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RESEARCH ARTICLE

"TASKS-SKILLS" MAPPING ELABORATION IN THE IVORIAN EDUCATIONAL CONTEXT: METHODOLOGY AND EXPERIENCE WITH THE MATHEMATICS DISCIPLINE

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Abstract

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Improving the quality of learning, particularly the adaptation of curricula to socio-economic realities, has always been a concern for the education-training sector. Recent studies, notably by PASEC and CREMIDE, have highlighted significant shortcomings in Côte d'Ivoire's educational programs, underlining the inadequacy of the tasks proposed to master basic skills, as well as the gap between the skills taught and those required by the job market. With this in mind, this paper proposes a methodological framework for developing "task-skills" mappings, also known as Q-Matrices, based on the curricula of the Côte d'Ivoire Ministry of Education. The study involved 11 teachers and two (2) cohorts of learners from Khalil High School, Daloa. In contrast to previous work focusing on learner evaluation, this study introduced teacher evaluation in terms of affinity and satisfaction with learning tasks. The results show an 86% improvement in the mapping proposed by the experts after comparison with that based on Academic Affinity Scores (AAS) and Skill Affinity Scores (SSS). In addition, the mapping based on these scores performed better than that developed by the experts. This work opens up new prospects for the cognitive diagnosis of learners and the validation of pedagogical models.

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Introduction:-

Improving the quality of learning has always been a concern for the education and training sector (Gerard, 2022). This has manifested itself in many situations through the development of curricula adapted to socio-economic realities. In the literature, numerous studies have shown that the development of curricula and more specifically of learning content in line with targeted skills, significantly improves learner performance.With this in perspective, authors such as Redondo (Díaz Redondo et al., 2021)and Hidayat (Hidayat et al., 2020)have proposed methods for elaborating task-skill mappings. Task-skill mapping, also known as Q-Matrix, is a standard representation used in psychometrics to specify the relationships between tasks and skills (Cai et al., 2018).Its development certainly helps to improve teaching programs, but above all it helps to determine the learner's state of knowledge (Birenbaum et al., 1993), and to understand his or her behavior and learning path (W. Wang et al., 2022)(W. Wang et al., 2021). Above all, it helps to evaluate learning systems. Unfortunately, recent evaluations of Côte d'Ivoire's education system show the difficulties encountered in terms of both the social integration of learners and the mastery of skills proposed by experts in the field. Indeed, a recent study carried out by the CONFEMEN Educational Systems Analysis Program

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(PASEC) revealed that Ivorian learners lack basic language and mathematical skills (PASEC, 2020).These results clearly highlight dysfunctions in the proposed teaching programs. Specifically, they show that the learning tasks proposed for mastering the underlying skills seem inadequate. Another study carried out by Center for Microeconomic Development Research (CREMIDE) with the support of the French Development Agency (AFD) on the determinants of skills-employment mismatch shows that 75.87% of the skills offered by the University of Felix Houphouet-Boigny (Côte d'Ivoire) do not meet the needs of the job market (KOUAKOU Kouadio Clément and YAPO Andoh Régis Vianney, 2019). So proposing skills, and more specifically “task-skills” mappings that meet the needs of the job market, is a major line of research. These mappings provide human tutors and expert systems with tools for cognitive diagnosis of the learner and validation of teaching models (Tatsuoka, 2009a).Unfortunately, accurate and effective mapping requires in-depth expertise and a detailed understanding of specific educational dynamics (Lange, 2014). As a result, it remains a preoccupation for the educational world. This gap has motivated us to propose a methodological approach to the development of “task-skills” mapping and its experimentation in the discipline of mathematics. More precisely, in this paper we propose a methodological framework for the elaboration of “task-skills” mapping in the Ivorian educational context.

The following section presents the different methodological approaches found in the literature in the context of developing “task-skills” mappings. Particular focus is placed on the learning task assessment stage of data collection.

State of art:-

Numerous studies have demonstrated the importance of task-skill mapping tools in the cognitive assessment of learners (Lee & Sawaki, 2009)(Y. Li et al., 2021). These tools remain a substantial concern in the research field, as they facilitate the revision of teaching programs, thus contributing to the improvement of learner performance.

In the associated literature, there is a wide variety of work related to the development of “task-skills” mappings. These works are generally based on orientations to the definition and identification of tasks and skills (Ünlü & Kiefer, 2011). Other authors focus on the construction and validation of such mappings (de la Torre & Douglas, 2004)(Tatsuoka, 2009b). In the same context, some works are related to the proposal of algorithms and estimation models for the prediction of mappings (Liu et al., 2012), to the practical application and implementation of these mappings (Desmarais, 2014).And finally, other works in the literature refer to reliability and validity studies of learning content (Nájera et al., 2020).All these orientations are closely linked.Indeed, the definition of skills influences the construction of task-skill mappings, which in turn affects the estimation algorithms (Havelková & Hanus, 2019). Practical applications provide essential data for reliability and validity studies, which can lead to adjustments at every stage of the process (H. Li & Suen, 2013). This link guarantees a consistent and rigorous approach to the development and application of task-skill mappings. This approach has often been used as a methodology by many authors in the development of task-skill mappings.

In this context, Alavi and Ranjbaran (Alavi & Ranjbaran, 2018) have proposed a “task - skill” mapping technique. This technique is based on a 3-step methodology. The first is the use of identified skills to construct learning tasks (20). The second step is the validation of these tasks by experts, followed by assessment (tests, MCQs) of the learners to collect quantitative and qualitative data based on the experts' judgments. Finally, a cognitive diagnostic model is used to analyze the data and diagnose the participants' strengths and weaknesses.The results suggest that nine (9) major skills are involved in mastering the 20 learning tasks. Other works, such as those in (D. Wang et al., 2020), address the challenges of creating “task-skill” mappings, proposing solutions to improve the accuracy and efficiency of task-skill mapping.In (Tonekaboni et al., 2021), the authors discussed the need to understand and model the cognitive processes that influence participants' performance, using “task-skills” mapping. To this end, they also adopted a similar methodology. The methodology presented is based on 5 steps, namely the specification of cognitive attributes, the construction and validation of the task-skill map, the use of a generalized deterministic input and noisy gate model (G-DINA) to assess the ability of the task-skill map to capture the underlying cognitive processes, and finally the interpretation of the results obtained. Gono andal., [25] proposed the WMRMF and Sk - WMRMF techniques as new alternatives to task-skill mapping. They drew on guides and programs made available by the Ivorian Ministry of Education (MEN) for the elaboration of a basic mapping called “Initial Q-Matrix”. Once the 200 learners had been assessed for the construction of the learning and performance matrix, an algorithm based on the stochastic gradient descent technique was applied to learn the WMRMF and S*k* - WMRMF models for the prediction of the “tasks - skills” mapping.Unfortunately, most of the work in the literature relies solely on learner performance and achievement data to draw up “task-skills” mappings. This learner-only data provides a limited perspective, often focused on test or exam results.

This approach neglects other essential dimensions of learning, such as the level of adherence and the teacher's index of satisfaction in accomplishing the various learning tasks.To address this issue, Garcıa-Ramırez and Bijelic (García-Ramírez & Bijelić, 2024) suggest a teacher evaluation aimed at optimizing the organization of academic activities, such as teaching, research and administrative tasks.Based on the work of Jacobs (Jacobs & Winslow, 2004), they propose a metric for assessing a teacher's degree of affinity and satisfaction score with an academic activity. Unfortunately, this significant dimension of learning is not taken into account in the methodological framework. Therefore, in this paper, we propose to extend this component to the context of task-skill mapping. We rely on the teacher's performance in the task-skill mapping construction and validation phase.

The following section presents the various steps in the development of the “task-skills” mapping by experts in the field. It begins with the identification of competencies based on the guides and curricula provided by the Ivorian Ministry of Education (MEN). This is followed by the development of the tasks underlying the skills identified, and finally by the linking of the skills identified with the underlying tasks developed.

Related works:-

The development of a “task-skills” map is a crucial process in the assessment of learning. It enables content to be matched to expected competencies, while clearly presenting the link between tasks and competencies. The study carried out in this paper is mainly based on the “task-skills” mapping methodology proposed in (GONO et al., 2023).

Programs and guide

Educational programs and their implementation guides are pedagogical tools made available to the educational community in general, and to teachers in particular, by the Ivorian Ministry of Education. These programs and implementation guides, which are used for basic education, are the fruit of a long process during which various contributions were made to their realization. For all levels of education, the program and guide define the output profile, the subject area, the pedagogical regime, and present the body of the subject program. The latter is broken down into several elements: the competency, the theme, the lesson, an example of a course application situation, and the pedagogical content.

In this study, the following lessons were used: limits and continuity, extension of the notion of limit and derivation. The program is organized into the following components:

1. Skill ;
2. The theme;
3. The lesson;
4. An example of a situation;
5. Skills: these are the smallest cognitive units expected of students at the end of a learning process;
6. Teaching content: these are the notions to be acquired by students.

The program's disciplines are grouped into five main areas:

1. Languages, including French, English, Spanish and German;
2. Science and Technology, including Mathematics, Physics-Chemistry, Life and Earth Sciences and ICT;
3. Social studies, including History-Geography, Human Rights and Citizenship, and Philosophy;
4. Arts, including Visual Arts and Music Education;
5. The field of educational, physical and sporting development, including Physical and Sports Education.

Mathematics, a science discipline, is the subject of this paper. The mathematics curriculum for Première D level comprises 3 skills, 7 themes and 15 lessons, an extract of which is presented in Table I.

Table I: - Extract From The Mathematics Program, Premiere D Level (2021 - 2022).

SKILL I	**Theme 1: Algebraic Calculations**	Lesson 1.1: Second-degree equations and inequalities in IR
		Lesson 1.2: Equations in IR2 and IR3
	Theme 2: Functions	Lesson 1.3: General information about functions
		Lesson 1.4: Limits and continuity.
		Lesson 1.5: Derivation
		Lesson 1.6: Extending the notion of limit
		Lesson 1.7: Study and graphical representation of a function
		Lesson 1.8: numerical sequences
...	...	...

The program is implemented during an academic year. In Côte d'Ivoire, the academic year is divided into three (3) terms.

Elaboration of learning tasks underlying - skills

The study focused on the Lycée Moderne Khalil (Daloa, Côte d'Ivoire) during the 2021 - 2022 school year. The study lasted three months, spanned the periods of October, November and December 2021 and covered five lessons. It involved all teachers in the Mathematics teaching unit (UE). For the purposes of this study, knowledge components (KC) are defined as the various pairs (skills - content) of the educational program. They are precise cognitive units expected of the learner at the end of a learning process. A KC can also be defined as an acquired unit of cognitive function or structure, deduced from performance on a set of related tasks (activities, assessments). These tasks are assessment events. In practice, we use the term KC broadly to refer to all elements of cognition or knowledge as well as domain-specific skills. For example, in the educational program for the Première D class, the following KCs can be cited: "KC002: Know the definition of the union of two finite sets" and "KC082: Justify that a line with equation x = a is vertically asymptotic to the graphical representation of a given function". From the five lessons explored, 84 skills were identified in line with the educational program studied. Table II gives an overview of some of these skills.

Table II: -Extract From Some Skills Studied.

Lesson 2: Enumeration	
Code	**Skills**
KC001	Know the definition of a finite set
KC002	Know the definition of the union of two finite sets
KC003	Know the definition of the intersection of two finite sets
KC004	Know the definition of the complementary of a set
KC005	Know the definition of two disjoint sets
KC006	Know the definition of the cardinal of a finite set
KC007	Know the definition of a tuple, an arrangement, a permutation, a combination
KC008	Know the definition of the Cartesian product of finite sets
KC009	Know the number of p-uplets in a set with n elements
KC010	Know the number of p-element arrangements of an n-element set ($n \geq p$)
...	...
Lesson 8: Extension of the notion of limit	
...	...

These different skills were codified to facilitate their representation and subsequent use. For each of these skills (KCs), the teachers participating in the study proposed learning activities (exercises or tasks) designed to assess the learners. These sample tasks were drawn from their usual didactic repertoire, and were therefore congruent with the didactic practices of the program. Several sessions were organized with these teachers to synthesize the proposed activities and eliminate duplication. Some examples of activities proposed by the teachers are shown in Table III. For example, for the KC1 skill “Knowing that tuples are sets containing n elements”, activities Q1 and Q2 were proposed. In all, these experts proposed 200 activities (tasks) for five lessons.

Table III: -Extract From Some Skills Studied.

KC001 : Know the definition of a finite set					
Q001: A finite set is a set whose number of elements is finite.		**Q002**: The set A={a;b;c;d;e;f;g;h} is a finite set		**Q003**: The set B=[0; 4[is a finite set.	
a	**b**	**a**	**b**	**a**	**b**
true	false	true	false	true	false

KC006 : Know the definition of the cardinal of a finite set					
Q004: The cardinal of a set is the number of elements in the set.		**Q005:** The cardinal of the set A is given by Car(A)		**Q006:** Let A= {2 ;3 ;4 ;5}. The cardinal of A is 5	
a	**b**	**a**	**b**	**a**	**b**
true	false	true	false	true	false

Task - skill matching by domain experts

These teachers were also invited, over the course of several work sessions, to propose a first version of the mapping between activities and skills provided by the MEN. For each of the 84 skills studied during the first quarter, the 11 teachers proposed tasks underlying the mastery of each skill. This “task-skill” matching activity produced the first version of the “task-skill” map, known as the experts' initial Q-Matrix (Figure 1).This cartography is represented in the form of a Q matrix, with $Q \in \square^{K \times I}$, I representing the set of tasks required to master skill K.

Figure 1:- Extract of mapping for 4 Skills and 5 Tasks.

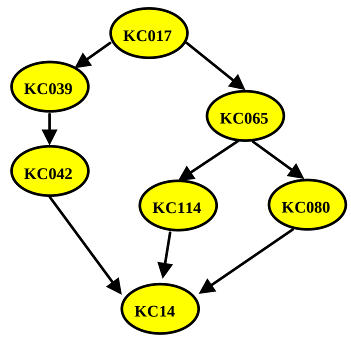
		Tasks				
		Q_{001}	**Q_{002}**	**Q_{003}**	**Q_{004}**	**Q_{005}**
Skills	**Kc_{001}**	1	0	1	0	0
	Kc_{002}	1	1	0	0	1
	Kc_{003}	1	0	0	1	0
	Kc_{004}	0	1	1	0	0

In this linking activity, a value of 1 is used to indicate the existence of a relationship between a task and a skill, while a value of 0 is used to indicate the absence of a relationship.

Validation of task-skill mapping

This first version of the mapping then passed through a validation procedure based on the principle of hierarchizing the different skills, as described in the work of Tatsuoka (Tatsuoka, 2009b)and Villanueva (Villanueva et al., 2021)(Tatsuoka, 2009a). This validation involves proposing a diagram (a tree graphically representing the different hierarchies between skills) to check whether each skill fits into the hierarchy of useful concepts to be taught to learners. This hierarchical diagram not only describes the hierarchy of tasks and sub-tasks used to achieve a skill, but also enables modifications to be made to the first version of the mapping (Figure 2).

Fig. 2:- Hierarchical skills diagram (GONO et al., 2023).



Proposed approach

Our approach to developing task-skill mapping is based on the methodology described in the previous section. To achieve the objectives of this paper, we propose firstly, at the data collection step, to rely on teacher evaluation. Then, we propose an algorithm to evaluate the degree of affinity and the satisfaction score of the teacher in the realization of the different learning tasks to help a better ordering of the “tasks - skills” mapping.

Proposed approach

The aim of this paper is to propose a methodological framework for the elaboration of “task - skill” mappings. Specifically, we plan to take into account a teacher's level of adherence and index of satisfaction in accomplishing different learning tasks in the process of elaborating “task - skill” mappings.

We therefore hypothesize that mastery of prerequisite tasks, as measured by the Academic Affinity Score (AAS), can have a significant impact on learner performance. Indeed, when tasks are assigned to skills based solely on their relevance, without taking into account the order of acquisition or the affinity felt by experts in the field, this can lead to difficulties in achieving learning objectives and to incorrect skill assignment. If mastery of one task requires another prerequisite task, and the learning order is not respected, the domain expert's satisfaction and affinity for the task may be affected. In this way, AAS can be used to identify not only the academic preferences of experts, but also potential barriers to learner performance when faced with tasks they dislike or find frustrating.

Suppose we have a finite set A and B, with the following elements: $A=\{1,2,3\}$ and $B=\{2,3,4\}$, let us define two tasks q_1 and q_2, with $q_1 = A \cup B$ and $q_2 = A \cap B$. Performing these tasks requires an understanding of set theory, but task q_1 requires prior mastery of q_2. If the domain expert has a low affinity or satisfaction with tasks involving notions of union, this could reflect negatively on the learner's performance in q_2. Thus, the “tasks - skills” mapping must take into account not only the order of the tasks, but also the domain expert's level of satisfaction and affinity with these tasks. This would make it possible to adjust the learning path by optimizing not only skill mastery but also the overall academic experience, thus fostering better performance and increased engagement in academic tasks.

Data set

To develop the dataset, we worked with eleven (11) mathematics teachers at Lycée Moderne Khalil in Daloa, Côte d'Ivoire, throughout the 2021-2022 school year. Based on tasks (tests, MCQs) designed to assess the skills of learners in the 1ere D class, a self-evaluation questionnaire is submitted to the experts to assess their degree of affinity and level of satisfaction in carrying out these tasks.

Determination of affinity and satisfaction score matrices

The various response values given by teachers are organized and then summed to represent satisfaction scores and degree of affinity. The expressions for the academic satisfaction score and the degree of affinity are given by equations (1) and (2).

$$SSS = \sum_{q_i=1}^{n} \left(S_{Q_i} \times \frac{P_{q_i}}{100}\right) \qquad (1)$$

$$AAS = \sum_{q_i=1}^{n} (A_{Q_i} \times \frac{P_{q_i}}{100}) \qquad (2)$$

Where n = total number of tasks
A = Degree of affinity with task q_i
S = Task satisfaction score q_i ,
P = Task weighting

These scores are evaluated on a scale of -100 to +100, where positive values represent high satisfaction or affinity and negative values represent lower dissatisfaction or affinity. The figures below (3 and 4) show a set of AAS and SSS values for four (4) teachers in the performance of five (5) tasks.

Fig. 3:-Example of a satisfaction score (AAS) calculation for 4 of the teachers (T) on completion of 5 tasks (*q*)

	t_1	t_2	t_3	t_4	T	
q_1	45	20	-20	90	33,75	q_1
q_2	70	50	30	-30	30	q_2
q_3	-10	-85	45	70	20	q_3
q_4	55	30	-70	40	13,75	q_4
q_5	60	10	90	75	58,75	q_5

The results of this "teacher - performer - task" relationship is denoted by a matrix K' with $K' \in \mathbb{R}^{Q\times T}$ for the satisfaction score matrix, with Q denoting the set of tasks and T the set of teachers. This matrix defines the teachers' level of satisfaction in carrying out the various learning tasks. Similarly, the affinity level matrix is designated *A*' with $A' \in \mathbb{R}^{Q\times T}$. This matrix defines the teachers' level of affinity in carrying out the various learning tasks.

Figure 4:- Example a degree of affinity (SSS) calculation for 4 teachers (T) on completion of 5 tasks (*q*).

	t_1	t_2	t_3	t_4	T	
q_1	80	65	-20	90	53,75	q_1
q_2	70	50	60	-30	37,75	q_2
q_3	-10	-80	30	-70	-32,5	q_3
q_4	20	90	-80	10	10	q_4
q_5	90	-10	40	25	36,25	q_5

Sequencing of tasks and skills

Based on the methodological approach outlined in Section III, we propose that experts take a supplementary step in the development of task-skill mapping, namely that of task-skill sequencing. This is based on the teacher's affinity and satisfaction with the teaching activity. Indeed, a teacher who is more satisfied and comfortable with the tasks assigned is likely to create a more positive learning environment, which can indirectly improve learner performance.Considering these indicators also makes it possible to tailor task assignments to teachers' strengths and preferences. This could lead to better use of individual talents within teaching teams. To this end, we propose a combinatorial optimization algorithm (Zimmermann et al., 2006)to find an optimal arrangement of tasks by minimizing a cost or maximizing a certain performance measure (based on AAS and SSS).It incorporates aspects of graph theory (Deo, 2016), scheduling (Sterna, 2011) and iterative optimization (Ezugwu et al., 2019).

Algorithm 1:AAS and SSS-based sequencing

Initialization
Q: task-skill mapping
A' : degree of affinity matrix
K': "satisfaction score level" matrix

Step 1 : G-graph construction with dependencies
Step 2 : Weight assignment (AAS and SSS)
Step 3 : Topological sorting of the G-graph
Step 4 : Re-ordering based on AAS and SSS
Step 5 : Optimization using the minimum cost method
Step 6 : Iteration and updating of *A'* and *K'*

Evaluation of the proposed approach

To evaluate our approach, we first used Cohen's Kappa similarity measure to compare the task-skill mapping based on task relevance proposed by the experts with that obtained after sequencing (based on SSS and AAS). The expression of Cohen's Kappa measure is given by equation (3), with Po representing the observed level of agreement and the proportion of cases on which assessors agree, and Pe the expected level of agreement or proportion of agreement expected by chance (Cohen, 1960).

$$Kappa = \frac{P_o - P_e}{1 - P_e} \quad (3)$$

With $Po = \sum_{i=1}^{r} p_{ii}$ and $Pe = \sum_{i=1}^{r} p_i + P_{+i}$

In parallel, an experimental study was carried out involving two groups of learners: the first group followed a course based on SSS and AAS, while the second followed a course based on task relevance. Although the tasks were identical for both groups, the order in which they were completed differed. At the end of the learning path, we compared the academic performance (tests, exams) of the two groups to determine which "task-skills" mapping led to the best results.

Simulations were run on a computer equipped with a 64-bit operating system, 16 GB RAM and an Intel Core i7 processor. Algorithm 1 was developed using the Python programming language.

Results:-

The similarity between the "tasks - skills" mapping proposed by the experts and the mapping based on SSS and AAS is 84%, denoting a correspondence gap of 352 links out of 2200 (84×11). Figure 5 shows the "tasks - skills" mapping proposed by the experts, and Figure 6 the mapping obtained after scheduling using Algorithm 1.

Figure 5:-Extract of the "tasks - skills" map proposed by the experts.

	Q_{081}	Q_{082}	Q_{083}	Q_{084}	Q_{085}	Q_{086}
Kc_{071}	1	0	1	0	0	0
Kc_{072}	1	0	0	1	0	0
Kc_{073}	1	1	0	1	0	0
Kc_{074}	1	0	1	1	0	1
Kc_{075}	1	1	0	1	0	0
Kc_{076}	1	0	1	0	1	1

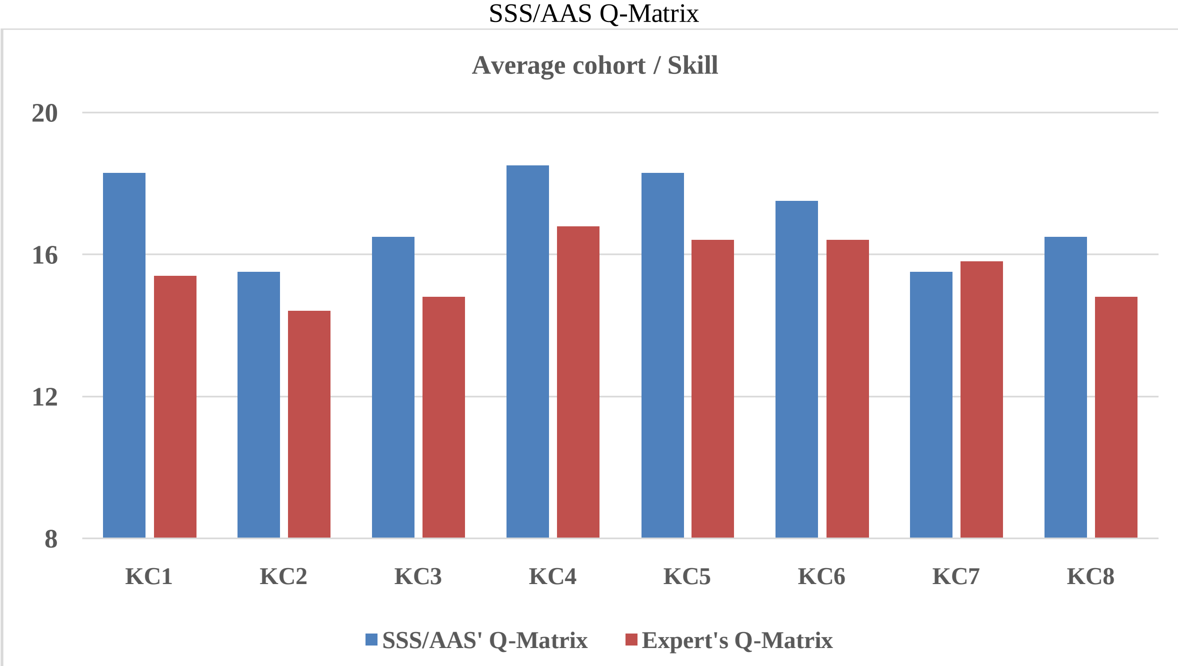
These links were submitted to the experts for validation. Of the 352 links highlighted by the ordering algorithm, 210 were found to be acceptable, representing an 86% improvement in the “tasks - skills” mapping proposed by the experts.

Figure 6:-Extract of the “tasks - skills” map proposed after sequencing.

	Q_{081}	Q_{082}	Q_{083}	Q_{084}	Q_{085}	Q_{086}
Kc_{071}	1	0	1	0	0	0
Kc_{072}	1	1	0	0	0	0
Kc_{073}	1	1	0	1	0	0
Kc_{074}	0	1	1	1	0	0
Kc_{075}	0	1	1	1	1	0
Kc_{076}	1	0	1	0	1	1

After evaluation of the skills acquired by the (2) groups of learners, it also emerged that the SSS/AAS-based mapping improved learners' performance in certain specific skills. Figure 6 shows the averages obtained by the two groups in mastering the various skills (8) presented.

Figure 7:-Q-Matrix Averages obtained by learners in mastering the skills proposed in the Expert Q-Matrix and the SSS/AAS Q-Matrix



The results obtained make it possible to adjust tasks according to teachers' affinities. The results often show an increase in teacher satisfaction, as their preferences and strengths are taken into account. They are more invested in teaching, which can lead to better quality learning and more positive results for learners. Learners can then be more motivated and successful.

Conclusion:-

In this paper, we have proposed a methodological framework for the development of “task-skills” mapping. The study was based on the guides and programs of the Côte d'Ivoire Ministry of Education, and was tested in the discipline of Mathematics. It involved 11 teachers (experts in the field) and 2 cohorts of learners from the Lycée Khalil de Daloa. Unlike the literature, which relies on learner assessment to optimize task-skills mapping, we proposed teacher assessment, more specifically the evaluation of affinity and satisfaction with learning tasks, as part of the task-skills mapping process. By applying Cohen's Kappa measure to assess the similarity between the “tasks - skills” mapping proposed by the experts and that based on SSS / AAS, we obtain a correspondence gap of 352 links. These links were submitted to the experts for their opinion, and it was found that 210 links were acceptable, representing an improvement rate of 86% on the “tasks - skills” mapping proposed by the experts. It was also found that the use of the SSS / AAS based “tasks - skills” mapping performed better than the one developed by the experts.

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