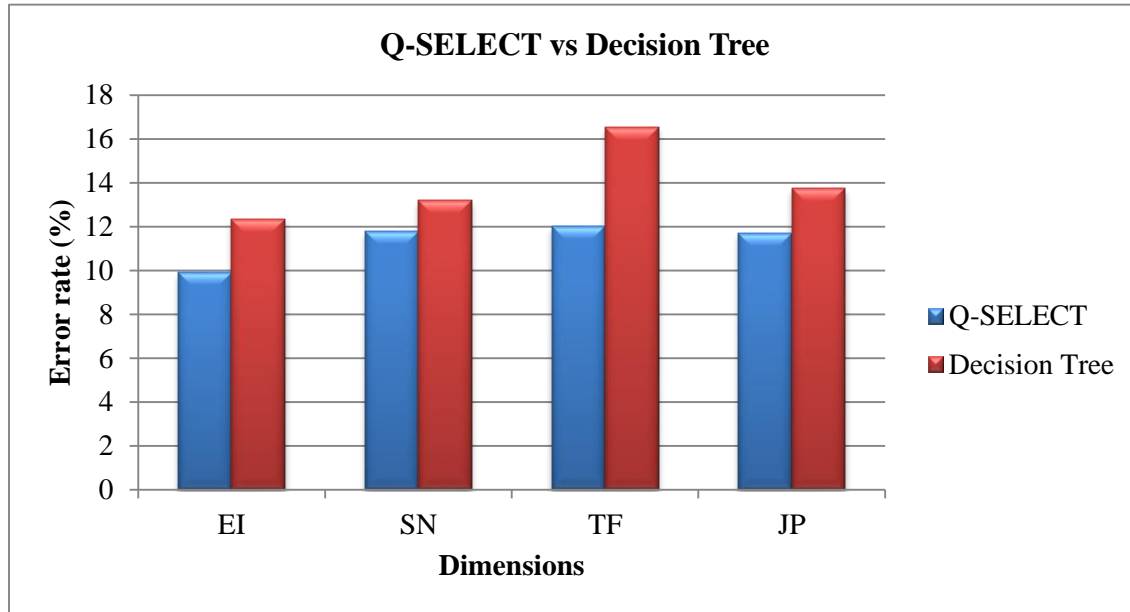


Figure 1.6: Q-SELECT vs Decision Tree

## I.6 Conclusion

Standardized questionnaires for learning style identification are long, time-consuming and require human intervention to determine an individual’s learning style. To address these issues, we presented an adaptive electronic questionnaire that reduces the number of questions asked and that automatically identifies the learning type or style, with a low error rate.

Our system is composed mainly of two modules. One predicts user answers with the intention of reducing the number of questions, by relying on association rules. The other module uses feed-forward neural networks to predict the learning types based on real and predicted answers obtained from the first module. User motivation is improved when a smaller number of questions is asked. However, reducing the number of questions asked increases the error rate in the learning style prediction module.

Experimental results with 1,931 questionnaires filled for the Myers Briggs Type Indicators show that our approach succeeds in the challenge of reducing the number of questions asked and in identifying the learning preferences with low error rates. Indeed, the combined median number of questions eliminated by the system is 28, representing 30.4% of the original MBTI questionnaire.

The system predicts the learning preferences for the four dimensions with error rates of 9.9%, 11.8%, 12% and 11.7% for the four dimensions EI, SN, TF and JP, respectively. The probability of predicting incorrectly the four preferences constituting a learning style of a particular user is only 0.02%. The probability of predicting three erroneous preferences simultaneously is 0.6%. The probability of predicting two erroneous preferences is 6.66%, while the probability of predicting only one erroneous preference is 33%, and the probability of a perfect prediction is 60%. We note that the combined probability of having no errors, or only one error among the four dimensions, i.e. the predicted learning style, is more than 93%.

We also note that our system gave better results than the decision tree for all the preference types. For the EI, SN, TF and JP dimensions, the corresponding error rates of the decision tree are 12.55%, 13.21%, 16.54% and 13.74%, while our system obtained two to four percent lower error rates for each of the four preferences.

Globally, our approach considerably reduces the number of questions asked by a median of 30%, while predicting learning styles with an error rate lower than 12%.

## CHAPITRE II. A DYNAMIC QUESTIONNAIRE TO FURTHER REDUCE QUESTIONS IN LEARNING STYLE ASSESSMENT

**Abstract.** The detection of learning styles in adaptive systems provides a way to better assist learners during their training. A popular approach is to fill out a long questionnaire then ask a specialist to analyze the answers and identify learning styles or types accordingly. Since this process is very time-consuming, a number of automatic approaches have been proposed to reduce the number of questions asked. However the length of the questionnaire remains an important concern. In this paper, we address this issue by proposing *T-PREDICT*, a novel dynamic electronic questionnaire for psychological type prediction that further reduces the number of questions. Experimental results show that it can eliminate 81% more questions of the Myers-Briggs Type indicators questionnaire than three state-of-the-art approaches, while predicting learning styles without increasing the error rate.

**Keywords:** dynamic adaptive questionnaire, classification, learning styles, Myers-Briggs Type Indicator, psychological types.

### II.1 Introduction

Knowing the learning style of learners is important to ensure enhanced and personalized interactions with teachers. Various studies established that presenting information in a manner that is adapted to the student's learning style facilitates learning (e.g. [2, 7]).

Two main approaches are used to carry out learning style or type assessment: the first approach consists of examining the learner's interaction with the system [9, 15]. The second approach entails using a standard questionnaire that is filled out by an individual before a specialist examines the responses and establishes the corresponding learning style.

Even though these approaches can correctly identify the learning type of a learner, they still suffer from various shortcomings. Using the first approach entails that an initial random learning style is assigned to the learner, implying that if the initial guess is

wrong, the system will offer wrong interactions with the learner and that could have negative impact on learning. In addition, the interaction will persist until enough data is stored so that an ideal learning style can be established [15]. The second approach has various limitations as well. First, the questionnaires tend to be long and time consuming. For instance, Myers-Briggs Type indicator questionnaire has more than 90 questions. Second, the fact that questionnaires are long implies that the person filling the questionnaire might be demotivated to reply to the questions with enough attention [15] which might lead to abandoning the test, skipping questions, answering falsely, etc. Consequently, an incorrect learning style might be adopted [19]. The third limitation of this approach is that in order to assign a learning style, there is a need for a specialist to analyze the learner's answers to questions.

To address these limitations, several approaches [17, 29, 33] have been proposed to automatically reduce the number of questions asked to learners in an effort to identify their learning styles or psychological types. For example, *Q-SELECT* [33] is an adaptive electronic questionnaire that uses association rules to predict part of the answers and hence shorten the questionnaire by up to 30%. However, even when applying these approaches, the length of questionnaires remains a concern. Therefore, an important research question is "could a new method be designed to further reduce the number of questions asked?"

In this paper, we answer this question positively by proposing a dynamic electronic questionnaire T-PREDICT that further reduces the number of questions and automatically recognizes the psychological types with high accuracy.

The rest of the paper is organized as follows. The Myers-Briggs Type Indicator model is presented in section 2. Section 3 discusses related work on adaptive questionnaires. Section 4 and 5 respectively present the proposed electronic questionnaire and the experimental results. Finally, section 6 draws the conclusions



## II.2 Myers-Briggs Type Indicator (MBTI)

The Myers-Briggs Type Indicators (MBTI) is a well-known personality assessment model that has been used for over three decades. It uses Carl Jung's personality type theory to categorize individuals into four dimensions. Each dimension consists of two opposite preferences that depict inclinations and reveal dispositions in personal mindsets and techniques of making decisions [21].

The E-I dimension (extraverted-introverted) centers its attention on establishing whether a person's approach is influenced by the outward environment such as other objects and individuals, or it is internally-oriented. The S-N dimension seeks to measure sensing-intuitiveness, illustrating the perception approach of an individual. As per the T-F dimension, thinking implies coherent reasoning and decision making processes while feelings influence personal, objective, and value oriented approach. The J-P dimension involves either a judging attitude and quick decision-making or perception that demonstrates more patience and information gathering prior to decision-making. Given these four dimensions, an individual's personality type is therefore designated by a four-letter code: {ISTJ, ISFJ, INFJ, INTJ, ISTP, ISFP, INFP, INTP, ESTP, ESFP, ENFP, ENTP, ESTJ, ESFJ, ENFJ, ENTJ}(see Table 1.1).

While a number of the preferences may be dominant, others are likely to be secondary and can be easily subjected by other dimensions. For instance, the J-P dimension influences the two function preferences namely T or F versus S or N [20].

Though the Myers-Briggs Type Indicator questionnaire has been used widely for a long time, it has some limitations. Its hypothetical and numerical imports are restricted to some extent by the use of dichotomous preference items [22]. In addition, the MBTI questionnaire contains numerous questions, a number which may put off some users. As a result, they may choose to answer the questionnaire without paying much thought or attention to the choices thus raising doubts on the reliability of the assessment [34]. Reducing the number of questions in a questionnaire has been a way to increase its efficiency [14, 22].

## II.3 Related work

Some major challenges in building an e-learning system that can adapt itself to a learner is giving it the capability of changing the type, the order, or the number of questions presented to the learner [8, 15, 25, 33]. For instance, McSherry [23] reports that reducing the number of questions asked by an informal case-based reasoning system minimized frustration, made learning easier and increased efficiency.

Various methods have been suggested in order to minimize the number of questions that are required to establish the learning style or preference of an individual. The AH questionnaire [15] uses decision trees to reduce the questions and categorize the students as per the Felder-Silverman theory of learning styles. From an experiment that had 330 students, it was likely to anticipate the learning styles with precision of up to 95.71% while only asking four or five questions among the eleven questions that are applied in each dimension.

EDUFORM is a software used for adaptation and dynamic optimization of questionnaire propositions for online profiling of learners, which was proposed by Nokelainen et al. [29]. The tool, that uses Bayesian modeling as well as abductive reasoning, minimized the questionnaire items by 30% to 50% while retaining an error rate of 10% to 15%. These results showed that shortening questionnaires does not detrimentally influence the correct categorization of individuals.

In previous work [17], two methods based on back-propagation neural networks and decision trees were proposed to predict learning types and reduce the number of questions asked in the MBTI questionnaire. We refer to these methods as *Q-NN* and *Q-DT*, respectively. The general experimental method tries to identify questions that are less influential in determining the learning types. These questions are then eliminated from the questionnaire and the learning types are predicted. This process is repeated until a maximum error rate of 12% is achieved. In an experimental study, that had 1,931 filled questionnaires, the *Q-NN* method clearly identified and eliminated 35% of the questions while establishing the learning preferences with an error rate of 9.4%. On the other hand, *Q-DT* eliminated 30% of the questions with an error rate of 14%.

Recently, we presented an alternative approach to reduce the number of questions in MBTI questionnaire [33]. This approach (*Q-SELECT*) comprises three modules: (1) an answer prediction algorithm, (2) a dynamic question selection algorithm and (3) an algorithm to accurately predict a person's learning style based on both user supplied and predicted answers. The two first modules rely on association rules between answers from previous users. The third module predicts learning types using a neural network. An experimental study with the same 1,931 MBTI filled questionnaires has shown that *Q-SELECT* reduces the number of questions asked by a median of 30% with an average error rate of 12.1%. The main advantage of *Q-SELECT* compared to *Q-NN* and *Q-DT* is its adaptability, i.e. the ability to ask a variable number of questions and to reorder them depending on the user answers, thus providing a personalized questionnaire to each user.

Reducing the MBTI questionnaire by up to 35% still leaves around 60 questions. This paper presents *T-PREDICT*, a new dynamic approach to further minimize the number of questions in MBTI questionnaires while predicting learning types with a comparable error rate.

Reducing the number of questions might bring to mind algorithms for dimensionality reduction such as PCA, ICA [35]. However, these methods would have reduced the same number of questions for all users as in *Q-NN*. Our choice was to continue our experiments with a dynamic user-adaptive approach. This choice was later confirmed by our results from *T-PREDICT*. We were sometimes able to predict the learning type with as little as six questions out of 92 but with a median of 11 questions.

Another popular theory that deals with questions and answers is Item Response Theory (IRT) [37]. It has been applied in education and psychology to assess an underlying ability or trait using a questionnaire. To apply IRT, users' answers need to be collected and analyzed. Using a technique such as factor analysis, a model (e.g. logistic function) is created for each question to represent the amount of information provided by each answer about the latent trait. The quality of the generated models varies depending on the data available. When a model does not fit well a question, this latter is typically removed, replaced or rewritten [38]. Applying IRT can be very time-consuming, since for each modification, more data may need to be collected to update models and human

intervention is required to analyze questions and tweak models. Furthermore, IRT does not provide means for user adaptability. In contrast, our proposal is automatic and user-adaptive in all steps: selecting important questions, reordering them, and later predicting learning types.

## II.4 The Electronic Questionnaire

The proposed electronic questionnaire *T-PREDICT* comprises two major components: a question sorting algorithm and a learning type prediction algorithm. The philosophy behind this division is that some questions might be more important than others i.e. their answers could easily classify the learners in one or the other personality type. Hence, the sorting algorithm sorts the questions by their ability to discriminate between classes, while the prediction algorithm uses them in this preferential order. An additional module is developed to dynamically select parameters needed for the prediction algorithm.

### II.4.1 The question sorting algorithm

The MBTI questionnaire evaluates each dimension (EI, SN, TF, and JP) by a distinct subset of questions. Thus, we split the questionnaire into the four sets of questions representing these dimensions. Each dimension consists of two opposite preferences, hence the need to classify individuals into one of these two preferences (classes). Since our goal is to reduce the number of questions asked, it is crucial to recognize which questions are more important for identifying the preferences. We define the importance of a question as its ability to discriminate between the two classes. Let  $q$  be a question and  $A(q) = \{a_1 \dots a_m\}$  be the set of possible answers to this question. Let  $T$  be a training set of filled questionnaires such that each questionnaire belongs to one of the two classes. For any answer  $a_i$  ( $1 \leq i \leq m$ ), let  $N_1(a_i)$  and  $N_2(a_i)$  respectively be the number of questionnaires in  $T$  containing the answer  $a_i$  that belong to the first class and the second class. The discriminative power of the answer  $a_i$  is denoted as  $DA(a_i)$  and defined as  $N_1(a_i) / N_2(a_i)$  if  $N_1(a_i) > N_2(a_i)$  or  $N_2(a_i) / N_1(a_i)$ , otherwise. Intuitively, it represents how many times one class is larger than the other for individuals having answered  $a_i$ , and thus how this answer helps to discriminate between the two classes.

The discriminative power of a question  $q$  is denoted as  $DQ(q)$  and defined as  $DQ(q) = \sum_{k=1}^{|A(q)|} DA(a_i) / |T|$ . The proposed adaptive questionnaire initially calculates the discriminative power of each question in the training set  $T$  and sorts them accordingly (see Fig. 2.1 for the pseudocode). The next subsection describes how the adaptive questionnaire asks the questions by decreasing order of discriminative power and predicts the preference (class) of each individual using the provided answers.

---

**QUESTION\_SORT** (a training set  $T$ , a list of questions  $Q$ , a set of possible answers  $A$ )

10. **FOR** each question  $q \in Q$
11.     **FOR** each possible answer  $a_i \in A(q)$
12.         **SCAN**  $T$  to calculate  $N_1(a_i)$  and  $N_2(a_i)$ .
13.         **IF**  $N_1(a_i) > N_2(a_i)$  **THEN**  $DA(a_i) := N_1(a_i) / N_2(a_i)$ .
14.         **ELSE**  $DA(a_i) := N_2(a_i) / N_1(a_i)$ .
15.     **END FOR**
16.      $DQ(q) = \sum_{k=1}^{|A(q)|} DA(a_i) / |T|$ .
17. **END FOR**
18. **SORT**  $Q$  such that  $q_a$  appears before  $q_b$  if  $DQ(q_a) > DQ(q_b)$ , for all questions  $q_a, q_b \in Q$ .
19. **RETURN**  $Q$ .

---

Figure 2.1: The question sorting algorithm

## II.4.2 The learning style prediction algorithm

The learning style prediction algorithm (see Fig. 2.2) automatically identifies the preference of a user in a given dimension based on supplied answers and their similarity to answers from previous users. The algorithm takes as input a training set of filled questionnaires  $T$ , the list of questions  $Q$  for the dimension, sorted by their discriminative power (see section 4.1), a maximum number of questions to be asked  $maxQuestions$  (by default set to  $|Q|$ ), and two additional parameters  $minMargin$  and  $minQ$  that will be defined later.

The algorithm first initializes a set  $U$  as empty to store the user answers. Then, a loop is performed to ask the questions to the user in decreasing order of their discriminative power. Each provided answer is immediately added to  $U$ . Then, the algorithm attempts to make a prediction by scanning through the set  $T$  to count how many users have the same answers as the current user and belong to class 1 or belong to class 2,

i.e.  $S_1 = |\{X \mid X \in T \wedge U \subseteq X \wedge X \text{ is tagged as class 1}\}|$  and  $S_2 = |\{X \mid X \in T \wedge U \subseteq X \wedge X \text{ is tagged as class 2}\}|$ . Two criteria must be met to make this prediction. First, the number of filled questionnaires, from the training set  $T$ , matching the answers of the current user should be higher or equal to a pre-set threshold ( $minQ$ ), i.e.  $S_1 + S_2 \geq minQ$ . Second, there should be a large enough difference between  $S_1$  and  $S_2$  in order to make an accurate prediction. This difference is defined as  $|S_1 - S_2| \geq minMargin$ , where  $minMargin$  is also a pre-set threshold. If both conditions are met, a prediction is made. The prediction is class 1 if  $S_1 > S_2$ , and class 2 otherwise. If no prediction can be made, the algorithm continues with other questions, one at a time, until it is able to make a prediction.

---

**PREDICT** (a training set  $T$ , a list of questions  $Q$  sorted by their discriminative power, a maximum number of questions to be asked  $maxQuestions$ , a minimum margin between classes  $minMargin$ , a minimum number of questionnaires to be matched  $minQ$ )

1.  $U := \emptyset$ .
2. **FOR** each question  $q_i \in Q$  until  $maxQuestions$  have been asked
3.     **ASK**  $q_i$  to the user and store the provided answer in  $U$ .
4.      $S_1 := S_2 := 0$ .
5.     **FOR** each questionnaire  $X \in T$  such that  $U \subseteq X$
6.         **IF**  $X$  is tagged as class 1 **THEN**  $S_1 := S_1 + 1$ . **ELSE**  $S_2 := S_2 + 1$ .
7.     **IF**  $S_1 + S_2 \geq minQ$  **AND**  $|S_1 - S_2| \geq minMargin$  **THEN**
8.         **IF**  $S_1 > S_2$  **THEN RETURN** “class 1”. **ELSE RETURN** “class 2”.
9.     **END FOR**
10.  $Y_1 := Y_2 := 0$ .
11. **FOR** each questionnaire  $X \in T$  such that  $C(X, U) \geq |U|/2$
12.     **IF**  $X$  is tagged as class 1 **THEN**  $Y_1 := Y_1 + C(X, U)$ . **ELSE**  $Y_2 := Y_2 + C(X, U)$ .
13. **IF**  $Y_1 > Y_2$  **THEN RETURN** “class 1”. **ELSE RETURN** “class 2”.

---

Figure 2.2: The learning type prediction algorithm

After  $maxQuestions$  questions have been exhausted and no prediction was possible with the exact matching, a prediction is made by considering an *approximate* match between the present user answers and questionnaires from the training set  $T$ . A questionnaire  $X \in T$  approximately matches  $U$  if it shares at least  $|U|/2$  answers with it. The number of answers common to  $X$  and  $U$  is denoted as  $C(X, U)$  and defined as  $C(X, U) = |X \cap U|$ . Let  $Y_1$  and  $Y_2$  be the sets of all questionnaires from  $T$  that approximately match  $U$  and are tagged as class 1 or class 2. The prediction is class 1 if  $Y_1 > Y_2$ . Otherwise, it is class 2.

### II.4.3 The parameters selection algorithm

As mentioned earlier, the prediction algorithm needs two preselected parameters  $minMargin$  and  $minQ$ . These parameters are not global. They are dynamically selected as per number of questions asked. The PARAMETERS\_SELECT algorithm (see Fig. 2.3) attempts to select the best values for these parameters exhaustively by simulating predictions and calculating the corresponding precisions on a test set of filled questionnaires  $TS$  by using a training set  $T$ .

The algorithm proceeds by considering each question from  $Q$  in the order that they will be asked by the PREDICT algorithm (in descending order of discriminative power). For every question  $q_k$  considered, all combinations of values  $i$  and  $j$  for parameters  $minQ$  and  $minMargin$  in their respective intervals  $[1, maxQ]$  and  $[1, maxMargin]$  are tested. For each combination, a certain number of predictions  $NbPredictions_k$  are obtained with a corresponding precision  $precision_k$ . The combination of values  $i$  and  $j$  that is considered the best is the one maximising the function  $score(i,j) = \alpha \times precision_k + NbPredictions_k \times (1 - \alpha)$ , where  $\alpha$  is a constant varied in the  $[0.5, 0.9]$  interval. The weight  $\alpha$  is used to calibrate the relative importance of the precision and the number of predictions on the selection of parameter values.

Furthermore, an additional constraint is that the best combination needs to have a precision higher than a moving threshold  $RequiredPrecision$ . For the first question, this threshold is equal to a pre-set minimum precision  $TargetPrecision$ . For any subsequent question  $q_k$ , the required precision is recalculated to take into account the precisions obtained with previous questions (called  $GlobalPrecision_k$ ). The reason is that if a high precision is obtained for the previous questions, it is possible to accept a lower precision for the next questions, while maintaining a global precision above  $TargetPrecision$ . The global precision is calculated by weighting the previous precisions with their corresponding number of predictions. Formally, the global precision is defined as:

$$GlobalPrecision_k = \sum_{f=1}^{k-1} precision_f \times NbPredictions_f).$$

The required precision for the  $k^{\text{th}}$  question is calculated as:  $RequiredPrecision_k = (|TS| \times TargetPrecision - GlobalPrecision_k) / |RemainingQ|$ , where  $RemainingQ$  is the number of unpredicted questionnaires.

---

**PARAMETERS\_SELECT** (a training set  $T$ , a test set  $TS$ , a list of questions  $Q = \{q_1, q_2, \dots, q_n\}$  sorted by their discriminative power, a target precision  $TargetPrecision$ , and the two upper bounds  $maxMargin$  and  $maxQ$ )

1.  $GlobalPrecision := 0$ .
2.  $RequiredPrecision := TargetPrecision$
3.  $P := \emptyset$ .
4.  $RemainingQuestionnaires := TS$ .
5. **FOR** each  $q_k \in Q$  and  $k := 1, 2 \dots n$
6.      $bestScore := 0$ .      $bestParameters := (0, 0, 0)$ .
7.      $bestResult := (0, 0, 0)$ .
8.     **FOR** each combination of values  $i, j, \alpha$  such that  $i := 1, 2 \dots maxQ$   
        **and**  $j := 1, 5, \dots maxMargin$   
        **and**  $\alpha := 0.5, 0.6 \dots 0.9$
9.     Predict a class for each questionnaire  $X \in RemainingQuestionnaires$  using the first  $k$  questions and the training set  $T$ .  
        Set parameters  $minQ := i$ ,  $minMargin := j$  for the  $k^{\text{th}}$  question, while keeping the best previously found parameters for questions 1 to  $k-1$ .  
        Let  $predicted_k$  be the set of questionnaires where a prediction was performed and  $precision_k$  be the precision.
10.      $score := precision_k \times \alpha + |predicted_k| \times (1 - \alpha)$ .
11.     **IF**  $score > bestScore$  **AND**  $precision_k \geq RequiredPrecision$  **THEN**
12.          $bestParameters := (k, i, j)$ .
13.          $bestScore := score$ .
14.          $bestResult := (k, predicted_k, precision_k)$ .
15.     **END IF**
16.     **END FOR**
17.      $P := P \cup \{bestParameters\}$ .
18.      $GlobalPrecision := GlobalPrecision + |bestResult.predicted| \times bestResult.precision$
19.      $RemainingQuestionnaires := RemainingQuestionnaires \setminus bestResult.predicted$ .
20.      $RequiredPrecision := (|TS| \times TargetPrecision - GlobalPrecision) / RemainingQuestionnaires$
21. **END FOR**
22. **RETURN**  $P$ .

---

Figure 2.3: The parameter selection algorithm

When the algorithm terminates, it returns a list  $P$  of triples of the form  $(k, y, z)$  indicating that parameters  $minMargin$  and  $minQ$  should be respectively set to values  $y$



and  $z$  for the  $k^{\text{th}}$  question to establish a prediction with a global precision not below *TargetPrecision*.

## II.5 Experimental Results

Two experiments were performed. The first one compares the performance of the learning type prediction algorithm *T-PREDICT* with other methods. The second one assesses the influence of question sorting and limiting the number of questions in *T-PREDICT*. A database of 1,931 MBTI filled out questionnaires were supplied for experimentation by Prof. Robert Baudouin, an expert of the MBTI technique at Université de Moncton. The number of samples used for training was 1,000 while 931 were used for testing. The proposed dynamic questionnaire *T-PREDICT* is implemented using Java. The goal of the experiments was to ask as few questions as possible while automatically identifying learning types with a minimum precision of 88%, i.e. a maximum error rate of 12%. This is the same error rate that was used in *Q-SELECT* [33], thus allowing a more precise comparison base.

Parameters used were automatically selected by the parameters selection algorithm (see section II.4.3). It varied *minQ* and *minMargin*, for each question, in the [0.01, 0.15] and [0.1, 0.9] intervals respectively and returned their optimal values to be used by the type prediction algorithm. These predictions were done for each of the four MBTI dimensions.

### II.5.1 Comparison with other methods

The first experiment compared the median number of questions asked in each dimension with results obtained by three specialized methods that have been specifically developed to reduce the number of questions for MBTI. These methods are based on back-propagation neural networks (*Q-NN*) [17], decision trees (*Q-DT*) [17], and association rules (*Q-SELECT*) [33]. Table 2.1 and Fig. 2.4 show the number of questions asked per dimension, as compared to the original higher number, and the corresponding error rates. Note that the *T-PREDICT* line shows that the number of questions asked for EI, SN, TF and JP dimensions were 2 out of 21 questions, 4 out of 25 questions, 2 out of 23 questions, and 3 out of 23 questions respectively. The corresponding error rates

obtained were 10.7% for EI, 13% for SN, 10.3% for TF and 13.1% for JP. Thus, maintaining a weighted average error rate of 12.1% for the four dimensions, which is practically the pre-set error rate of 12% mentioned earlier. All dimensions for the four compared methods maintained error rates below 13.1% except the TF and JP dimensions for the *Q-DT*, which respectively had error rates of 16.3% and 13.7%. Overall, *T-PREDICT* asked a median of only 11 questions, out of 92 questions, to predict learning types with an average error rate of 12.1%, while *Q-SELECT*, *Q-NN*, and *Q-DT* asked 62, 60, and 64 questions to achieve error rates of 11.4%, 9.4%, and 14% respectively. In sum, the number of questions was greatly reduced by *T-PREDICT* while maintaining a very comparable error rate.

Table 2.1: Median number of questions asked by T-PREDICT per dimension, compared to other methods

	EI (21 quest.)	SN (25 quest.)	TF (23 quest.)	JP (23 quest.)	Total (92 quest.)
<i>T-PREDICT</i>	<b>2</b>	<b>4</b>	<b>2</b>	<b>3</b>	<b>11</b>
Avg. error rate	10.7%	13.0%	10.3%	13.1%	12.1%
<i>Q-SELECT</i>	14	16	14	18	62
Avg. error rate	9.9%	11.8%	12.0%	11.7%	11.4%
<i>Q-NN</i>	14	16	16	14	60
Avg. error rate	8.3%	10.9%	9.3%	8.9%	9.4%
<i>Q-DT</i>	14	17	17	16	64
Avg. error rate	12.8%	13.1%	16.3%	13.7%	14.0%

Since the above table presents median numbers of questions asked, one might wonder how the actual numbers of questions asked are distributed. For example, Table 2.2 shows the distribution of questions asked for the SN dimension. Note that 34% of individual learning types were predicted using just one question, a cumulative 76% were predicted using four questions, and the remaining 24% were predicted using more questions. All 100% of the predictions were possible with at most thirteen questions. However, the error rate increases to 25% when thirteen questions are used. This is due to the fact that after the maximum number of questions (*maxQuestions*) has been exhausted, predictions are made by approximate matching.

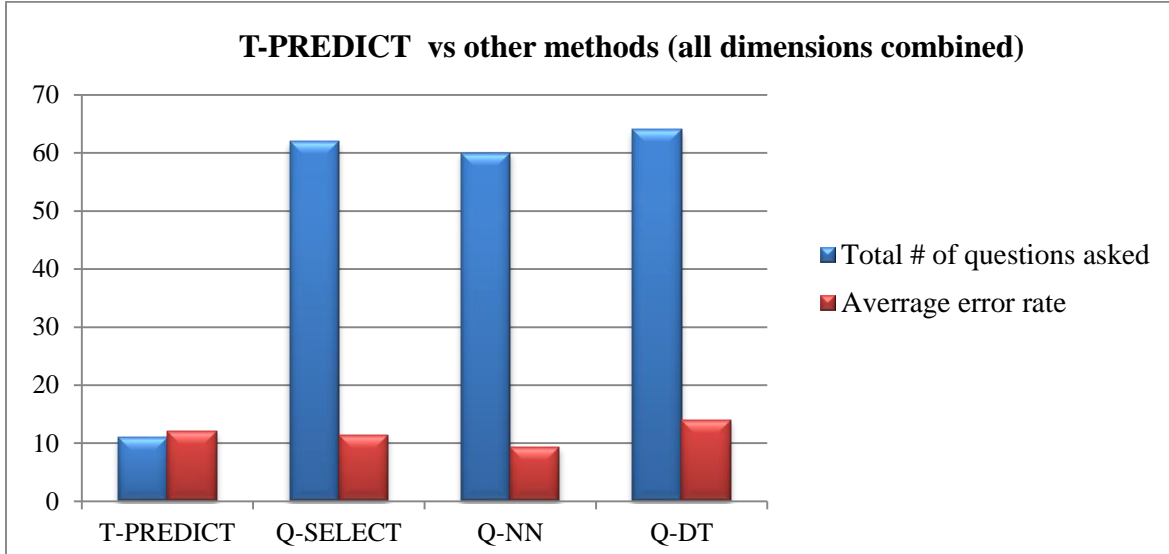


Figure 2.4: T-PREDICT vs other methods

Note that some questions, such as the second question in Table 2.2, did not generate any additional predictions. These are the questions where the two established criteria necessary to make a prediction, as set by the *prediction algorithm*, were not met.

Table 2.2 : Distribution of questions asked by T-PREDICT for the SN dimension

Number of questions asked $m$	Number of learning types predicted using $m$ questions (in %)	Error rate for predictions using $m$ questions	Cumulative percentage of learning types predicted using up to $m$ questions
1	313 (34%)	4.8%	34.0%
2	0 (0%)	-	34.0%
3	96 (10%)	5.2%	44.0%
4	298 (32%)	17.1%	76.0%
5	0 (0%)	-	76.0%
6	0 (0%)	-	76.0%
7	0 (0%)	-	76.0%
8	47 (5%)	14.9%	81.0%
9	0 (0%)	-	81.0%
10	0 (0%)	-	81.0%
11	0 (0%)	-	81.0%
12	0 (0%)	-	81.0%
13	0 (0%)	-	81.0%
13 (approx. match)	177 (19%)	25.0%	100.0%

## II.5.2 Influence of sorting and limiting number of questions

The following experiment assesses the influence of two optimizing strategies on error rate and median number of questions asked. These are (1) sorting questions by discriminative power and (2) limiting the maximum number of questions asked. *T-PREDICT* results were compared with a modified version that does not sort questions (*UT-PREDICT*). Moreover, the maximum number of questions asked (*MaxQuestions*) was varied from one to all questions.

Tables 2.3 to 2.6 and Fig. 2.5 to 2.8 show the obtained results. It can be observed that the median number of questions is higher and the error rate is much higher when the questions are unsorted. It can also be noticed that limiting the maximum number of questions gives better results. For example Table 2.3 and 2.4 show that asking a maximum of half questions in the SN and EI dimensions gave the lowest error rate.

Results from other dimensions are nearly the same. The reason for that latter observation is that as more questions are asked, the harder it is to find filled questionnaires that exactly matches a set of provided answers. Thus, questionnaires that cannot be predicted using few questions will likely not be predicted using more questions. And in those cases, the *maxQuestions* limit is eventually reached. If *maxQuestions* is set to a high value, everytime that the limit is reached, it will greatly contribute toward increasing the median number of questions asked. Similarly, questions that cannot be predicted using few questions are also not likely to be predicted with a high accuracy when the approximate matching is used (after the limit is reached). Thus, increasing *maxQuestions* above a certain value does not increase accuracy.

Table 2.3 : Influence of *MaxQuestions* and sorting questions by discriminative power on error rate and median number of questions asked for the EI dimension

Parameter <i>MaxQuestions</i>	Median number of questions ( <i>T-PREDICT</i> )	Average error rate ( <i>T-PREDICT</i> )	Median number of questions ( <i>UT-PREDICT</i> )	Average error rate ( <i>UT-PREDICT</i> )
1	1	19.6%	1	19.6%
2	2	21.6%	2	27.0%
3	2	15.5%	3	20.4%
4	2	15.4%	3	20.2%
5	2	13.7%	3	19.1%
6	2	13.3%	3	16.7%
7	2	12.3%	3	15.3%
8	2	11.7%	3	14.5%
9	2	11.7%	3	13.3%
10	2	11.6%	3	13.2%
<b>11</b>	<b>2</b>	<b>10.7%</b>	<b>3</b>	<b>13.6%</b>
12	2	11.1%	3	13.2%
13	2	11.4%	3	13.7%
14	2	11.8%	3	15.6%
15	2	10.8%	3	14.7%
16	2	11.5%	3	15.0%
17	2	11.5%	3	14.0%
18	2	11.4%	3	15.1%
19	2	11.2%	3	14.2%
20	2	11.8%	3	14.4%
21	2	15.1%	3	13.0%

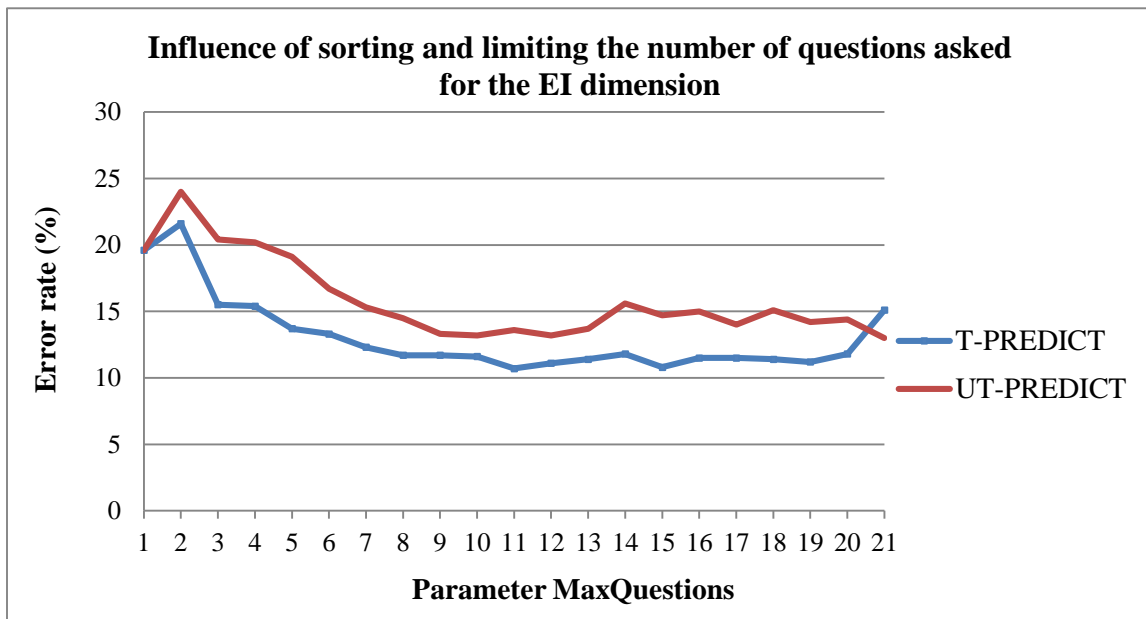


Figure 2.5: Influence of sorting and limiting the number of questions asked for the EI dimension

Table 2.4 : Influence of *MaxQuestions* and sorting questions by discriminative power on error rate and median number of questions asked for the SN dimension

Parameter <i>MaxQuestions</i>	Median number of questions ( <i>T-PREDICT</i> )	Average error rate ( <i>T-PREDICT</i> )	Median number of questions ( <i>UT-PREDICT</i> )	Average error rate ( <i>UT-PREDICT</i> )
1	1	32.8%	1	32.8%
2	2	32.8%	2	32.8%
3	3	18.1%	3	28.0%
4	4	18.1%	4	32.3%
5	4	15.4%	5	20.8%
6	4	18.4%	5	22.6%
7	4	16.3%	5	20.0%
8	4	14.7%	5	21.4%
9	4	14.5%	5	17.9%
10	4	15.0%	5	19.2%
11	4	14.0%	5	17.9%
12	4	13.7%	5	19.2%
<b>13</b>	<b>4</b>	<b>13.0%</b>	<b>5</b>	<b>17.8%</b>
14	4	13.9%	5	19.6%
15	4	13.4%	5	17.9%
16	4	14.7%	5	19.1%
17	4	14.1%	5	18.7%
18	4	14.7%	5	19.1%
19	4	14.2%	5	18.7%
20	4	15.0%	5	19.1%
21	4	14.4%	5	18.5%
22	4	15.1%	5	19.0%
23	4	14.8%	5	18.1%
24	4	15.3%	5	19.0%
25	4	15.1%	5	18.3%

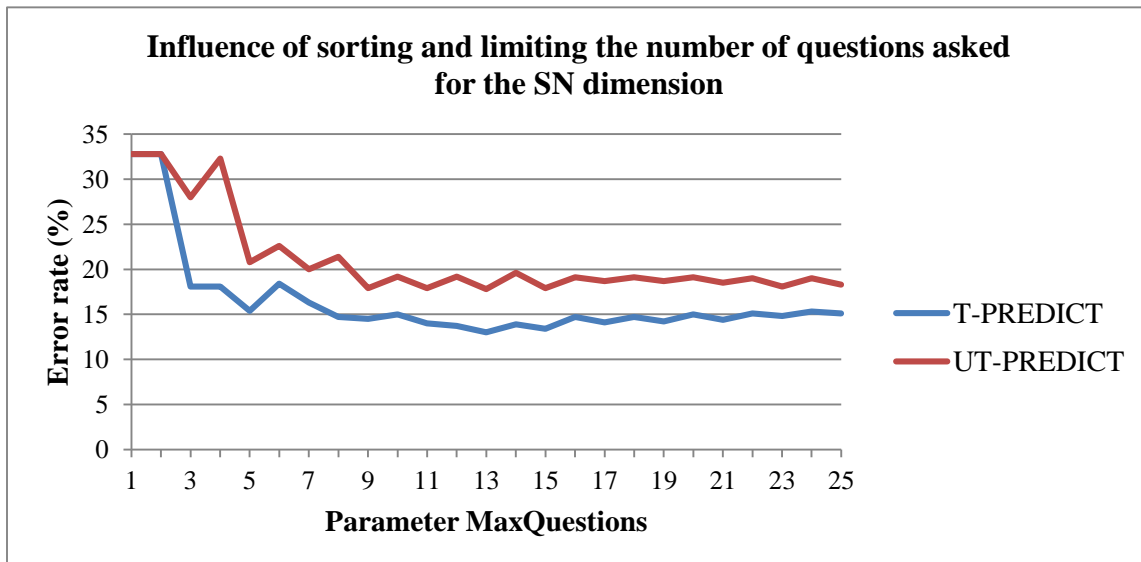


Figure 2.6: Influence of sorting and limiting the number of questions asked for the SN dimension

Table 2.5 : Influence of *MaxQuestions* and sorting questions by discriminative power on error rate and median number of questions asked for the TF dimension

Parameter <i>MaxQuestions</i>	Median number of questions ( <i>T-PREDICT</i> )	Average error rate ( <i>T-PREDICT</i> )	Median number of questions ( <i>UT-PREDICT</i> )	Average error rate ( <i>UT-PREDICT</i> )
1	1	28.1%	1	27.4%
2	2	23.7%	2	27.4%
3	2	20.2%	3	26.2%
4	2	18.6%	4	23.0%
5	2	17.6%	5	21.6%
6	2	17.4%	5	18.8%
7	2	16.4%	5	17.8%
8	2	16.2%	5	17.6%
9	2	14.7%	5	15.6%
10	2	14.8%	5	14.4%
11	2	13.2%	5	12.8%
<b>12</b>	<b>2</b>	<b>13.3%</b>	<b>5</b>	<b>13.4%</b>
13	2	13.3%	5	13.0%
14	2	11.6%	5	11.4%
15	2	11.8%	5	12.2%
16	2	11.1%	5	11.2%
17	2	10.7%	5	12.9%
18	2	10.8%	5	12.3%
19	2	11.8%	5	12.3%
20	2	11.1%	5	11.3%
21	2	11.1%	5	11.8%
22	2	11.1%	5	11.3%
23	2	10.3%	5	10.7%

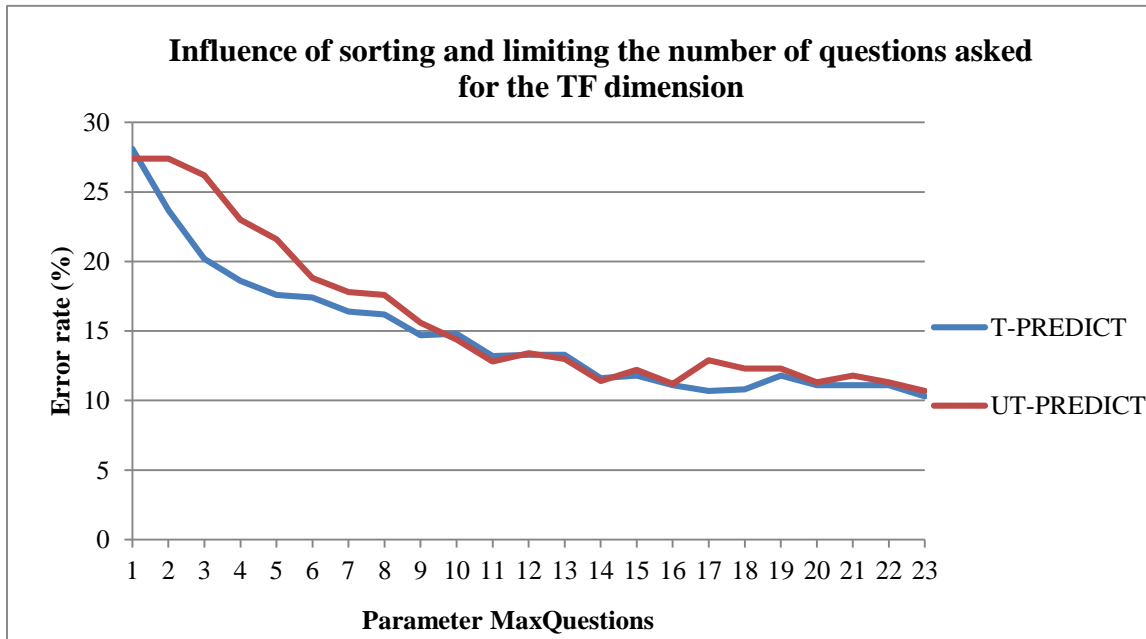


Figure 2.7: Influence of sorting and limiting the number of questions asked for the TF dimension

Table 2.6 : Influence of *MaxQuestions* and sorting questions by discriminative power on error rate and median number of questions asked for the JP dimension

Parameter	Median number of questions of questions ( <i>T-PREDICT</i> )	Average error rate ( <i>T-PREDICT</i> )	Median number of questions of questions ( <i>UT-PREDICT</i> )	Average error rate ( <i>UT-PREDICT</i> )
1	1	24.3%	1	24.8%
2	2	24.1%	2	23.6%
3	3	18.4%	3	22.8%
4	3	18.4%	4	22.6%
5	3	15.5%	4	21.4%
6	3	16.5%	4	17.8%
7	3	15.0%	4	20.1%
8	3	15.3%	4	18.6%
9	3	14.5%	4	16.7%
10	3	14.9%	4	16.9%
11	3	14.9%	4	16.9%
<b>12</b>	<b>3</b>	<b>15.1%</b>	<b>4</b>	<b>16.5%</b>
13	3	14.6%	4	16.0%
14	3	15.1%	4	16.1%
15	3	14.9%	4	15.9%
16	3	14.7%	4	15.2%
17	3	14.7%	4	14.8%
18	3	14.8%	4	15.5%
19	3	14.3%	4	15.8%
20	3	14.4%	4	16.1%
21	3	14.3%	4	15.2%
22	3	14.3%	4	15.2%
23	3	14.1%	4	15.1%

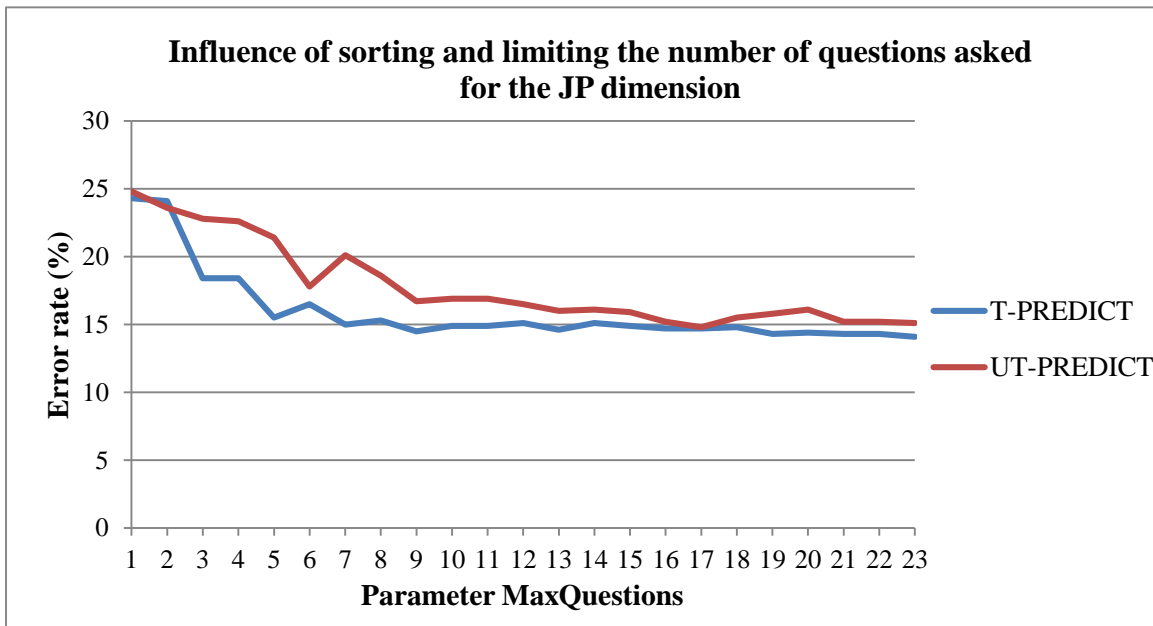


Figure 2.8: Influence of sorting and limiting the number of questions asked for the JP dimension



## II.6 Conclusion

Filling questionnaires for learning style assessment is a very time-consuming task, which might lead to abandoning the test, skipping questions, answering falsely, etc. To address this issue, various approaches have been proposed to reduce the size of questionnaires. In this paper, we have presented a novel dynamic electronic questionnaire *T-PREDICT* to further reduce the number of questions needed for learning type identification. It comprises three modules: a question sorting algorithm, a prediction algorithm and an automatic parameter selection algorithm.

Experimental results with 1,931 filled questionnaires for the Myers Briggs Type Indicators show that our novel approach asked a median of only 11 out of 92 questions to predict learning types, with an average error rate of 12.1%, while previous approaches *Q-SELECT* [33], *Q-NN* and *Q-DT* [16] asked between 60 and 64 questions to achieve error rates between 9.4% and 14%. Another defining characteristic of *T-PREDICT* is its ability to ask a variable number of questions, thus providing an automatic personalized questionnaire to each user, like *Q-SELECT* but unlike *Q-NN*, *Q-DT*, *PCA* and *IRT* that apply the same reduction to all users.

## CONCLUSION GENERALE

Cette thèse a exploré la possibilité de concevoir des questionnaires électroniques adaptatifs afin de pallier aux problèmes de l'utilisation de formulaires papiers. Un très grand nombre de questions peut démotiver les répondants et nécessite de recourir à un spécialiste pour analyser les réponses.

Les principales contributions de la thèse sont deux questionnaires adaptatifs conçus pour le questionnaire de Myers-Briggs. Ces questionnaires électroniques sont capables de (1) réduire le nombre de questions du formulaire de façon dynamique en fonction des réponses d'un répondant, et (2) de prédire le type psychologique instantanément, sans avoir recours à un spécialiste humain.

Le premier questionnaire électronique, Q-SELECT, emploie les règles d'association et les réseaux de neurones pour prédire les réponses aux questions et détecter de manière automatique les types psychologiques des répondants. Les résultats expérimentaux obtenus avec un jeu de données de 1,931 questionnaires remplis par des étudiants ont montré que Q-SELECT permet d'éliminer 30% des questions tout en prédisant les types psychologiques avec un taux d'erreur inférieur ou égal à 12%.

Le second questionnaire, nommé T-PREDICT introduit l'idée que les questions n'ont pas toutes la même importance ou efficacité. Il entreprend de mesurer la capacité de chaque question à différencier les types psychologiques pour ainsi les réordonner et tenter de prédire le type de chaque apprenant en utilisant le moins de questions possible. L'expérimentation montre que T-PREDICT pose en moyenne 81% moins de questions que Q-SELECT tout en offrant un taux d'erreur similaire.

Bien que Q-SELECT et T-PREDICT aient été validés avec le questionnaire MBTI, ils ont été conçus pour être génériques. Ils pourraient donc être appliqués à d'autres questionnaires à choix multiples où les classes d'un répondant sont représentées par des symboles. Pour des travaux futurs, il serait intéressant d'appliquer Q-SELECT et T-PREDICT à d'autres questionnaires d'évaluation de styles d'apprentissage ou à des questionnaires d'autres domaines pour en évaluer la performance. Finalement, une seconde perspective de recherche est d'étendre le travail pour prédire et

établir des cotes numériques afin d'indiquer le degré d'appartenance d'un répondant aux classes. Ceci serait une amélioration intéressante et utile. Par exemple, cela donnerait une prédiction plus précise pour la méthode MBTI qui associe en pratique une note numérique pour désigner le taux d'appartenance des individus aux types psychologiques.

## **ANNEXE 1 – Le questionnaire MBTI**

Le questionnaire comprend 126 questions, dont seulement 92 sont utilisées par les experts pour l'identification du type psychologique selon Myers-Briggs.

PREMIÈRE PARTIE : Quelle réponse décrit le mieux votre façon habituelle d'agir ou de vous sentir ?

1. Quand vous allez quelque part pour toute la journée, préférez-vous
  - (a) planifier ce que vous allez faire et quand vous allez le faire, ou bien
  - (b) simplement y aller ?
2. Si vous étiez professeur, préféreriez-vous enseigner
  - (a) des cours pratiques ou
  - (b) des cours qui comportent de la théorie ?
3. Êtes-vous d'habitude
  - (a) une personne qui se mêle facilement aux autres, ou
  - (b) une personne plutôt tranquille et réservée ?
4. Préférez-vous
  - (a) organiser vos sorties et vos rendez-vous longtemps à l'avance, ou
  - (b) décider sur le moment ce qui semble le plus amusant à faire ?
5. D'habitude vous entendez-vous mieux
  - (a) avec des personnes qui ont beaucoup d'imagination, ou
  - (b) avec des personnes réalistes ?
6. De façon générale, laissez-vous
  - (a) votre cœur contrôler votre tête, ou
  - (b) votre tête contrôler votre cœur ?
7. Lorsque vous êtes dans un groupe préférez-vous plutôt
  - (a) prendre part à la conversation du groupe, ou

- (b) parler avec une seule personne à la fois ?
8. Réussissez-vous mieux
- (a) lorsque vous devez faire face à des imprévus et décider rapidement ce qui doit être fait, ou
  - (b) lorsque vous avez à suivre un programme soigneusement mis au point ?
9. Préférez-vous être considérée
- (a) comme une personne pratique, ou plutôt
  - (b) comme une personne ingénieuse ?
10. Dans un groupe composé de nombreuses personnes, généralement
- (a) présentez-vous les autres, ou
  - (b) vous faites-vous présenter ?
11. Admirez-vous davantage les personnes
- (a) qui sont conventionnelles au point de ne jamais se faire remarquer, ou
  - (b) qui sont originales et individualistes au point de ne pas se préoccuper de savoir si elles sont remarquées ou non ?
12. Vous conformer à un horaire
- (a) vous tente-t-il, ou
  - (b) vous gêne-t-il ?
13. Êtes-vous porté(e)
- (a) à des amitiés profondes avec quelques personnes seulement, ou
  - (b) à des amitiés superficielles avec un grand nombre de personnes différentes ?
14. L'idée de dresser une liste de ce que vous devez faire pendant le weekend
- (a) vous plaît-elle
  - (b) vous laisse-t-elle indifférent(e)
  - (c) vous déprime-t-elle complètement ?

15. Est-ce un plus grand compliment de dire d'une personne
- (a) qu'elle a des sentiments sincères, ou
  - (b) qu'elle est toujours raisonnable ?
16. Dans votre groupe d'amis
- (a) êtes-vous une des dernières personnes à savoir ce qui se passe, ou
  - (b) êtes-vous très bien renseignée sur tout le monde ?

(Pour la question suivante seulement, si deux réponses sont vraies, marquez les deux)

17. Dans votre travail de tous les jours,
- (a) préférez-vous les imprévus qui vous forcent à travailler contre la montre, ou
  - (b) détestez-vous travailler sous pression, ou
  - (c) d'habitude vous tracez-vous un plan de façon à n'avoir pas besoin de travailler sous pression ?
18. Préférez-vous avoir pour amie
- (a) une personne qui a toujours de nouvelles idées, ou
  - (b) une personne qui a les deux pieds sur terre ?
19. Dans vos conversations,
- (a) parlez-vous facilement avec presque n'importe qui aussi longtemps que nécessaire, ou
  - (b) trouvez-vous beaucoup de choses à dire seulement à certaines personnes et dans certaines conditions ?
20. Lorsque vous avez un travail spécial à faire, préférez-vous
- (a) l'organiser soigneusement avant de le commencer, ou
  - (b) découvrir ce qui est nécessaire au fur et à mesure ?
21. Avez-vous tendance à
- (a) donner plus d'importance au cœur qu'à la raison, ou

- (b) donner plus d'importance à la raison qu'au cœur ?
22. Lorsque vous lisez par plaisir,
- (a) aimez-vous les façons originales ou différentes de dire les choses, ou
- (b) préférez-vous que l'auteur exprime ce qu'il pense avec précision ?
23. Est-ce que les personnes que vous rencontrez pour la première fois peuvent dire quels sont vos intérêts
- (a) immédiatement, ou
- (b) seulement une fois qu'elles vous connaissent bien ?
24. Lorsqu'il est prévu à l'avance que vous feriez telle chose à telle heure, trouvez-vous
- (a) agréable d'avoir ainsi l'occasion de vous préparer, ou
- (b) un peu désagréable d'y être tenu ?
25. Quand vous faites quelque chose que d'autres personnes font couramment, préférez-vous
- (a) le faire de la façon ordinaire, ou
- (b) inventer une nouvelle manière de le faire ?
26. D'habitude
- (a) exprimez-vous vos sentiments ouvertement, ou
- (b) gardez-vous vos sentiments pour vous-même ?

DEUXIÈME PARTIE : Lequel des deux mots de chaque paire vous attire le plus ?  
Pensez à ce que le mot signifie, non pas à l'écriture ou au son.

27. (a) organisé imprévu (b)
28. (a) doux(ce) ferme (b)
29. (a) faits idées (b)
30. (a) pensées sentiments (b)
31. (a) empressé(e) tranquille (b)

32. (a) convaincant(e) touchante (b)
33. (a) déclaration concept (b)
34. (a) analyser compatir (b)
35. (a) systématiques spontané (b)
36. (a) justice pitié (b)
37. (a) réservé(e) bavard(e) (b)
38. (a) compassion prévoyance (b)
39. (a) systématique accidentel (b)
40. (a) calme vif(ve) (b)
41. (a) profits bienfaits (b)
42. (a) théorie certitude (b)
43. (a) décidé(e) dévoué(e) (b)
44. (a) littéral figuratif (b)
45. (a) ferme chaleureux(se) (b)
46. (a) imaginatif(ve) pratique (b)
47. (a) médiateur(trice) juge (b)
48. (a) faire créer (b)
49. (a) mou dur (b)
50. (a) sensée fascinant (b)
51. (a) pardonner tolérer (b)
52. (a) production conception (b)
53. (a) impulsion décision (b)
54. (a) qui quoi (b)
55. (a) parler écrire (b)
56. (a) permissif(ve) critique (b)



57. (a) ponctuel(le) à loisir (b)
58. (a) concret(e) abstrait(e) (b)
59. (a) changeant(e) permanent(e) (b)
60. (a) méfiant(e) confiant(e) (b)
61. (a) construire inventer (b)
62. (a) méthodique nonchalant(e) (b)
63. (a) fondation tour (b)
64. (a) rapide minutieux(se) (b)
65. (a) théorie expérience (b)
66. (a) sociable détaché(e) (b)
67. (a) signe symbole (b)
68. (a) «party» théâtre (b)
69. (a) accepter changer (b)
70. (a) être d'accord discuter (b)
71. (a) connu inconnu (b)

TROISIÈME PARTIE : Quelle réponse décrit le mieux votre façon habituelle d'agir ou de vous sentir ?

72. Pensez-vous que

- (a) vous êtes plus enthousiaste que la moyenne des gens, ou
- (b) que vous montrez moins d'enthousiasme pour les choses que la moyenne des gens ?

73. Pensez-vous que c'est un défaut plus grave

- (a) d'être froid, ou
- (b) de ne pas être raisonnable ?

74. Est-ce que

- (a) vous préférez faire les choses à la dernière minute, ou
  - (b) trouvez-vous que faire les choses à la dernière minute vous tape sur les nerfs ?
75. Dans les rencontres sociales
- (a) vous arrive-t-il de vous ennuyer, ou
  - (b) vous amusez-vous toujours ?
76. Pensez-vous qu'une routine quotidienne est
- (a) agréable, ou
  - (b) pénible même si nécessaire ?
77. Lorsque quelque chose devient à la mode
- (a) êtes-vous une des premières personnes à l'essayer, ou
  - (b) est-ce que cela vous intéresse peu ?
78. Lorsque vous pensez à une petite chose que vous devez faire ou acheter, est-ce que
- (a) vous l'oubliez pour un certain temps
  - (b) d'habitude vous le mettez sur papier pour vous le rappeler, ou
  - (c) vous la faites toujours sans avoir besoin d'aide-mémoire ?
79. Êtes-vous
- (a) facile à vous faire connaître, ou
  - (b) difficile à vous faire connaître ?
80. Dans votre style de vie, préférez-vous être
- (a) original(e), ou
  - (b) traditionnel(le) ?
81. Lorsque vous vous sentez gêné(e),
- (a) changez-vous la conversation, ou
  - (b) tournez-vous ça en blague, ou

- (c) quelques jours plus tard, pensez-vous à ce que vous auriez dû dire ?
82. Éprouvez-vous davantage de difficultés à vous adapter
- (a) à la routine, ou
- (b) aux changements continuels ?
83. Considérez-vous que c'est un plus grand compliment de dire à une personne
- (a) qu'elle est perspicace, ou
- (b) qu'elle a du bon sens ?
84. Lorsque vous commencez un travail important qui doit être remis dans une semaine,
- (a) prenez-vous le temps de planifier par écrit ce qui est à faire, ou
- (b) vous adonnez-vous à la tâche immédiatement ?
85. Pensez-vous qu'il est plus important d'être capable
- (a) de voir toutes les possibilités dans une situation, ou
- (b) de s'adapter aux faits tels qu'ils se présentent ?
86. Pensez-vous que les gens de votre entourage connaissent vos sentiments
- (a) envers à peu près tout, ou
- (b) seulement si vous avez une raison spéciale de les communiquer ?
87. Préférez-vous travailler pour une personne
- (a) toujours gentille, ou
- (b) toujours juste ?
88. Pour mener un travail à bonne fin, êtes-vous porté(e)
- (a) à commencer trop tôt, de façon à finir avant le temps, ou
- (b) à compter sur un effort de dernière minute ?
89. Pensez-vous que c'est un plus grand défaut
- (a) de montrer trop de zèle, ou

- (b) de ne pas en manifester assez ?
90. Quand vous êtes à un «party », aimez-vous
- (a) animer le groupe, ou
- (b) laisser les autres s'amuser à leur façon ?
91. Avez-vous tendance à
- (a) accepter les façons traditionnelles de faire, ou
- (b) analyser ce qui ne va pas et vous attaquer aux problèmes encore non résolus ?
92. Portez-vous plus d'attention
- (a) aux sentiments des autres, ou
- (b) à leurs droits ?
93. Si on vous demandait un samedi matin comment vous avez l'intention d'occuper votre journée,
- (a) seriez-vous capable de le dire avec précision, ou
- (b) donneriez-vous une liste deux fois trop longue, ou
- (c) adopteriez-vous une attitude d'attente ?
94. Face à une décision importante,
- (a) trouvez-vous que vous pouvez vous fier à vos sentiments sur ce qui est le mieux à faire, ou
- (b) croyez-vous que vous devez faire ce qui est logique, quels que soient vos sentiments ?
95. Trouvez-vous les moments les plus routiniers de votre journée
- (a) reposants, ou
- (b) ennuyeux ?
96. Est-ce que l'importance que vous donnez à bien réussir un test fait qu'il est
- (a) plus facile pour vous de vous concentrer et de faire de votre mieux, ou

(b) plus difficile pour vous de vous concentrer et de rendre justice à vos habiletés ?

97. Êtes-vous

(a) enclin à aimer prendre des décisions, ou

(b) tout aussi heureux que les circonstances décident à votre place ?

98. Quand vous écoutez une idée nouvelle, êtes-vous plus préoccupé(e)

(a) de vous renseigner le plus possible sur cette idée, ou

(b) de juger si elle est juste ou fausse ?

99. Devant les imprévus de tous les jours, préférez-vous

(a) recevoir des ordres et vous rendre utile, ou

(b) donner des ordres et prendre des responsabilités ?

100. Après une rencontre avec des personnes superstitieuses,

(a) vous êtes-vous trouvé(e) légèrement influencé(e) par leurs superstitions,  
ou

(b) y êtes-vous demeuré(e) insensible ?

101. Êtes-vous plus porté(e) à faire

(a) des éloges, ou

(b) des reproches ?

102. Quand vous devez prendre une décision, d'habitude

(a) la prenez-vous tout de suite, ou

(b) attendez-vous le plus longtemps possible avant de décider ?

103. Au moment de votre vie où les problèmes se sont accumulés autour de vous, aviez-vous l'impression

(a) que vous étiez mis dans une situation impossible, ou

(b) qu'en faisant seulement le nécessaire, vous pourriez vous tirer d'affaire ?

104. De toutes les bonnes résolutions que vous avez pu prendre, y en a-t-il

- (a) que vous avec tenues jusqu'à présent, ou
  - (b) aucune qui n'ait vraiment duré ?
105. Au moment de résoudre un problème personnel,
- (a) vous sentez-vous plus confiant si vous avez demandé l'opinion des autres, ou
  - (b) pensez-vous que personne d'autre ne soit dans une meilleure position que vous pour juger ?
106. Lorsqu'une nouvelle situation se présente qui entre en conflit avec vos projets, essayez-vous en premier lieu
- (a) de changer vos projets pour vous adapter à la situation, ou
  - (b) de changer la situation pour l'adapter à vos projets ?
107. Les «hauts et les bas » émotionnels que vous pouvez ressentir sont-ils
- (a) très prononcés, ou
  - (b) plutôt modérés ?
108. Dans vos croyances personnelles,
- (a) tenez-vous à des choses qui ne peuvent pas être prouvées, ou
  - (b) croyez-vous seulement aux choses qui peuvent être prouvées ?
109. Chez vous, lorsque vous avez terminé une tâche,
- (a) voyez-vous clairement ce qui doit être fait par la suite, et vous sentez-vous prêt(e) à le faire, ou
  - (b) vous contentez-vous de vous détendre jusqu'à ce qu'une nouvelle inspiration vous vienne ?
110. Lorsqu'une occasion se présente,
- (a) vous décidez-vous assez rapidement, ou
  - (b) la manquez-vous parfois pour avoir mis trop de temps à vous décider ?
111. Si une panne ou un mélange force l'arrêt du travail dans lequel vous et plusieurs autres personnes sont engagées, votre première réaction serait de

- (a) profiter de l'interruption pour vous reposer, ou
  - (b) chercher quelle partie du travail vous pourriez poursuivre, ou
  - (c) vous joindre à ceux qui s'efforcent de résoudre les difficultés ?
112. Quand vous n'êtes pas d'accord avec ce qui vient d'être dit, d'habitude
- (a) vous le laissez passer, ou
  - (b) vous commencez une discussion ?
113. Sur la plupart des sujets
- (a) avez-vous une opinion bien définie, ou
  - (b) aimez-vous être sans parti pris ?
114. Préférez-vous avoir
- (a) une occasion qui pourrait aboutir à des grandes choses, ou
  - (b) une expérience que vous êtes sûr d'aimer ?
115. Dans votre vie, êtes-vous porté(e)
- (a) à entreprendre trop et à vous trouver dans une situation difficile, ou
  - (b) à vous limiter à ce que vous pouvez faire facilement ?
116. Qu'est-ce qui vous satisfait le plus en jouant aux cartes
- (a) la compagnie, ou
  - (b) le plaisir de gagner, ou
  - (c) le défi d'un gain maximum à chaque tour
  - (d) ou bien vous n'aimez pas jouer aux cartes ?
117. Quand la vérité n'est pas polie, êtes-vous plus portée à
- (a) mentir par politesse, ou
  - (b) dire la vérité même si elle n'est pas polie ?
118. Laquelle de ces deux raisons serait plus convaincante si vous aviez à accepter une charge de travail supplémentaire

- (a) pouvoir obtenir plus de confort et de luxe, ou
  - (b) avoir l'occasion d'accomplir quelque chose d'important ?
119. Lorsque vous n'approuvez pas de la conduite d'un(e) ami(e), est-ce que
- (a) vous attendez pour voir ce qui se passera, ou
  - (b) vous faites ou vous dites quelque chose à ce sujet ?
120. D'après votre expérience,
- (a) d'habitude, vous enthousiasmez-vous souvent avec une idée ou un projet qui plus tard devient une déception de sorte que votre enthousiasme monte en flèche pour retomber de plus belle, ou
  - (b) conservez-vous un jugement équilibré au milieu de votre enthousiasme de façon à ne pas vous sentir déçu(e) ?
121. Lorsque vous devez prendre une décision, est-ce que
- (a) vous arrivez presque toujours à une décision claire et nette, ou
  - (b) parfois il est tellement difficile de prendre une décision que vous ne suivez aucun choix avec enthousiasme ?
122. D'habitude
- (a) profitez-vous le plus possible du moment présent, ou
  - (b) avez-vous l'impression que le moment suivant est plus important ?
123. Quand vous travaillez en groupe, êtes-vous plus impressionné(e)
- (a) par la coopération, ou
  - (b) par l'inefficacité
  - (c) ou bien vous ne participez pas à des actions de groupe ?
124. Quand vous rencontrez une difficulté inattendue dans quelque chose que vous êtes en train de faire, avez-vous l'impression qu'il s'agit
- (a) d'un coup de malchance, ou
  - (b) d'un embêtement, ou
  - (c) d'une partie du travail comme une autre ?



125. Quelle erreur serait plus acceptable pour vous
- (a) vous laisser aller d'une chose à l'autre toute votre vie, ou
  - (b) vous figer dans une routine qui ne vous convient pas ?
126. Auriez-vous aimé discuter le sens
- (a) d'un grand nombre de ces questions, ou
  - (b) de quelques-unes seulement ?

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