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Cognitive assessment of motivation to perform classroom or online math tasks among engineering students

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ABSTRACT

This study explored the cognitive algebra mechanism underlying mathematical motivation in 672 engineering students. The experimental design included the combination of four factors (task modality versus task difficulty versus task structure versus task relevance) to compose 36 written experimental scenarios. Each one described a hypothetical situation about assigned activities in math class. The participant's task was to read each scenario and estimate how much motivation they would experience if performing the assigned math activity. The results indicated five cognitive motivational patterns among the participants. All the clusters considered the task's relevance as an essential factor in judging their mathematical motivation. Besides this, Clusters 1, 2, 3, and 5 considered the assigned task's difficulty and structure in judging their degree of motivation, but they evaluated the factors differently. The low math motivation cluster integrated the factors according to a summative cognitive rule. Clusters 2, 3, and 5 used a multiplicative rule to integrate the information, and Cluster 4 did not show an information integration systematic mechanism. These findings pointed to the diversity of motivational cognitive profiles among students. This type of cognitive characterization can help design programs that encourage students to learn and enjoy science subjects that will impact their professional development and daily life.

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1. INTRODUCTION

The human mind tends to be purpose-oriented. One of the essential objectives of students is the learning of knowledge and skills. Furthermore, students aim to achieve a passing grade. Classroom tasks and homework provide students with mathematical opportunities to learn and obtain passing grades [1], [2]. The tasks are the interface that mediates a student's interaction with the mathematical information of his educational environment [3]. In this case, classroom tasks and homework allow the student to get closer to the nature of mathematics, contextualize mathematical knowledge, and test their mathematical abilities at different cognitive levels [4], [5]. Homework is one of the mechanisms commonly used to help students obtain, enrich, practice and learn the material reviewed in class, or prepare to receive new learnings [2].

Young, Dollman, and Angel [6] suggested that completing an assignment at home can help students to master a field of study, increase their confidence, and motivate them to work with complex materials. They also found that the grade achieved by a student on a task is a predictor of the student's academic performance. However, as they mention, the effect of homework on the learning process is still a subject of debate. The effectiveness of a task depends on how these tools are designed and implemented [2]. Also, factors such as the school's level, socioeconomic status, the student's gender, ability, and student motivation affect the extent to which a task can help students learn the contents or the skills [7]. The present work explored the cognitive processes underlying mathematical motivation since firm conclusions on the psychological nature of motivation towards math task performance have not been drawn from an integrationist cognitive approach.

2. LITERATURE REVIEW

2.1. The role of motivation in performing math tasks

Motivation is an internally energized process by which people initiate and sustain their actions to achieve a short- or long-term goal in one or more contexts. Furthermore, it requires the commitment to continue acting despite difficulties, failures, or setbacks [8]. Initiating or maintaining an action can be modulated by internal rewards such as the satisfaction of having learned (intrinsic motivation) or by external factors such as a reward (extrinsic motivation) [9].

Mazumder [10] mentions that, in the educational context, academic motivation level influences a student's goal achievement. A high motivation level contributes to the student's focus on solving problems and facing challenges. At the same time, the motivation type influences how students make choices about selecting the material they want to learn; it also modulates their time administration and approximates their learning [8]. Biggs and Tang [11] mention three approaches to learning. The first one, the superficial approach, is modulated by extrinsic motivation (e.g., desire to obtain a better job), and it is associated with the use of learning strategies such as a photographic memory. Students select details and reproduce them exactly as they have learned them. An intrinsic motivation facilitates the deep approach to learning (e.g., in seeking to satisfy curiosity about a topic, learning by itself is intrinsically reinforcing), and it is linked to the use of learning strategies such as reading widely on the subject, reflecting on the task, and forming hypotheses about the elements found in it. The achievement approach implies that the student is motivated by extrinsic factors that increase his ego (e.g., obtaining recognition, obtaining high grades) and uses learning strategies that include the systematic organization of time and tasks to get the highest grades possible.

Intrinsic or extrinsic motives encourage a student to begin a task, while other organizational, environmental, perceptual, and interpersonal factors increase the desire to continue performing the task to completion. Among the organizational factors which influence the outcome is the task structure, which refers to the clarity and definition of the task instructions that the student must follow. Generally, students prefer structured tasks. Designing tasks which take into consideration students' opinions about the task's structuring level would probably increase the motivation for doing the task and their performance [2].

There are other intrinsic properties of the tasks (the task's difficulty, the cognitive level of the task, the amount of time required to carry out the task, how interesting the task is for the student, the task's perceived relevance) that influence the level of involvement and degree to which a student engages with a task when performing it [12]. A mathematical problem must be clear, easily understood, and have a difficulty level that represents an attractive challenge for people [13]. However, it should not be utterly inaccessible because very complicated content repels the person's interest in dealing with it [14].

Lynch, Patten, and Hennessy [14] reported that the task's difficulty level is inversely proportional to the effort that a student invests in completing a task. However, Dietrich *et al.* [15] mentions that, the effect of the task's difficulty on the mental effort that the students dedicate to solving problems varies from student to student. Several motivational conditions, such as the task's subjective value, contribute to these variations. The task´s value relates to the student's perception about the task's relevance to achieving personal, instructional, or learning objectives. In this regard, the National Academies of Sciences, Engineering, and Medicine [16] and Brophy [17] suggested that the task's subjective value has three primary components. The first is the impact that the task has on the student's self-concept (achievement value), the second is the degree of that the task provokes enjoyment in the student (intrinsic value or interest). The third is the degree to which the task contributes to achieving the student's long- and short-term goals.

One of the main interest of students is in obtaining a passing grade and homework and classroom tasks are essential to students because they provide opportunities for them to receive additional course credits. Planchard *et al.* [18] explored the motivation of college students to do an assigned task and they observed that among the three most relevant motivating factors to complete homework assignments were the opportunity to get credits and extra-credits. The average amount of homework submitted was greater when students obtained credit for doing the activity compared to when they received only feedback and the expectation that the task would help them to improve their performance [18]. However, it is important to keeping in mind that the credit is just one variable among a multiplicity of factors influences motivation to perform tasks [19]. For example, other organizational factors that influence the students' persistence and degree of constancy in terms of carrying out a task are the place and time available to perform the task [2].

The context influences the student's motivation to focus on a task. For example, if a task is online, the technology provides temporal and spatial flexibility. Then the student can choose the most appropriate time and place to do it. Besides, Magalhaes *et al.* [20] mentioned that technology can encourage student participation to complete a task since instant feedback tools are available. However, they clarify that the effect of task delivery method on learning is inconsistent.

Generally speaking, the evidence indicates that the student´s values and interests [21], the factors related to instructional experiences, and the academic context regulate student involvement in tasks. The inclusion of studies on the cognitive mechanisms that integrate these factors in students' minds in the context of engaging them in the study of mathematical content can help enhance our understanding of the cognitive nature of math motivation. The authors describe the advantages of using information integration theory (IIT) to unveil these cognitive mechanisms in the following section.

2.2. Cognitive algebra as a valuable tool to explore the cognitive nature of mathematical motivation

The IIT's functional view posits that the human being can extract pieces of information from the external and internal environment, give these pieces of information a psychological value or weight, and integrate them through mental algebraic operations, collectively called cognitive algebra. The formation of cognitive rules involves the action of three cognitive operators. The valuation function (V) enables the mind to convert the stimulus's physical properties into psychological values. The integration function (I) combines psychological values in a unified response. Moreover, the action operator (A) transforms the unified response into an external response (R) [22].

The mind frequently uses cognitive operations of averaging, addition, or multiplication to integrate information [22]. These cognitive algebraic rules are present in very diverse human life domains such as ethical behavior [23], love, sexuality, and intellectual disability [24], and human health [25]. In the educational field, there are studies on the cognitive algebra underlying attitudes towards school inclusion [26], job training for people with intellectual disabilities [27], the desire to cheat on exams [28], test anxiety [29], [30] and students' mathematical self-efficacy [31], [32]. In general, these studies indicate that participants make systematic judgments when evaluating school situations. Using a cognitive algebra design to explore students' math motivation will lead to insights about styles of information integration underlying students' engagement in the performance of mathematics tasks.

3. RESEARCH METHOD

3.1. Research goal

The core of this study was to determine the integration information mechanism underlying mathematical motivational judgments. This intention is expressed in (1):

$$MM= f(w_M \text{ task modality}*w_D \text{ task difficulty}*w_S \text{ task structure}*w_R \text{ task relevance}) \quad (1)$$

where the mathematical motivation (MM) level depends on a cognitive operation (*) that combines the factors' relevance weights (w) in a cognitive answer. The solution to this equation involved identifying the mechanism for factor selection, and that was achieved by determining how many and which factors were essential to the participants in judging their motivation; the second step was to determine if the students used a systematic thinking pattern to judge their mathematical motivation.

3.2. Study design, sample and data collection

The experiment in this study used Briones *et al.* [31] factorial design of 2 (task modality: face-to-face versus online) x 2 (task difficulty: high versus low) x 3 (task structure: low versus medium versus high) x 3 (task relevance: high versus medium versus low). This experimental design produced a total of 36 experimental conditions. The study participants were 672 engineering students (241 women and 431 men). Their ages ranged from 16 to 37 (M=19, SD=1.9). All the participants were volunteers.

3.3. Instrument

The instrument included 36 written scenarios based on the experimental conditions of the study. Each scenario described a hypothetical story about a math activity. The study factors (task modality, difficulty, structure, and relevance) framed the context of each story. A question about the level of math motivation level which students judged they would feel appeared at the end of each scenario. An 11-point scale accompanied each question. The left anchor was "Not motivated" and the right anchor was "Fully motivated" as shown in Figure 1.

- Your math teacher assigned an online activity to you; he/she will clarify your doubts about the instructions for completing the assignment through a virtual platform (no aspect of the activity is discussed in the classroom; it is entirely online).
- The activity requires you to solve a series of complicated problems within a time limit. You may not use any device or additional help to carry out the activity.
- The teacher provided unambiguous instructions; he/she asked you to perform the math operations on paper, following all procedures in the exact way they were done during class.
- The activity is just a class exercise. You will not get points for doing it. The activity is only to reinforce your learning in class.

In this situation, how motivated would you feel to perform the assigned task?
Not at all 0---0---0---0---0---0---0---0---0---0---0 A lot

Figure 1. Example of experimental scenario

3.4. Procedure

First, the students received an invitation to participate in the study through Facebook. Subsequently, the participants received a detailed description of the study's objectives and the procedure. After they had given their verbal consent to participate, participants practiced the experimental task using a subset of the study scenarios presented randomly. Finally, the participants read the 36 study scenarios, one by one, then they indicated on the scale how motivated they would feel about performing each assigned math task.

4. RESULTS AND DISCUSSION

4.1. Cluster analysis

A cluster analysis (Euclidean distance, K-means) was carried out on the participants' raw data to identify different response patterns. An ANOVA was applied to the data for each cluster to observe the cognitive integration mechanism. The analysis identified five motivational cognitive patterns (η_p^2=.83) in the data set. The first cluster (N=80, 12%) grouped participants with the lowest motivation level in carrying out mathematical tasks (M=3). The second grouping (N=104, 15.47%) included participants whose scores showed a moderately low motivational level (M=4). The third group (N=207, 6%) grouped participants who showed a moderate motivational level (M=6). The fourth cluster (N=87, 13%) included participants whose scores showed a moderately high motivational level (M=7). The last grouping (N=194, 29%) comprised participants with the highest motivation level to perform the math task (M=8).

4.2. ANOVA for each cluster

The raw data in each cluster were analyzed with a repeated-measures ANOVA of 2 (task's modality: face-to-face versus online) x 2 (task difficulty: high versus low) x 3 (task structure: low versus medium versus high) x 3 (task relevance: high versus medium versus low) as presented in Table 1. The level of significance was established at $p<.001$. The results indicate that the first cluster's participants, who reported low mathematical motivation (M=3.14) to solve the assigned problems, used a bifactorial model to elaborate their mathematical motivation judgments. They selected two factors as relevant: the task's difficulty and relevance. The most significant factor was the task's difficulty (η_p^2=.37), followed by the task's relevance (η_p^2=.10). According to the data, the students in this first cluster are more motivated when the task's difficulty is low (M=3.64) and the relevance is low (M=3.41). No statistically significant interactions were found between the two factors with the greatest weight, suggesting that this cluster cognitively integrated the two factors through a summative cognitive rule as shown in Figure 2.

The group with moderately low mathematical motivation (M=4.473) made its judgments based on a three-factor model. The highest factor was the task's relevance (η_p=.57), followed by the task's difficulty (η_p^2=.48), and the task's structure (η_p^2=.08). The participants were more motivated when the task's relevance was high (M=5.07) than when the task's difficulty was low (M=4.60) and the task's structure was high (M=5.71). A statistically significant interaction was observed between the task's relevance and difficulty. This suggests that this cluster cognitively integrated the information using a multiplicative rule as presented in Figure 2.

Table 1. ANOVA results for each cluster

Cluster	Source	df	MS	df	MS	F	p	η_p^2
Cluster 1 <Low mathematical motivation>	Modality (M)	1	38.042	79	10.015	3.798	.054	.04
	Difficulty (D)	1	703.100	79	14.908	47.161	.001	.37
	Structure (S)	2	11.742	158	3.155	3.721	.026	.04
	Relevance (R)	2	90.492	158	9.706	9.322	.001	.10
	M*D	1	.078	79	3.140	.024	.875	.00
	M*S	2	4.348	158	2.914	1.492	.228	.01
	D*S	2	1.148	158	2.423	0.473	.623	.00
	M*R	2	13.246	158	2.223	5.957	.003	.07
	D*R	2	12.412	158	2.637	4.706	.010	.05
	S*R	4	3.344	316	2.111	1.584	.178	.01
Cluster 2 <Moderately low mathematical motivation>	Modality (M)	1	24.521	103	4.417	5.550	.020	.05
	Difficulty (D)	1	1346.160	103	14.136	95.227	.001	.48
	Structure (S)	2	48.895	206	4.968	9.841	.001	.08
	Relevance (R)	2	2803.875	206	20.096	139.523	.001	.57
	M*D	1	.060	103	2.536	.023	.877	.00
	M*S	2	.563	206	2.534	.222	.800	.00
	D*S	2	1.755	206	3.163	.554	.575	.00
	M*R	2	.471	206	3.051	.154	.856	.00
	D*R	2	93.239	206	3.908	23.857	.001	.18
	S*R	4	1.249	412	3.008	.415	.797	.00
Cluster 3 <Moderate mathematical motivation>	Modality (M)	1	9.566	206	3.213	2.977	.085	.01
	Difficulty (D)	1	2833.336	206	14.441	196.189	.001	.48
	Structure (S)	2	119.539	412	4.048	29.527	.001	.12
	Relevance (R)	2	80.541	412	11.210	7.184	.001	.03
	M*D	1	5.750	206	2.158	2.664	.104	.01
	M*S	2	1.653	412	2.258	.732	.481	.00
	D*S	2	0.338	412	2.174	.155	.855	.00
	M*R	2	2.492	412	2.237	1.113	.329	.00
	D*R	2	89.420	412	2.858	31.277	.001	.13
	S*R	4	1.0001	824	2.420	.413	.799	.00
Cluster 4 <Moderately high mathematical motivation>	Modality (M)	1	1.992	86	2.315	.860	.356	.00
	Difficulty (D)	1	32.084	86	11.480	2.794	.098	.03
	Structure (S)	2	7.847	172	2.591	3.027	.051	.03
	Relevance (R)	2	8410.605	172	21.084	398.896	.001	.82
	M*D	1	1.267	86	2.056	.616	.434	.00
	M*S	2	3.230	172	2.348	1.375	.255	.01
	D*S	2	.576	172	2.227	0.2589	.772	.00
	M*R	2	2.417	172	2.380	1.015	.364	.01
	D*R	2	3.622	172	2.684	1.349	.262	.01
	S*R	4	6.90	344	2.306	2.993	.018	.03
Cluster 5 <High mathematical motivation>	Modality (M)	1	6.993	193	1.022	6.840	.009	.03
	Difficulty (D)	1	281.042	193	4.752	59.133	.001	.23
	Structure (S)	2	9.574	386	1.489	6.427	.001	.03
	Relevance (R)	2	367.837	386	6.497	56.610	.001	.22
	M*D	1	.007	193	1.247	.005	.940	.00
	M*S	2	.835	386	1.014	.824	.439	.00
	D*S	2	9.500	386	1.109	8.565	.001	.04
	M*R	2	1.153	386	.951	1.213	.298	.00
	D*R	2	5.361	386	1.349	3.974	.019	.02
	S*R	4	.186	772	.999	.186	.945	.94

The third cluster (moderate mathematical motivation) (M=6.121) considered three factors to affect their mathematical motivation judgments. The task's difficulty was the factor with the most significant weight (η_p^2=.48), after the task's structure (η_p^2=.12), and the task's relevance (η_p^2=.03). This cluster was more motivated when the difficulty was low (M=6.73) than when the structure was high (M=6.28), and the relevance was low (M=6.314). They combined the three factors through a multiplicative cognitive rule as seen in Figure 3.

The grouping with moderately high mathematical motivation (M=6.66) used a single factor model to make their judgments. They selected the task's relevance as the most relevant factor (η_p^2=.82) and reported greater motivation when the task's relevance was high (M=9). It was impossible to determine a cognitive rule for this group since the participants in this cluster selected just one factor.

The fifth cluster (high mathematical motivation) (M=8.4) used a three-factor model to judge its math motivation. Participants selected the task's difficulty (η_p^2=.23), the task's relevance (η_p^2=.22), and the task's structure (η_p^2=.03) as the core factors in judging their motivation to perform the math tasks. The participants expressed greater mathematical motivation when the task's difficulty was low (M=6.73), and the task's structure (M=6.28), and the task's relevance (M=6.314) were high. They integrated the factors with a multiplicative rule is described in Figure 3.

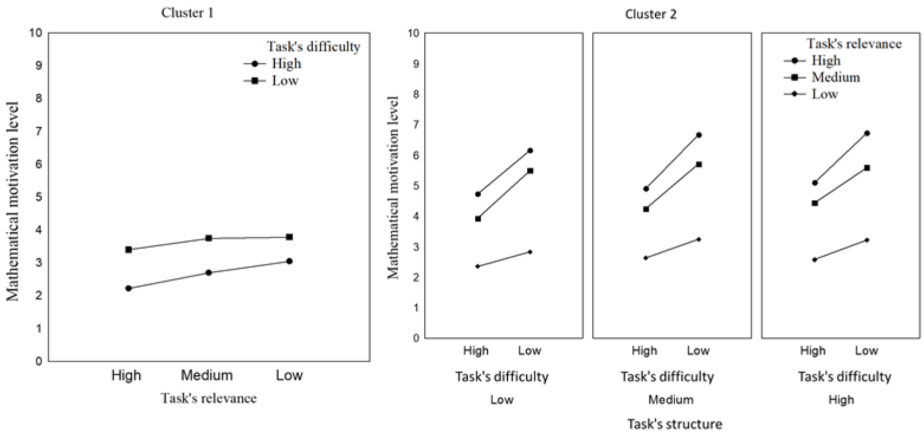

Figure 2. Interaction graph for most relevant factors in Cluster 1 and 2

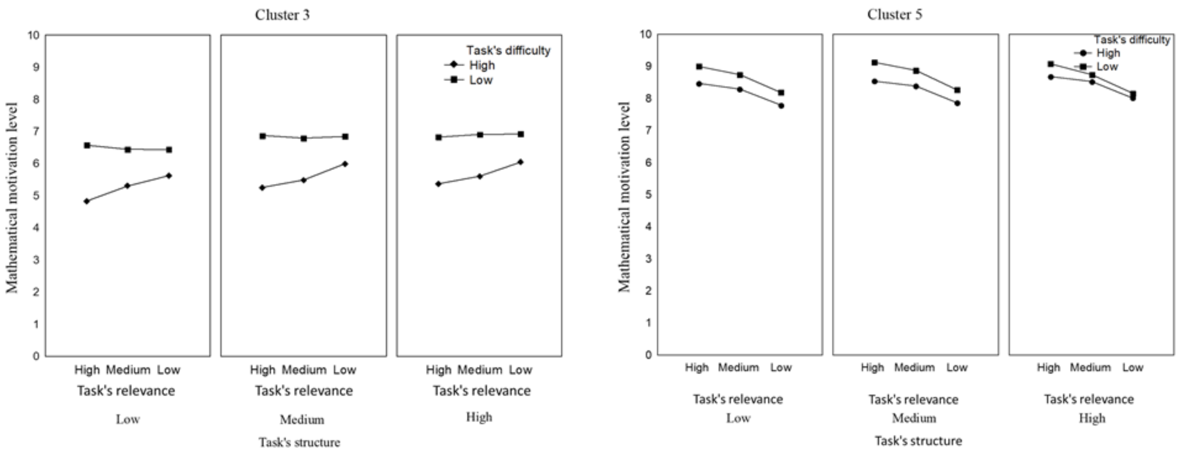

Figure 3. Interaction graph for most relevant factors in Cluster 3 and 5

The interaction patterns among the factors for each cluster are shown in Figure 2 and Figure 3. The behavior of the curves denotes parallelism between the lines for Cluster 1 (summative rule). Meanwhile, in the other three clusters, the pattern of the lines is fan-shaped (multiplicative rule). The valuation of the factors is different across the groupings, regardless that they share the same integration mechanism.

4.3. Discussion

For decades, researchers have explored students' mathematical motivation at all educational levels. This effort has made it possible to indicate the influence of individual, contextual, and situational factors on students' motivation to carry out mathematical tasks. However, there is little information about the contribution made by different factors under a paradigm that contemplates their joint action. For that reason, this study explored the cognitive mechanism through which students select, value, and integrate the situational (task's modality) and intrinsic factors (task difficulty, relevance, and structure).

Regarding factor selection, all the groups considered the task's relevance to be one of the most critical factors when making motivation judgments (Table 1). However, the weight of this factor was different across the clusters. Clusters 2, 4, and 5 reported increased motivation to perform mathematical tasks when they obtained extra credits. In comparison, Clusters 1 and 3 experienced increased motivation when the task reinforced mathematical learning. According to Brophy [17], the task's subjective value in Clusters 1 and 3 would be centered on its intrinsic value, while in Clusters 2, 4, and 5, it would be focused on the utility value. This last result is consistent with the previous study [18] stated that motivation increases when an external reinforcer is built into the assigned task.

On the other hand, Clusters 1, 2, 3, and 5 considered the task's difficulty to be a relevant factor mathematical motivation. The decrease in motivation level was very marked for the four groups when the problems presented were very complicated. This result seems to contradict the research by Lynch, Patten, and Hennessy [14]; however, it is possible that the greater the difficulty, the greater the attempt to perform a task; however, if the difficulty level exceeds the person's tolerance threshold, then an individual's effort drops to a low level.

Regarding the task structure, Clusters 2, 3, and 5 experienced increased motivation when the task's clarity and definition were high. The task structure preferences implicitly offer information about students' learning styles. Field-dependent students tend to prefer more detailed and clear instructions and tend to require marked supervision.

Besides this, the results indicated that task modality was not relevant when judging motivation level. This finding contrasts with the assumption of Magalhaes *et al.* [20] about using technological resources to encourage student participation. However, students who participated had little time exploring online learning; perhaps they could adopt one of the two modalities with more experience.

With regard to the valuation process, the data indicate that regardless of the similarities in terms of factor selection across the clusters, there are differences in the number of factors selected, their weighting, and the cognitive mechanism used to form a mathematical motivational judgment in each case. For example, the moderately low and high mathematical motivation groups selected the same factors (task difficulty, structure, and relevance); however, their factor valuation was different. On the other hand, in terms of the integration process, the data indicated that there are five thought modes among the participants. Three of them showed a multiplicative cognitive pattern, one group used a summative cognitive rule, and one cluster did not demonstrate systematic integration since participants used a univariate model to make their judgements on motivation. These results suggest that there is variability in the cognitive patterns that modulate the mathematical motivation of students. This diversity in the cognitive appraisal of academic experiences is constant through different phenomena such as anxiety tests [29], [30], desire to cheat [28], and mathematical self-efficacy [31], [32].

A limitation in the present study is the disparity between the number of female and male participants. Given this, it would be useful to increase the sample of female participants to compare the gender factor rules. On the other hand, given that, in factorial designs, only a limited number of factors can be handled, this study considered only a single situational factor (task modality) and three factors related to the intrinsic nature of the mathematical task (task difficulty versus task structure versus task relevance). New combinations of factors could be included in subsequent studies to broaden the understanding of mathematical motivation across various contexts.

5. CONCLUSION

This study provided information about the cognitive regulatory mechanisms that students use to involve and to maintain their attention in the development of mathematical learning activities. The cognitive algebra analysis indicated five cognitive patterns of mathematical motivation among the participants. Each pattern accounts for a unique motivational cognitive style when performing mathematical tasks. In this regard, the data indicated different factor selection patterns (univariate, bifactorial, and trifactorial) among participants, and different cognitive valuation patterns even when some clusters shared similar information integration models.

In sum, the results indicated that cognitive algebra experimental designs could become high-value diagnostic tools since they provide information on the motivation level that students experience when performing a mathematical task. Furthermore, these studies shed light on the cognitive mechanisms underlying this math motivation. The inclusion of cognitive algebra designs to explore other situational, contextual, and individual factors could empower stakeholders in this field with valuable information on the individual and collective impact of the factors that influence or determine the cognitive stylistics that underpin students' mathematical motivation.

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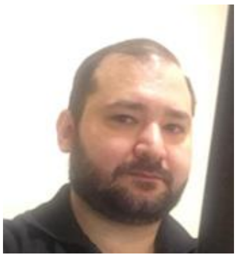

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