

Engineering students' judgments on the favorable effect that the class context has on their academic learning

Guadalupe Elizabeth Morales-Martínez¹, Maria Isolde Hedlefs-Aguilar², Ricardo Jesus Villarreal-Lozano², Maria Guadalupe Santos-Alcantara¹

¹Institute of Research on the University and Education, National Autonomous University of Mexico, Mexico City, Mexico

²Mechanical and Electrical Engineering School (FIME), Nuevo Leon Autonomous University, San Nicolas City, Mexico

Article Info

Article history:

Received Apr 2, 2021

Revised Oct 29, 2021

Accepted Nov 30, 2021

Keywords:

Cognitive algebra

Engineering students

Face-to-face class

Favorable effect judgment

Online class

ABSTRACT

The COVID-19 pandemic has impacted human life, including educational settings. In Mexico, teachers and students found it necessary to adopt the online modality at all levels. As a result, both students and teachers face new demands and a re-conceptualization of their everyday academic lives. This study explored the engineering students' perception of the favorable effect level that the class context has on their learning. There were 551 participants who took a cognitive algebra study. The experimental task involved reading 12 scenarios that described hypothetical online or face-to-face learning situations; then, each participant judged the degree to which these types of situations favor their learning, using an 11-point scale. The results indicated three cognitive styles when judging the degree to which each class context favors the learning. These styles share a similar cognitive mechanism in terms of information integration; however, the selection process and valuation of the factors differed across the groups. The students' perception of the class context influences their involvement and motivation level for courses on which they are enrolled. The present study's findings suggest that the cognitive algebra approach helps diagnose students' cognitive and emotional approach styles for different class contexts and provides information about the nature of their cognitive processes in terms of how students' judgments and attitudes towards classes are generated.

This is an open access article under the [CC BY-SA](https://creativecommons.org/licenses/by-sa/4.0/) license.



Corresponding Author:

Guadalupe Elizabeth Morales-Martínez

Institute of Research on the University and Education (IISUE), National Autonomous University of Mexico (UNAM)

Circuito Cultural Universitario, Coyoacan 04510, Mexico City, Mexico

E-mail: gemoramar@hotmail.com

1. INTRODUCTION

Every day, millions of students worldwide attend schools and universities to take face-to-face classes. However, due to the isolation caused by the COVID-19 pandemic, educational institutions have changed from face-to-face classes to online ones to continue with the academic teaching-learning cycle. Zia [1] mentions that this change happened suddenly and abruptly, so there was very little time to prepare; consequently, the students and teachers faced a new educational scenario without the necessary training for modality change.

Although the evidence indicates no significant differences between the effectiveness of online learning compared to face-to-face learning [2], [3], students perceive the online classes as different to those face-to-face [4]. They report that both class modes are helpful to increase knowledge; however, they perceive online classes as less effective than those face-to-face when learning skills or social competencies [5]. In this

line, some studies indicate that students prefer face-to-face learning activities compared to online ones [3]. However, few studies have explored students' perceptions of and engagement with online learning programs [6] and compared students' experiences under the two learning modalities [3]. So, it is difficult to know if the e-learning experiences meet the current expectations of students. Some studies indicate that students' preferences regarding face-to-face and online activities vary depending on the activity type. Kemp and Grieve [3] observed that students prefer to carry out discussions in person while they are more inclined towards the online mode when it comes to written assignments [7].

The temporal proximity between the student's academic action and the teacher's feedback influences the student's preferences towards a specific class delivery mode. In this regard, Kemp and Grieve [3] found that students tend to prefer face-to-face classes due to the immediacy of feedback compared to the relative delay for classes held online. Another factor that influences students' preferences is the emotional connection with others during the classes. Otter *et al.* [8] mention that online classes generate a feeling of greater disconnection in students with their classmates and teachers. This factor can affect the student's motivation to continue in an academic environment. Moreover, online classes require self-regulatory learning skills, independence, and responsibility in terms of academic training [6], [8], technological skills, and knowledge so that students may feel overwhelmed by online learning [9], [10]. Finding strategies for students to invest their energy in their primary business of "learning" rather than wearing themselves out with collateral concerns about their academic work would create more pleasant and productive educational environments for them.

Assessing the perception of students and teachers about the quality of online education requires consideration of the learning sources (learning material, infrastructure, teaching), processes (guidance, learning delivery mode), and context [11], [12]. For example, the material that students will review during a class represents a central learning source for knowledge and skills acquisition. Knowing the cognitive nature of the material to be reviewed is relevant for choosing or creating delivery strategies that facilitate the students' access to information and allow them to appropriate the knowledge or skill properly. In this regard, two aspects of the nature of educational material are relevant. The first is the knowledge type that material promotes, and the second is the cognitive level at which the material is revised. Each discipline requires different types of knowledge to be learned: factual, conceptual, procedural, and metacognitive [13], and that these can be handled at different cognitive levels (remembering, understanding, applying).

Paechter and Maier [14] found that students know which class mode promotes the cognitive processes underlying the achievement of academic objectives. According to this study, students prefer face-to-face learning when acquiring conceptual knowledge or skills for applying knowledge. This preference is marked when students consider that interaction with the teacher is helpful building terms of building their knowledge. However, when they are acquiring regulated learning skills, they prefer online learning. On the other hand, Paechter and Maier observed that students' preferences for online or face-to-face activities changed depending on the task objective. Students preferred face-to-face delivery for tasks that involved cooperative learning or the exchange of meanings. Where the objective was disseminating information to other classmates, students favored the online mode. Familiarity, self-efficacy, and technology skills level are factors that affect student preference. Salloum *et al.* [15] found that students' computer self-efficacy, when they use the computer, positively influences the level of acceptance of e-learning.

In general, most of the research in this field comprises studies focused on identifying the factors influencing students' judgments and preferences towards the different delivery modes for classes and the materials presented. In this regard, the empirical evidence available indicates that the type of activity to be carried out, the objective and nature of the class material, the immediacy of feedback, the degree of involvement and connection that students experience in the activities influence students' preferences in terms of class mode. However, Kemp and Grieve [3] point out that it is difficult to determine the specific differences in the influence of these factors in terms of the delivery mode for each class because few studies directly compare the contribution of these factors across different class modes. On the other hand, as far as the authors know, there are no studies about how the situational, individual, and contextual factors act together on the students' preferences for online or face-to-face classes.

One way to approximate these two problems is to explore the phenomenon from an integrationist perspective that allows the contribution of each of the factors to be determined separately and jointly in elaborating student preferences. In this regard, the inclusion of studies based on information integration theory (IIT) [16] may be an optimal alternative for this purpose. IIT proposes that there are psychological laws that govern the processing of information. These laws influence human thought and action. According to IIT, people systematically select and integrate the information they extract from their internal and external environment through information processing modes called cognitive algebraic rules. Three psychological laws of information integration: averaging, adding, and multiplying, are the expressions of the systematic modes of thinking [16]–[18].

The cognitive mechanism of these psychological laws involved three cognitive processes. First, people select bits of information from their internal or external environment that they consider relevant. These pieces of information are then subjected to a valuation function (V) to assign a psychological value to each one. The person's mind combines these values in an implicit response (r) through an information integration function (I), and this mechanism ends in the generation of an observable response through the response function (R) [16], [17], [19].

The cognitive mechanism of the valuation, integration, and response is present across different human life domains [16], [17], [20]–[23]. In the educational field, Morales-Martinez *et al.* [24] mention that there are cognitive algebra studies that explore the cognitive rules underlying the attitudes of teachers and students regarding the inclusion of people with disabilities [25], [26], mathematical self-efficacy [27], [28], desire to cheat academically [29], and test anxiety [25], [30]. These studies suggest that there is a systematic way of processing academic situations. However, there are no studies on systematic thinking modes underlying the judgments about how favorable the class context is for students' learning, as far as the authors know. Therefore, in this work, it was interesting to observe how different factors are integrated into the student's mind to form a judgment about the degree to which the class context favors their learning.

Due to COVID-19, 3,942,544 students who are enrolled in university programs/secretary of public education (SEP) [31] in Mexico are receiving their academic training through online classes. Students have had to face internet access problems, the challenge of learning new digital skills in a short time, the change in family dynamics, problems with adapting a suitable space to take online classes, among other difficulties. Also, the new digital context has changed how information is delivered to students and teachers. These contextual and individual factors affect online learning and teaching [1], [32] and students' attitudes toward the class mode.

This work explored the perception that engineering students have about the favorable effect level that the class context exerts on their learning. First, the authors identified the factors with the greatest weight when students make their judgments. Second, the authors determined if there was a systematic information integration mechanism underlying the perceived favorable effect level (P-FEL) of class context on students' learning. In order to do this, the authors examined if there was a linear function underlying P-FEL among students:

$$P-FEL = (w_{CKT} \text{ Class's knowledge type} * w_{CM} \text{ Class's delivery mode} * w_{TF} \text{ Teacher's feedback})$$

P-FEL results are based on a cognitive operation (*) that combines the relevance weights (w) given by participants to the factors that they consider to be relevant.

2. RESEARCH METHOD

This study explored students' judgments about the degree to which the class context favors their learning through an experimental study based on the paradigm of cognitive algebra. From this perspective, human beings form their judgments using three cognitive processes: V, I, and R. Here, the intention was to determine these three functions in the engineering students' response patterns when forming their judgments.

2.1. Design

The authors used a within-subject design. This factorial design orthogonally combined three factors and their sublevels: class knowledge type (declarative versus procedural), class delivery mode (face-to-face versus synchronous online versus asynchronous online), and teacher feedback (immediate versus delayed). From this experimental design, the authors obtained 12 experimental conditions.

The model to select the factor levels was fixed; the authors chose the factors and their experimental levels based on empirical evidence about what variables affect students' attitudes and perceptions concerning face-to-face and digital educative environments. For example, there is broad agreement among learning connoisseurs that knowledge learned in a school environment can be classified as either declarative and procedural. Students process semantic information about different knowledge domains and learn procedural skills inside the classroom [13]. Additionally, the authors selected the levels for class delivery mode based on the class modes used in Mexico since the start of the COVID-19 pandemic. Furthermore, only a handful of studies explore students' perceptions and engagement in online learning programs and compare students' experiences under the two learning modalities [3], [6]. Consequently, these levels have practical and theoretical relevance for this study. Finally, teacher feedback levels are based on empirical evidence from various studies pointing out the effect of this factor on students' preferences for a specific class delivery mode [3].

2.2. Instrument

The experimental conditions were the basis for creating the instrument that comprised 12 experimental scenarios. Each one described the context in which the student experienced a class. Each story was accompanied by a question about the favoring degree students believed the described context would exert on learning and an 11-point scale for them to indicate their judgment on this (Figure 1).

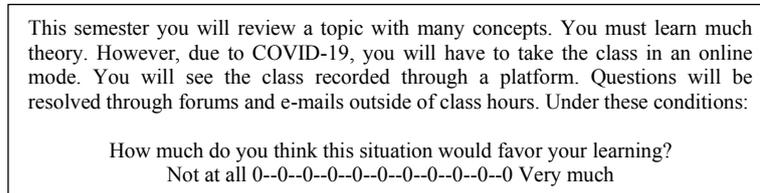


Figure 1. Example of an experimental scenario

2.3. Participants

The participants were 551 engineering students (29% female, 71% male). Their ages ranged between 17 and 33 years old ($M=19.58$, $SD=1.67$). All the participants were volunteers without financial remuneration.

2.4. Procedure

The study comprised three phases. First, the authors sent electronic invitations to ask students to participate voluntarily in the study through a digital survey platform and e-mail. During the second phase, participants provided their informed consent, demographic data, and they could view the instructions and access a practice phase of the study. This was so that participants to gain familiarity with the experimental task. The third phase was the application of the study. Here, the participants read the 12 experimental scenarios one by one and judged the degree to which the class context described in each experimental scenario would favor their learning. The time required for the application of the instrument ranged between 20 and 30 minutes.

3. RESULTS AND DISCUSSION

After the authors determined that there were no statistically significant differences by gender [$F(1,549)=.267$, $p=.60$, $\eta_p^2=.0004$]; they applied two statistical analyses to the participants' raw data. First, a cluster analysis allowed us to determine if there were different cognitive patterns in responses across the sample. Hofmans and Mullet [19] recommend using a nonhierarchical centroid-based method to observe cognitive patterns because this technique is resistant to extreme values and is less sensitive to irrelevant variables and the distance measure used [33].

Subsequently, the authors applied a mixed ANOVA to determine the clusters' discriminability and applied a repeated-measures ANOVA to each cluster's data to observe the cognitive functions V, I, and R. Since ANOVA interaction graphs allow the participants' cognitive patterns to be observed [18], these tools were used to observe this study's cognitive rules. For example, the summative cognitive rule is characterized by a parallel curve pattern, while the multiplicative rule is expressed through a linear fan pattern [16].

3.1. Cluster analysis

The cluster analysis (Euclidean distance, K-means) identified three different sets of responses among the participants ($\eta_p^2=.79$). The first one ($N=159$, 29%) included participants with the lowest scores ($M=3$). The second group ($N=233$, 42%) was typified by moderate scores ($M=5$), while the third group ($N=159$, 29%) showed high scores ($M=8$).

3.2. Mixed ANOVA

The authors applied a mixed ANOVA to the raw data in line with the following design 3 (cluster: low versus moderate versus high level) x 2 (class knowledge type: declarative versus procedural) x 2 (class delivery mode: face-to-face versus synchronous online versus asynchronous online) x 2 (teacher's feedback: immediate versus delayed). The level of significance was $p<.001$.

There was a statistically significant difference in the P-FEL among the clusters [F(1,548)=25291.632, $p=.001$, $\eta_p^2=.79$]. There were three factors that had a significant effect: class delivery mode [F(2, 1096)=508.078, $p=.001$, $\eta_p^2=.48$], teacher's feedback [F(1,548)=200.521, $p=.001$, $\eta_p^2=.26$], and class knowledge type [F(1,548)=50.735, $p=.001$, $\eta_p^2=.08$]. The knowledge type factor was relevant only to cluster 2 ($\eta_p^2=.20$). The analysis pointed to several significant interactions among the factors. In addition, the authors explored the specific patterns of these effects in each cluster by using a repeated-measures ANOVA.

3.3. Repeated-measures ANOVA

For each identified cluster, a repeated-measures ANOVA of 2x3x2 was carried out based on the factors: class delivery mode, teacher's feedback, and class knowledge type. The level of significance was $p<.001$. In general, the results indicate that there are three different styles for P-FEL. There were differences among clusters throughout the three cognitive processes (V, I, R). For example, clusters 1 and 3 used a bifactorial model to make their judgments, while cluster 2 used a three-factor mental model. Table 1 shows a statistically significant effect on the class mode and feedback factors across all three clusters. Cluster 2 was the only one that considered the class knowledge type factor to be relevant in its judgments, with a moderate effect size.

Table 1. ANOVA results for each cluster

Cluster	Source	df	MS	df	MS	F	p	η_p^2
Cluster 1: Low level of perceived favorable effect	Knowledge type (K)	1	10.867	158	3.219	3.375	.06	.02
	Class mode (M)	2	3112.023	316	10.310	301.830	.000	.65
	Teacher's feedback (F)	1	404.027	158	5.123	78.861	.000	.33
	K*M	2	81.004	316	2.821	28.713	.000	.15
	K*F	1	4.245	158	2.193	1.935	.16	.01
	M*F	2	67.359	316	2.499	26.951	.000	.14
	K*M*F	2	2.878	316	1.960	1.468	.23	.009
Cluster 2: Moderate level of perceived favorable effect	Knowledge type (K)	1	490.429	232	8.254	59.415	.000	.203
	Class mode (M)	2	1116.792	464	5.554	201.064	.000	.203
	Teacher's feedback (F)	1	1044.592	232	8.334	125.340	.000	.464
	K*M	2	251.925	464	4.243	59.367	.000	.203
	K*F	1	6.137	232	2.070	2.964	.086	.012
	M*F	2	84.792	464	2.012	42.142	.000	.153
	K*M*F	2	29.519	464	1.777	16.606	.000	.066
Cluster 3: High level of perceived favorable effect	Knowledge type (K)	1	42.570	158	4.805	8.857	.003	.053
	Class mode (M)	2	133.165	316	4.282	31.093	.000	.164
	Teacher's feedback (F)	1	140.088	158	4.809	29.130	.000	.155
	K*M	2	40.001	316	2.244	17.820	.000	.101
	K*F	1	11.635	158	2.573	4.521	.035	.027
	M*F	2	316	16.620	1.84	8.991	.000	.053
	K*M*F	2	316	.884	1.636	.540	.583	.003

The three clusters perceived that the face-to-face class mode was most advantageous for their learning (Table 1 and Figure 2). This judgment was particularly strong in cluster 1. Moreover, the data from cluster 2 suggest that when the knowledge is procedural, the class delivery mode and the teacher's feedback affect students' perceptions to a greater extent (Figure 2).

Related to function I, the cluster 1 participants perceived a context's low favorable effect level on learning in all experimental scenarios. They used two out of three factors to form their judgments and integrated them into a multiplicative cognitive rule: $P-FEL=f(\text{class delivery mode} \times \text{teacher's feedback})$. Figure 2 shows a fan pattern that indicates a systematic interaction between the two factors. Cluster 2 used three factors to form its judgments and integrated them through the following function: $P-FEL=f(\text{class delivery mode} \times \text{teacher's feedback} \times \text{class knowledge type})$. Meanwhile, cluster 3 judged the P-FEL by multiplying two factors: $P-FEL=f(\text{class delivery mode} \times \text{teacher's feedback})$.

Finally, about function R, the authors observed three types of responses among the participants; a specific P-FEL characterized each cluster. Cluster 1 showed a relatively low P-FEL for all the experimental conditions. Cluster 2 judged that the contexts described in the scenarios favored their learning at a moderate level, while cluster 3 indicated that the circumstances described in the scenarios favored their learning at a high level.

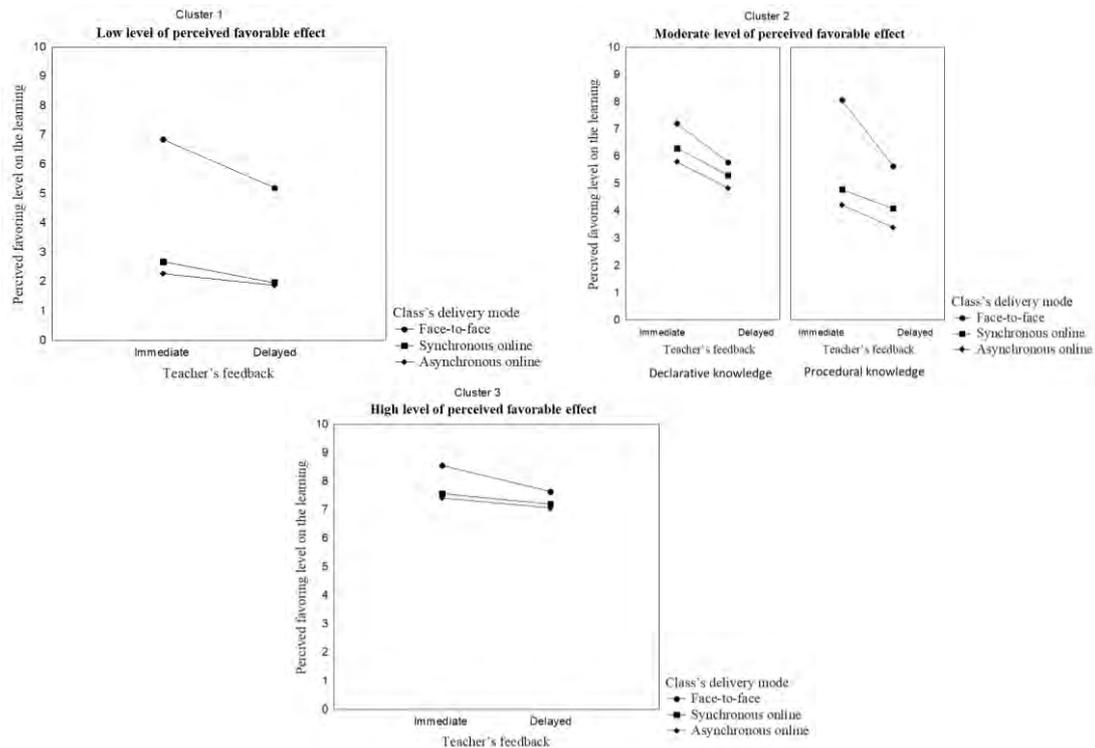


Figure 2. Interaction graphs for the factors that obtained statistically significant effect in each cluster

4. DISCUSSION

The way students perceive classes and their effects on learning influence student motivation to persevere and achieve their academic goals. This study examined three cognitive processes (V, I, R) involved in generating judgments about the P-FEL of class context on students' learning. In general, the results indicated the existence of three cognitive styles to elaborate favoring judgments (Table 1 and Figure 2). These judgment styles were characterized by different cognitive patterns in the selection and valuation of the factors (V), in the information integration mechanism (I), and the explicit response (R).

Concerning the factor selection mechanism, the data indicated three cognitive models for selecting factors. Clusters 1 and 3 used a bifactorial cognitive model to judge the favoring degree for learning. Meanwhile, cluster 2 used a tripartite model to elaborate its judgments. Interestingly, in IIT studies in other academic life domains (test anxiety), some groups with moderate judgment tend to have a broader range of factor selection than clusters with lower or higher scores on the phenomenon measured [24]. The reasons for these results are not clear; thus, exploring the nature of this finding would offer information about whether this selection mechanism is characteristic of all groups that show moderate judgments in other phenomena. If this is the case, this would suggest that when people's cognitive system presents a moderate level of tension or excitement, the cognitive factor selection mechanism seems to be more receptive to a more significant number of elements that allow it to balance the judgments by taking into account a bigger picture of the situations or scene.

Relating to the V function, each grouping showed a different valuation pattern for the selected factors. The most critical factor for the three groups was the class delivery mode. For all groups, the most favorable perception was for the face-to-face class mode, followed by the synchronous online mode and finally the asynchronous online mode. This result coincides with the observations of previous studies [4], [5] that students perceive both modes of delivery differently and tend to prefer the face-to-face mode [3]. An interesting variable to consider is that the student sample made their judgments in the context of two months of taking online classes given confinement due to COVID-19. Students were uneasy because they wanted to go back to face-to-face classes and mentioned that online classes were not as much to their liking. The authors believe that this new condition broke the expectation of continuing the semester in person, and it would be essential to measure these preferences in a sample more familiar with the digital education world since one of the factors affecting students' attitudes to online classes is self-efficacy and preparation regarding the use of technological tools [15].

The second most relevant factor for the students was the level of access to feedback. All three groups judged that more immediate feedback was more conducive to their learning. The immediacy of feedback is among the most significant factors determining whether students prefer face-to-face classes or not [3]. From the present authors' point of view, immediacy of feedback plays an essential role because it provides students with a significant feeling of connection with their teachers or classmates. In this regard, Otter *et al.* [8] noted that students feel more disconnected from their peers and teachers in online courses.

The knowledge type factor was relevant only for cluster 2. The authors assume that this result may be related to the metacognitive abilities of the students. Paechter and Maier [14] noted that students could infer the class mode that best suits them according to their knowledge about the nature of the material and the activities they will carry out in class. For example, in this study, the participants in cluster 2 showed a greater feedback effect when the class was face-to-face and the knowledge type for learning was procedural. This finding may indicate that this group considered that procedural learning could be learned more efficiently in face-to-face classes than in online classes. One of the students commented that he felt that it was challenging to acquire learning concerning carrying out calculations and operating machinery online. These data suggest the need to implement digital teaching strategies that are more in line with the knowledge type that the teacher or educational system intends to promote as the learning objective.

With regard to function I, the three clusters presented a multiplicative information integration mechanism. It is interesting to observe how the class mode does not have the same effect across all feedback factor levels. In cluster 2, this multiplicative effect can be observed to a greater extent when the learning is procedural. This result sheds light on how the student's mind approaches judgments about preference for a particular class mode.

Regarding the R function, the data indicated three cognitive patterns (low, moderate, and high P-FEL). IIT studies in other academic development fields found similar cognitive behavior among students [24]. The diversity of cognitive patterns related to the R function suggests that the students have different cognitive and affective approaches to the academic context. As the authors mentioned, in relation to the moderate judgment cluster, the participants generated their judgments on the basis of the class context (mode of delivery, feedback immediacy). Furthermore, they included a factor related to a metacognitive aspect to weigh the context in their equation since they appeared to contrast the nature of the learning with the resources available in the class delivery mode. They then judged that the learning of a procedural skill was not necessarily guaranteed with the online tools available. The authors assume that if the appropriate means of imparting procedural skills were available, students' judgments would probably be different.

On the other hand, in contrast with the studies only provide information on preferences globally, this study provides information about three levels of preference concerning specific class modes. In order to reveal the reasons for these different styles, new research should include other variables such as the student's cognitive flexibility, the ability to adapt to changes, and metacognitive skills. One of the study's limitations was the lack of an instrument that measured students' levels of learning self-regulation. Since online learning by definition requires the student to have a higher level of independence and self-motivation for learning [6], [8], the preference for face-to-face classes may be related to the perception that they have about their self-efficacy to regulate their learning and manage technologies efficiently to achieve their academic objectives. Thus, this study makes way for new studies that consider new variables and explore the cognitive integration mechanisms that underlie students' mental and affective activities in any mode of class delivery.

5. CONCLUSION

In sum, the participants judged that the P-FEL of class context on students' learning was highly dependent on the class delivery mode. Students showed a greater preference for a face-to-face environment. The three groups identified were able to use a systematic way of thinking to make their judgments. The data indicated three ways to approximate this systematic way of thinking, all of them characterized by a multiplicative cognitive rule. Two groups of students with low and high judgment used a bifactorial model to elaborate their judgments. They selected two of the three factors evaluated, while the moderate cluster used the three pieces of information. The difference in the selection mechanism between clusters 1 and 3 and cluster 2 may be related to a metacognitive ability factor present in the moderate judgment cluster.

The study results suggest that the inclusion of algebraic instruments can help diagnose students' judgments, perceptions, and attitudes to their learning experiences. Furthermore, as shown in this work, this approach allows comparisons to be made between different class modes when considering the same factors in each situation. Then, IIT tools help identify the levels of judgment among students. They also determine the isolated and joint contributions of the factors to any phenomenon and compare these two aspects in different situations and samples.

REFERENCES

- [1] A. Zia, "Exploring factors influencing online classes due to social distancing in COVID-19 pandemic: a business students perspective," *International Journal of Information and Learning Technology*, vol. 37, no. 4, pp. 197–211, Sep. 2020, doi: 10.1108/IJILT-05-2020-0089.
- [2] Y. Cao and S. Sakchutchawan, "Online vs. traditional MBA: An Empirical study of students' characteristics, course satisfaction, and overall Success," *The Journal of Human Resource and Adult Learning*, vol. 7, no. 2, pp. 1–12, 2011.
- [3] N. Kemp and R. Grieve, "Face-to-face or face-to-screen? Undergraduates' opinions and test performance in classroom vs. Online learning," *Frontiers in Psychology*, vol. 5, no. NOV, Nov. 2014, doi: 10.3389/fpsyg.2014.01278.
- [4] H. Kauffman, "A review of predictive factors of student success in and satisfaction with online learning," *Research in Learning Technology*, vol. 23, Aug. 2015, doi: 10.3402/rlt.v23.26507.
- [5] M. Bączek Michałand Zagańczyk-Bączek, M. Szpringer, A. Jaroszyński, and B. Woźakowska-Kapłon, "Students' perception of online learning during the COVID-19 pandemic: A survey study of Polish medical students," *Medicine*, vol. 100, no. 7, p. e24821, Feb. 2021, doi: 10.1097/MD.00000000000024821.
- [6] A. Ituma, "An evaluation of students' perceptions and engagement with e-learning components in a campus based university," *Active Learning in Higher Education*, vol. 12, no. 1, pp. 57–68, Mar. 2011, doi: 10.1177/1469787410387722.
- [7] S. Krishnan, "Students' Perceptions Of Learning Mode In Mathematics," *Malaysian Online Journal of Educational Sciences*, vol. 4, no. 2, pp. 32–41, 2016.
- [8] R. R. Otter *et al.*, "Comparing student and faculty perceptions of online and traditional courses," *Internet and Higher Education*, vol. 19, pp. 27–35, Oct. 2013, doi: 10.1016/j.iheduc.2013.08.001.
- [9] W. A. Suliman, F. A. Abu-Moghli, I. Khalaf, A. F. Zumot, and M. Nabolsi, "Experiences of nursing students under the unprecedented abrupt online learning format forced by the national curfew due to COVID-19: A qualitative research study," *Nurse Education Today*, vol. 100, p. 104829, May 2021, doi: 10.1016/j.nedt.2021.104829.
- [10] D. Holley and M. Oliver, "Student engagement and blended learning: Portraits of risk," *Computers and Education*, vol. 54, no. 3, pp. 693–700, Apr. 2010, doi: 10.1016/j.compedu.2009.08.035.
- [11] N. Liu and Q. Pu, "Factors influencing learners' continuance intention toward one-to-one online learning," *Interactive Learning Environments*, pp. 1–22, Dec. 2020, doi: 10.1080/10494820.2020.1857785.
- [12] Y. Li, N. Nishimura, H. Yagami, and H. S. Park, "An empirical study on online learners' continuance intentions in China," *Sustainability (Switzerland)*, vol. 13, no. 2, pp. 1–18, Jan. 2021, doi: 10.3390/su13020889.
- [13] D. Fardin and F. Radmehr, "A Study on K5 students' mathematical problem solving based on Revised Bloom Taxonomy and psychological factors contribute to it," *European Journal of Child development, Education and Psychopathology*, vol. 1, no. 3, pp. 97–123, 2013.
- [14] M. Paechter and B. Maier, "Online or face-to-face? Students' experiences and preferences in e-learning," *Internet and Higher Education*, vol. 13, no. 4, pp. 292–297, Dec. 2010, doi: 10.1016/j.iheduc.2010.09.004.
- [15] S. A. Salloum, A. Qasim Mohammad Alhamad, M. Al-Emran, A. Abdel Monem, and K. Shaalan, "Exploring students' acceptance of e-learning through the development of a comprehensive technology acceptance model," *IEEE Access*, vol. 7, pp. 128445–128462, 2019, doi: 10.1109/ACCESS.2019.2939467.
- [16] N. H. Anderson, "Unified Psychology Based on Three Laws of Information Integration," *Review of General Psychology*, vol. 17, no. 2, pp. 125–132, Jun. 2013, doi: 10.1037/a0032921.
- [17] N. Gaj, *Unity and Fragmentation in Psychology: The Philosophical and Methodological Roots of the Discipline*. New York: Routledge, 2016.
- [18] G. E. Morales, "Functional measurement to cognitive mechanisms underlying attitudes toward sexuality and intellectual disability: New empirical directions," in *Handbook on Sexuality Perspectives, Issues and Role in Society*, N. E. Peterson and W. Campbell, Eds. New York: Nova Science Publishers, Inc, 2012, pp. 29–54.
- [19] J. Hofmans and E. Mullet, "Towards unveiling individual differences in different stages of information processing: A clustering-based approach," *Quality and Quantity*, vol. 47, no. 1, pp. 455–464, Jan. 2013, doi: 10.1007/s11135-011-9529-7.
- [20] M. D. Cano Romero, M. T. Muñoz Sastre, B. Quintard, P. C. Sorum, and E. Mullet, "The ethics of postoperative pain management: Mapping nurses' views," *International Journal of Nursing Practice*, vol. 23, no. 2, p. e12514, Apr. 2017, doi: 10.1111/ijn.12514.
- [21] J. Cretenet, E. Mullet, and V. Dru, "Motor and cognitive integration: Effect of bilateral behaviors on judgment," *Acta Psychologica*, vol. 161, pp. 64–72, Oct. 2015, doi: 10.1016/j.actpsy.2015.08.004.
- [22] M. T. Munoz Sastre, C. Olivari, P. C. Sorum, and E. Mullet, "Minors' and adults' views about confidentiality," *Vulnerable Children and Youth Studies*, vol. 9, no. 2, pp. 97–103, Apr. 2014, doi: 10.1080/17450128.2013.832827.
- [23] E. Lopez, G. E. Morales-Martinez, Y. Norberto, and L. R. Patino-Munguia, "Perceived Self Efficacy To Cope With Earthquakes," *Advances in Social Sciences Research Journal*, vol. 6, no. 8, pp. 444–457, 2019, doi: 10.14738/assrj.68.6975.
- [24] G. E. Morales-Martinez, A. Garcia-Collantes, M. I. Hedlefs-Aguilar, D. J. Charles-Cavazos, and Y. N. Mezquita-Hoyos, "Information integration cognitive mechanisms underlying the face-to-face or online statistics test anxiety judgments of engineering students," *European Journal of Educational Research*, vol. 10, no. 1, pp. 23–37, Jan. 2020, doi: 10.12973/EU-JER.10.1.23.
- [25] G. Mora, E. Lopez, M. Guadalupe, E. Samantha, Y. Norberto, and M. Castro-Sanchez, "Cognitive Algebra Underlying Special Education Teachers' and Psychology Students' Attitudes Towards School Inclusion of People with Intellectual Disability," *Journal of Intellectual Disability - Diagnosis and Treatment*, vol. 2, no. 1, pp. 33–41, May 2014, doi: 10.6000/2292-2598.2014.02.01.4.
- [26] G. E. Morales-Martinez, E. O. Lopez-Ramirez, M. G. Villarreal-Treviño, and Y. N. Mezquita-Hoyos, "Functional Measurement of Special Education Teachers' and Students' Expectations Toward Job Training for Persons with Intellectual Disability," *Journal of Intellectual Disability - Diagnosis and Treatment*, vol. 3, no. 1, pp. 35–42, Mar. 2015, doi: 10.6000/2292-2598.2015.03.01.5.
- [27] C. Briones-Rodriguez, G. E. Morales-Martinez, M. G. Santos-Alcantara, E. O. Lopez-Ramirez, and M. E. Urdiales-Ibarra, "Cognitive Algebra Underlying High School Student's Self-Efficacy Judgment to Solve Mathematical Problems in the Classroom or Online," *International Journal of Education*, vol. 8, no. 2, p. 136, Jun. 2016, doi: 10.5296/ije.v8i2.9148.
- [28] G. E. Morales-Martinez, "Engineering Student's Self-Efficacy Judgment to Solve Mathematical Problems in the Classroom or Online," *European Journal of Educational Research*, vol. 6, no. 4, pp. 465–473, Oct. 2017, doi: 10.12973/eu-jer.6.4.465.
- [29] G. E. Morales-Martinez, E. O. Lopez-Ramirez, Y. N. Mezquita-Hoyos, R. Lopez-Perez, and A. Y. Lara Resendiz, "Cognitive mechanisms underlying the engineering students' desire to cheat during online and onsite statistics exams," *European Journal of*

- Educational Research*, vol. 8, no. 4, pp. 1145–1158, Oct. 2019, doi: 10.12973/eu-jer.8.4.1145.
- [30] P. J. Moore, J. S. Chrabaszcz, and R. A. Peterson, “The cognitive processing of somatic anxiety: Using functional measurement to understand and address the fear of pain,” *Psicologica*, vol. 31, no. 3, pp. 605–627, 2010.
- [31] Secretary of Public Education, “Principales cifras del sistema educativo nacional [Main statistical records of the national education system].” 2019, [Online]. Available: https://www.planeacion.sep.gob.mx/Doc/estadistica_e_indicadores/principales_cifras/principales_cifras_2018_2019_bolsillo.pdf.
- [32] K. Syauqi, S. Munadi, and M. B. Triyono, “Students’ perceptions toward vocational education on online learning during the COVID-19 pandemic,” *International Journal of Evaluation and Research in Education*, vol. 9, no. 4, pp. 881–886, Dec. 2020, doi: 10.11591/ijere.v9i4.20766.
- [33] J. F. Jr. Hair, W. C. Black, B. J. Babin, and R. E. Anderson, *Pearson New International Edition*, 7th ed. Pearson Education Limited, 2014.

BIOGRAPHIES OF AUTHORS



Guadalupe Elizabeth Morales-Martinez    received the Ph.D. degree in psychology from Nuevo Leon Autonomous University, Monterrey, Mexico. She is a researcher at the Institute of Research on the University and Education, National Autonomous University of Mexico (UNAM). Her current research interest includes academic learning cognitive assessment and the students’ cognitive and emotional styles. She can be contacted at email: gemoramar@hotmail.com



Maria Isolda Hedlefs-Aguilar    obtained her PhD in psychology at the Nuevo Leon Autonomous University. She is a professor at the Department of Mechanical Engineering and Electronics in this University. Her research relates to cognition and computational usability. She can be contacted at email: maria.hedlefsag@uanl.edu.mx.



Ricardo Jesus Villarreal-Lozano    is a Ph.D. on Evaluation and Innovation on Educational Practice, Monterrey Institute of Specialties. He is a professor at the Department of Mechanical Engineering and Electronics in Nuevo Leon Autonomous University. His research focuses on cognition and attitudes toward school in university students. He can be contacted at email: ricardo_j_villarreal@hotmail.com.



María Guadalupe Santos-Alcantara    is a researcher assistant at the Institute of Research on the University and Education, National Autonomous University of Mexico. Her research relates to knowledge representation and academic learning. She can be contacted at email: alc.san.mar.gua@hotmail.com.