Using an Expert System to Automatically Map the Learning Profile of Individuals

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***Abstract*—This paper presents a new integrated, web-based system for assessing the learning aptitudes, the learning styles, and the potential of the brain hemispheres of individuals. Specially designed psychometric questionnaires are adopted and a new battery of tests – that is, a combination of factors – is proposed. The analysis of the factors is carried out by the Ariston expert system shell, and statistical data is presented regarding the reliability–validity of the system.**

Keywords–learning styles; aptitudes; personality; psychometric testing; expert systems

I. INTRODUCTION

The higher education environment presents several challenges for students who are frequently faced with the task of taking decisions that affect directly their academic progress, and ultimately their career prospects. For successful academic decisions, a student must consider carefully several different matters, investigate all possible alternatives (e.g., the electives), think analytically, and above all, apply logic of the form "What-if…". The environment itself poses several demands regarding learning, while frequently the students are disappointed because it becomes rather difficult for them to understand the reasons they cannot master certain concepts, and generally why they fail.

One of the most demanding tasks is that of acquiring new knowledge while mastering new concepts and solving problems. This process raises several issues related to the duration of learning, the degree to which the student can actually master new concepts, and of course the degree to which the student is content and happy with the progress made [1].

In order to study alternative modes of learning, we frequently theorise on the way people a) understand things, b) acquire experience, and c) realise the world around them [2]. In all cases, we have to distinguish between "Learning that…", which is related to knowledge itself, and "Learning how…", which is related to knowledge through practical experience, or platforms and modes of learning. In both cases, learning is influenced by well-defined categories of factors, including the following:

a) The degree to which the personality of the person – measured on the Holland scale [3] – matches with the academic course–subjects being studied, and ultimately the career planned. The personality is analysed under six types: Realistic, Investigative, Artistic, Social, Enterprising, Convention. The scores of these types are compared and matched with the requirements (scores) of professions from a large database.

b) The learning styles of the person (e.g., auditory, visual, kinaesthetic, etc.) [4].

c) The way the teacher / professor treats the individual, and generally the way the course material is presented to the learner [5].

d) The background knowledge of the learner, given that a person can learn practically, independently of academic environments.

The research results and findings we see in the literature [4][5][6] cover partially and in isolation aspects of the problem of learning, discussing individual factors without offering an integrated approach that will help a student discover the actual causes of problems with learning and then take remedy action. Also, most of the tests and questionnaires available are based on the so called "norms", whereby the measurements of a person are compared with those from a selected sample, underestimating the person's standards and potential. In other words, we claim that the use of only the norm scores is not adequate, and can sometimes do injustice to those learners with special talents and personality traits that are on the borderlines of the norms. Besides, there isn't any tool available for use by the students themselves who need to know: a) the reasons of their poor academic performance, and b) ways and modes of studying that can improve their rate of learning.

This paper addresses this issue, and proposes a web-based system that adopts a complete set of psychometric factors that measure: a) the learning aptitudes and difficulties, b) the learning styles, and c) the potential of learning of the brain hemispheres of an individual. Besides, the web-based system [7] provides a universal centralised database that enables the dynamic assessment of all students–newcomers being tested. Evidently, a desk-top application cannot provide universal, dynamic norms. The learning profile is created without any human intervention, offering in effect a "map" with detailed measurements

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regarding learning factors. Although we refer to “Students”, our research results are equally applicable to everyone, regardless of whether they are students or working adults.

The academic–school environment is often the setting where the learning disabilities of a person first become apparent. We usually notice problems in one or more of the following basic areas: Mathematics, Language, Cognitive development, Short- and Long-term Memory, Attention, Concentration, Organization, and Fine Motor Skills, where a difficulty is otherwise known as dyspraxia or kinaesthetic. Generally speaking, a person with learning difficulties faces problems in a) identifying, b) collecting, c) organizing, d) manipulating, and e) acting on verbal or non-verbal information. These problem areas are directly related to the learning aptitudes of an individual and must therefore be translated to their equivalent psychometric factors, as we explain later.

Evidently [1][2], a person learns and gains knowledge or skill through action, study, schooling, experience, education, training, and generally, by processing data and information selected by their basic senses (sight, smell, taste, touch, and hearing). A learning difficulty, regardless of its cause or nature, does not indicate subnormal intelligence, but rather a learning environment that is not suitable for the person under investigation. This means that individuals must be compensated for, with special tutoring and a learning environment that is in congruence with their personality traits. Our aim here is to discover how a person learns best, that is, the modes under which the person gains maximum knowledge or skill. The modes we adopted following extensive investigations on their reliability are: a) Auditory, utilising the sound, b) Visual, utilising vision, c) Linguistic, utilising the written word, d) Kinaesthetic, utilising movement, touching, e) Interpersonal, utilising interpersonal relationships, and f) Intrapersonal, showing a preference to study alone and to think independently.

Finally, we cannot ignore the physiology of the human brain with its two hemispheres, each one specialising in specific functions and services, utilising its own sensors and information processors. It appears that each hemisphere prefers to deal with certain activities and cerebral functions, performing the best it can. We adopted well-formed items that measure the “laterality”, that is, the degree to which a hemisphere is developed in relation to the other – in other words, the potential of each hemisphere. This enables us to gain insight on whether a person learns best using top-down or bottom-up techniques [5][6].

Through specially designed and normalised psychometric questionnaires, we have managed to diagnose inherent and acquired traits of learning, with the ultimate objective to help the learner adopt effective modes and means of learning, that is, to learn how to learn. At the same time, the findings help the teacher adopt the best approaches to impart new knowledge.

For practical applications, experimentation and measurement of the reliability–validity of our approach, we used the Ariston shell [8], which is an expert system for multifactorial analysis of psychometric data. The knowledge contained in the expert database is classified by age, sex, nationality, academic departments, occupations and specializations, aptitudes, abilities, and several other psychometric data regarding thousands of young people and working adults. We selected and tested 7 factors with 49 items for learning aptitudes–difficulties, 6 factors with 76 items for learning styles, 2 factors with 21 items for both brain hemispheres, and 4 factors with special algorithms that measure the degree of sincerity in the answers of the person being tested, computing an overall truth score. One of the reasons these 4 factors are not included in the report is that they are not really useful to the teacher. They are used by the expert system to measure the various levels of sincerely in the answers and take appropriate action (e.g., to recommend re-sit of the test).

This paper presents research work carried out during the last two years. Section II begins with the assessment of learning aptitudes–difficulties, Section III continues with learning styles, and Section IV analyses the potential of brain hemispheres. Section V presents an overview of a real-example profile, and Section VI concludes with evaluation results regarding the reliability–validity of our battery, and directions for future research.

II. LEARNING APTITUDES–DIFFICULTIES

Our approach adopts state-of-the-art theory for testing cognitive abilities using spatial and diagrammatic reasoning, beyond the Cattell-Horn-Carroll theory of cognitive abilities [9] and the Wechsler scales [10], which evolve around the traditional approach that includes language and mathematical knowledge. Our approach utilises those realms of thought where the person appears to have learning difficulties and problems in assimilating new information beyond previous experience and reasoning [11]. By assessing the ability to quickly understand and assimilate new information, we can predict how responsive to education and training the person will be.

Well-established approaches to item design were adopted in order to assess specific areas of learning. The questionnaires consist of items that require the recognition of patterns and similarities between shapes and figures, the inference of rules from given sequences (e.g., diagrams, symbols, etc.), the application of rules to new situations, and reasoning from given data and information. Figure 1 presents a typical question where the learner is expected to select the shape from the second row that is assembled from the partial images of the first row.

The Factors Tested and Adopted

The factors we have tested and adopted were first introduced by Yannakoudakis [11], and are independent of attainment. They can also be used to provide an indication of intellectual potential.

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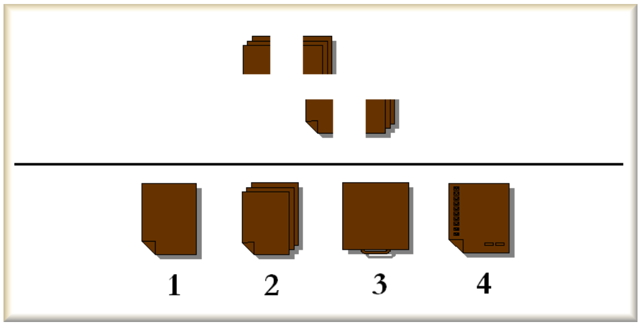

Figure 1. Learning aptitudes: Example item.

1) Matching concepts: This factor assesses aptitude to match elements, look for common attributes amongst given sets, and identify similarities. A high score implies that the person is in a position to spot identical elements, avoid "re-invention of the wheel", match similar concepts, and recall successfully from memory as and when necessary.

2) Composing concepts: This factor investigates aptitude to analyse incorrectly-ordered or isolated elements of knowledge, put these in the correct order, identify common attributes, and synthesise supersets of concepts or objects. A high score implies that the person is in a position to examine elements of knowledge (individually, as well as in union), evaluate these, and synthesise new hyper-sets of elements or objects.

3) Understanding intersection: This factor assesses aptitude to compare sets of elements and identify those elements that form the intersection between them (i.e., the elements that are common among the given sets). A high score implies that the person is in a position to detect overlap amongst concepts, isolate common elements, count elements with common attributes, and ignore non-homogeneous elements.

4) Reconstructing concepts: This factor assesses aptitude to analyse incomplete data and information, in order to reconstruct objects and concepts. A high score implies that the person is in a position to utilise partial knowledge and come to logical conclusions, integrate knowledge, fill gaps, reconstruct mutilated objects or concepts, and guess correctly.

5) Understanding rules: This factor assesses aptitude to detect the rules and regulations that govern the formation of logical sequences that bind objects or concepts together. A high score implies that the person is in a position to analyse the data given and identify logical structures and "if…then…else…" constructs, forecast the next step successfully, apply the rules to new situations, and come to logical conclusions using a stochastic approach to reasoning.

6) Understanding subsets: This factor assesses aptitude to compare sets of elements given, and identify subsets. A high score implies that the person is in a position to compare sets on the basis of their cardinality and features, count homogeneous elements, identify narrow terms, separate narrow terms from broad terms, and generally understand well the concept of "*A* is included in *B*".

7) Identifying analogies: This factor assesses aptitude to analyse a given state of objects or concepts, and determine whether there is an analogy between them. A high score implies that the person is in a position to identify and process analogies, explain how we can go from one concept to another, process functions, and generally compare and contrast elements of the information available.

An overall high score indicates that the learner has the ability to grasp new ideas and assimilate new information, has responsiveness to training, and a high level of natural ability. A low score indicates that the learner has difficulty in grasping new ideas, and needs more time to solve problems consisting of unfamiliar concepts, new procedures or tasks.

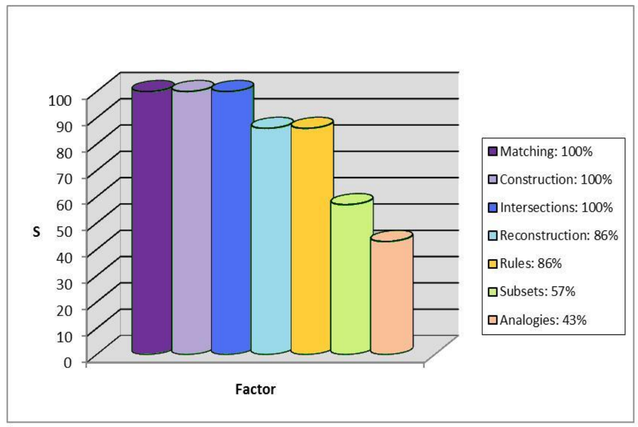

Figure 2. A real example with learning aptitudes, where "S" represents the score, and "Factor" the factor tested.

Figure 2 presents a real example. Here, we can see the results of an individual that experiences serious problems with analogies and subsets. The teacher can then take action to help the person improve low-score factors by giving appropriate exercises and realistic examples that cover each domain of knowledge.

III. LEARNING STYLES

The aim here is to investigate the distribution of well-established learning styles, that is, modes under which the person gains knowledge or skill. Each mode is related to a corresponding type of emotional intelligence [4], which affects directly the rate of learning of a person. Note that some learning styles remain stable throughout the life of a person (Auditory, Visual, Linguistic), while others can change with time (Kinaesthetic, Interpersonal, Intrapersonal). In any case, the longer a person is left with a learning disability, the more difficult it becomes to train them to alternative methods of knowledge acquisition. Moreover, the longer a person remains under an unsuitable learning environment, the slower his rate of learning will be, even after special tutoring [2][4].

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The Factors Tested and Adopted

1) Auditory: This type assesses ability to learn by utilising auditory information, including lectures, speeches, tape recordings, etc. Auditory learners like singing, whistling, making rhythmic sounds by tapping their fingers or legs, playing musical instruments, and listening to music. They are also good at distinguishing sounds and rhythms in music, remembering melodies, and listening with their "inner ear". Their rate of learning increases when speaking rhythmically or turning speech into lyrics.

2) Visual: This type assesses ability to learn utilising visual information, including images, diagrams, drawings, transparencies, moving pictures, etc. Visual learners like modelling, drawing, painting, imagining, dreaming, making notes, and building things. They are good at imagining, finding their way, reading maps, and remembering things from images. They are motivated by visiting art galleries, museums, cinemas and theatres. Finally, they express themselves through drawings, paintings and constructions generally.

3) Linguistic: This type assesses ability to learn utilising linguistic data and information, including the written word, relationships between concepts, summarisation of texts, conclusions from texts, etc. Linguistic learners like talking, reading, writing, spelling, listening to and telling stories, playing word games, and having conversations. They are good at remembering names, places, dates and everyday things. They are motivated by visits to libraries, meeting writers, and the experience of words in theatre and music. Finally, they express themselves through discussions, interviews, and the written word generally.

4) Kinaesthetic: This type assesses ability to learn utilising kinaesthetic information, including touch, movement, personal experience, experimentation, etc. It also assesses ability for scientific exploration by various means and instruments. Kinaesthetic learners like moving, running, jumping, constructing, gesturing, dancing, and touching things. They are good at sports, dancing, acting, and making things with their hands. Finally, they express themselves through their body, action, repetition, and making things with their hands.

5) Interpersonal: This type assesses ability to learn through interpersonal relationships, socialisation, exchange of ideas, parties, etc. Interpersonal learners like testing themselves and their thoughts in relation to others, having many friends, and being part of a community. They are good at organising and playing a leading role, mediating between people, and playing the role of a referee. They are motivated by taking part in social meetings, parties, festivals, and artistic events. In general, they express themselves by participating in social groups.

6) Intrapersonal: This type assesses ability to learn in isolation, including studying alone, thinking and acting independently. Intrapersonal learners prefer to retrieve information from their own sources, having total control of the learning environment, selecting the books that suit them, concentrating on the subject they choose at a time, and so on. They like setting their own goals, dreaming, planning and relaxing. They are good at working alone at their own pace, they are persistent, and they follow their intuition. They need diaries and planning, keeping notes, but above all, they need privacy while studying. Finally, they express themselves through uniqueness and authenticity.

Figure 3 presents a real example of a learner who experiences problems when studying alone, and is also not keen to learn by reading books and notes. Instead, this particular person learns effectively by talking to others, having others commenting on their solutions, and so on. This person also learns best through kinaesthetic processes.

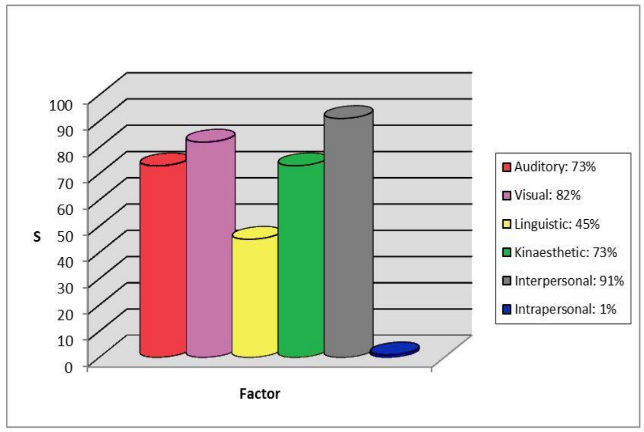

Figure 3. A real example with learning styles, where "S" represents the score, and "Factor" the factor tested.

An example question is presented below:

Which of the following would you readily choose?
1. To act as a referee for a match
2. To act as a score keeper for a match

IV. POTENTIAL OF BRAIN HEMISPHERES

The left hemisphere is specialised in the linear processing of data and information, and in the analysis of data, placing emphasis on the detection of the constituent parts rather than the whole. For example, an individual with a developed left hemisphere first notices the details in a picture and then the whole. Thus, the individual recognises the partial objects of a puzzle first, and then proceeds to the synthesis of the picture. The individual therefore learns more easily in a classroom where knowledge is communicated beginning from the detail and ending with the general. The left hemisphere controls the logical and the rational way of thinking, and has an aptitude for linguistics, academic research and science. Left-hemisphere learners are methodical, use rules and axioms, and tend to complete the project they are working on before they engage in something else [5][6].

The fields that the left hemisphere prefers are: Future, Logic, Syllogism, Methodology, Analysis, Research, Intellectuality, Language, Scientific Thought, Mathematics, and Conscious Thought.

The right hemisphere is specialised in the simultaneous processing of data and information, in composing information, and prefers the whole, rather than the constituent parts. For example, individuals with a developed right hemisphere first analyse the image as a whole, and afterwards pay attention to the details. Thus, they delineate the whole image of a puzzle, and then they proceed to the synthesis of its constituent parts. Right hemisphere learners acquire knowledge more easily after they have been informed about the subject of a lecture or have read a summary. Therefore, they are prepared having formed the necessary educational framework, which in turn is enriched by the knowledge and the details that follow. These individuals are capable of beginning an activity before completing another one; they conduct two actions simultaneously, leaving some projects unfinished, and as a result, they are forced to make the same effort twice, consuming precious resources and energy. Moreover, they have an aptitude for analysing space, demonstrate a creative way of thinking, prefer artistic activities, have intuition, and like mysticism and rituals.

The fields that the right hemisphere prefers are: Past, Intuition, Unconscious Thought, Creativity, Synthesis, Analysis of Space, Instinctive Side, Imagination, Sensuality, Music, Arts, and Practical Intelligence.

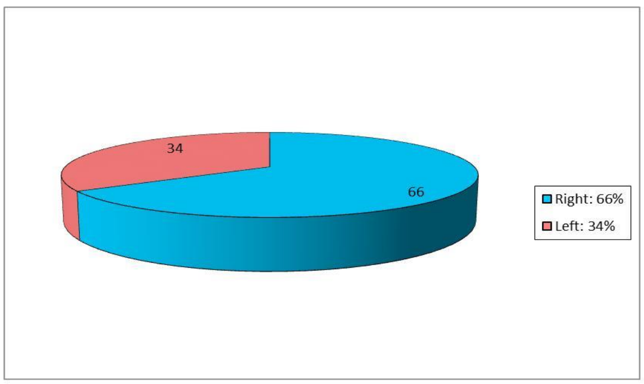

Figure 4. A real example with brain hemispheres.

Figure 4 presents the results of a real example, showing that this individual learns best when knowledge is presented in a top-down manner, that is, from the whole to the detail. An example question is presented below:

What would you readily select?
1. To do something with mathematics
2. Uncertain
3. To do something with language

V. OVERVIEW OF A PROFILE

For the reader to have an overview of a profile, we present some further statistics, all related to the same individual we have used in all the examples throughout this paper. We also explain the concept “probability of errors” in the answers given.

While answering the questions, the person may be distracted due to several reasons or events that cannot be predicted – noise, systematic error, psychological state, and so on – resulting to answers that do not necessarily represent his/her personality. The same can happen when the person answers randomly or inconsistently. In other words, direct or indirect distraction of individuals during the test can lead to incorrect classification of their learning factors. In this context, the probability of errors is considered to be a complementary measure to the truth scores.

In order to calculate the probability of errors, on the basis of the aforementioned, we make a hypothesis test and utilise the theory of stochastic processes [12]. Subsequently, we take the category of errors into consideration, in order to make corrections to the measures of the corresponding factors and, therefore, increase the validity and reliability of the conclusions reached by the expert system. The statistics that follow present a clear picture of the scores, while Table I shows the source and the equivalent Sten scores (scale 1–10), as well as the norms derived from our sample of over 500 cases, where N is interpreted as “Norrnal”, L as “Low”, H as “High”, and VL as “Very Low”.

Mean: 70.37
Variance: 796.51
Standard deviation: 28.22
Mean absolute deviation: 22.15
Coefficient of variation: 0.401
Overall truth score: 7 Sten
Probability of errors in answers: 0
Duration – Learning aptitudes: Shorter than usual
Duration – Learning styles: Normal
Duration – Hemispheres: Normal

TABLE I. SOURCE AND NORMALISED SCORES

Factor	Score	Sten	Norm
Right hemisphere	66	5	N
Left hemisphere	34	4	L
Interpersonal style	91	7	H
Visual style	82	6	H
Auditory style	73	6	N
Kinaesthetic style	73	6	N
Linguistic style	45	4	N
Intrapersonal style	1	2	VL
Matching concepts	100	7	N
Constructing concepts	100	7	H
Understanding intersections	100	7	H
Reconstructing concepts	86	6	N
Understanding rules	86	6	H
Understanding subsets	57	5	N
Understanding analogies	43	4	L

VI. RELIABILITY–VALIDITY AND CONCLUSIONS

The learning difficulties are often (but not always) highlighted when we detect disparities between the intelligence of a person (in whatever way you define this) and the academic–school performance. This does not mean that people with learning disabilities have low intelligence. In fact, they have average or above average intelligence, but their academic performance, as measured by standardised tests, is below what we would expect of people with the same age, intelligence, and academic grades (performance). Therefore, a person with low academic grades may be a person with learning disabilities (in terms of the factors presented here), rather than a person with low intelligence. Note that the battery of tests proposed here aims at analysing the inherent learning traits of a person, whereas the Wechsler scales [10] aim at analysing the intelligence of a person and the degree to which this affects learning.

Some difficulties will disappear with maturity, but some will not. The longer we allow wrong, or inefficient intellectual or physical tasks to continue (e.g., misspelling, incorrect use of a tool, handwriting grip, etc.), the harder they become to correct, because repetition of actions or reactions produces, if not always an inclination, at least an aptitude to act or react in the same manner and thus the habit. Also, if learning difficulties are left too long, some persons begin to display avoidance behaviour because they are not experiencing success.

In order to evaluate our battery, we studied the academic progress of 200 University students, and correlated their grades with the measurements from the battery presented here. The mean age of the participants was 18.9 years (SD = 4.1), of which 42% were males and 58% were females. We also administered equivalent tests from the Computer Academy Psychometric Series (CAPS) [7], in parallel with the battery presented here, and then carried out detailed statistical analyses, a subset of which is presented here due to space limitations.

TABLE II. RELIABILITY CORRELATION COEFFICIENTS

Factor	Parallel Test	*r*
Right hemisphere	Holland scale Artistic	0.72
Left hemisphere	Holland scale Investigative	0.73
Interpersonal style	Holland scale Social	0.91
Visual style	Diagrammatic	0.92
Auditory style	Music while studying	0.79
Kinaesthetic style	Holland scale Artistic	0.74
Linguistic style	Language (overall)	0.89
Intrapersonal style	Holland scale Realistic	0.79
Matching concepts	Language 1	0.88
Reconstructing concepts	Language 2	0.80
Constructing concepts	Language 3	0.79
Understanding intersections	Numerical 1	0.91
Understanding rules	Logic	0.85
Understanding subsets	Numerical 2	0.92
Understanding analogies	Analogies	0.87

Table II shows the factors of our battery, the equivalent tests used, and the Pearson product-moment correlation coefficient (r), which is very high in most factors, particularly with Interpersonal style, Visual style, Linguistic style, Matching concepts, Intersections, Subsets, and Analogies. Another interesting finding is that the correlation coefficient between the overall grade of students and the overall grade from the battery is 0.86, further supporting the reliability–validity of our approach.

Evidently, our approach can map the learning profile of individuals with a high degree of accuracy, since most coefficients are significantly higher than the minimum requirement of 0.7. We intend to continue the research by collecting and analysing profiles of students from different Universities, faculties and departments. Our next step will also aim at answering clearly the fundamental question: "*Now that I know my profile, what can I actually do to improve my rate of learning*?".

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