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CHAPTER 30

Embracing educational resilience: A retrospective analysis of the impact of emergency remote teaching on programming students in-pandemic

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ABSTRACT

This study reflects on the experiences of 52 programming students during the Emergency Remote Teaching (ERT) semester at a university due to the COVID-19 pandemic. The findings reveal that the sudden shift had a lasting impact on the emotional states and motivation levels of students, highlighting the persistent influence of ERT. The role of technological infrastructure remains a significant factor, shaping students' perceptions of ERT. The paper offers actionable insights to enhance teaching methods and support structures. The research emphasizes the need to consider the emotional and motivational dimensions when orchestrating changes in educational delivery modes. The study provides valuable insights for shaping effective learning environments during the ongoing recovery from the pandemic.

Keywords: Emergency Remote Teaching (ERT), Programming Students, In-Pandemic Education, Educational Resilience, Technological Infrastructure.

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INTRODUCTION

In 2020, the declaration of COVID-19 as a pandemic by the World Health Organization led to a global upheaval, compelling sanitation measures and social isolation. With over 1.5 billion students worldwide affected, schools and universities suspended face-to-face activities ([1]), ushering in an era marked by irreparable damage, evasion of opportunities, and exacerbated social inequalities. This crisis prompted a swift transition to remote learning, with Emergency Remote Teaching (ERT) emerging as a crucial solution ([2]).

The shift to ERT presented unprecedented challenges for professors, students, and academic institutions, manifesting in difficulties in adapting curriculum, maintaining student motivation ([3, 4]), and coping with issues such as loneliness, stress, and inadequate infrastructure ([5, 6]). Challenges extended globally, with students from different regions facing hurdles like unfamiliarity with online tools and distractions at home ([7, 8]).

Notably, most of the studies found often overlooked technology-savvy cohorts, such as computer science students, potentially yielding distinct outcomes. Focusing on this population, the study of [9] explored the experiences of computer science students in the UK, revealing more positive attitudes toward online learning compared to those in other disciplines. However, concerns from practitioners regarding the delivery of specific core topics and the impact on formal assessments were observed. Similar results emerged in the research of [10] with North American computer science students reporting similar or lower stress levels and course similarities. Nonetheless, challenges such as reduced peer connections and higher drop/fail rates in some classes were noted. Additionally, the work of [11] with computer science students in the USA highlighted challenges in interacting with instructors and asking questions. The study revealed a more significant impact on students in lower-level courses, across race and residence status. It emphasized that students fared better if their courses relied on online tools before the transition.

It is possible to notice that adapting to a new teaching paradigm can be challenging for students, particularly those with limited technology access. Pre-existing digital knowledge and collaboration with the school community can help ease the transition to remote learning ([12]). Emotional state is also important to consider since it can influence technology acceptance and performance ([13, 14]). In the case of a radical change, like the shift to remote learning during the pandemic, physiological adaptation can be costly and cause emotional stress ([15]). Therefore, it is important to monitor students' emotional states, particularly those in this educational environment for the first time.

Motivation is crucial to learning success, but it is often overlooked in studies concerning the transition to remote learning. Unmotivated students cannot produce nor learn effectively, so it is crucial to consider motivation in these scenarios. Motivation can come from external or internal sources ([16]), and sudden changes in the educational methodology, such as the transition to homeschooling, can be an external source of influence. Teachers should create situations to increase motivation, especially when not physically present, as it can be challenging to engage students remotely ([17]). Therefore, monitoring students' motivation throughout the academic semester is essential to take actions to prevent unmotivated students.

Although a home can be a comfortable space, it may not always be suitable for studying. This can be especially detrimental for students participating in distance learning, particularly those from low-income families ([18]). Creating a positive and supportive learning environment at home is crucial, but it is not the only factor to consider when adjusting to a new educational methodology. This document measured student life factors such as emotional, technological, familial, and perspectives.

Our work defines the perspective factor as two features: how students think they will handle the programming subject and how they believe remote teaching will be regarding their professors. We measured the level of motivation and feelings to verify whether these factors negatively influenced students' transition. While feelings are often compared to emotions, they differ ([19, 20]). Emotions refer to mental images and bodily changes, whereas feelings refer to the perception of bodily changes. In other words, emotions contain a subjective and observable element, whereas feelings are subjective and private.

The research described in this document followed a similar procedure mentioned in [21], where the authors measured 1011 undergraduate students from various courses of a university regarding the influence of some factors (e.g., tech skills, technological infrastructure, local of study, and perspectives regarding the educational methodology) on the feelings of optimism and awareness of learning. The feeling of optimism is a positive state about future events, and its level may reflect the better or worse quality of life [?]. Another feeling that we believe reflects a state of future events is learning awareness. Students must feel that they will learn at least as much as before a significant change in how academic content will be taught. In this sense, we believe that the feeling of optimism and learning awareness can be affected by several factors, such as the person's emotional state and familial, social and technological structure, especially in a homeschooling environment. Differently, where in [21] the authors measured before the ERT semester started, in this study, we measured during the semester (pre, mid, and post) and only the computer science students.

MOTIVATION

Our motivation for having chosen this population is because this scenario can be more challenging for subjects that students have learning difficulties even in traditional classes, such as programming subjects. In this component, the students are motivated to develop skills such as logical reasoning in a specific programming language. These subjects are complicated and complex and represent a significant challenge for Computer Education ([22, 23]). According to [24], the difficulty concerning the student's ability to understand abstract terms in programming can be considered a factor for the high failure rates in programming subjects. Besides, the professor's material for the students, the lack of lectures or experiences in laboratories, and students' problem-solving skills and the control of time and self-confidence can be considered factors that directly impact students' performance ([25]). These challenges contribute to programming disciplines' highest failure rates in higher education institutes ([22]). Given this, we believe that the pandemic can accentuate existing problems in the traditional education model and create new educational challenges. For example, how can students who do not have adequate infrastructure follow the ERT classes or even programming classes?

The present study adopts a social-ecological perspective based on Bronfenbrenner's system theory ([26]). This theory emphasizes that an individual's development is based on their interactions with the environment in which they are situated. Considering the complete transformation of the student's environment when transitioning from onsite to distance schooling, this perspective is relevant. We focus on the microsystem layer of the multilevel ecological model identified by [27], which refers to the closest factors that affect the individual's development, such as the educational institution, family, neighbors, and peers. Furthermore, we used a pragmatic study ([28]) approach to collect data and understand the current reality of academic students and find solutions for this context.

RESEARCH QUESTIONS

This study investigates the effects of ERT on undergraduate programming students' motivation, perspectives, and feelings in a computer science course. Three questionnaires were administered at different points in the academic semester to measure students' emotional state and factors such as technological infrastructure, local of study, perspective on learning programming, and feelings about ERT. The study aims to answer five research questions.

1. Did students perceive a need to improve their technological infrastructure and local of study? Also, did students' perspectives on learning programming and ERT change during the semester?
2. Does the student's motivation to take programming classes in ERT have different levels during the semester?
3. Are the student's technological infrastructure, local of study, perspectives on learning programming and ERT factors influencing students' motivation?

4. Does the emotional state level of students vary in each academic semester stage, and does this influence their motivation level?
5. Are the students' technological infrastructure, local of study, perspectives on learning programming and ERT factors influencing their feelings about ERT (optimism and awareness of learning)?

We believe that factors that can further jeopardize programming students' difficult transition and adaptation to a teaching modality unfamiliar to them will be presented by finding the answers to the questions formulated in this study. Thus, providing education institutes with elements that must be monitored to understand better their students' technological, social, and familial conditions. In this sense, personalized actions can be carried out to achieve a healthier transition and adaptation for students already facing a significant challenge: taking one of the most difficult subjects in the course.

RELATED WORKS

This section reviews previous studies on the impact of Emergency Remote Teaching (ERT) on students' motivation and emotional states, the role of technological infrastructure in ERT, and the adaptability of teaching methods in post-crisis educational landscapes.

IMPACT OF ERT ON STUDENTS' MOTIVATION AND EMOTIONAL STATES

Several studies have explored the effects of ERT on students' motivation and emotional states. For example, the work of [29] explores ERT's effects on teachers' well-being, emotions, and motivation levels in Spain. It also identifies the most affected groups of teachers and provides recommendations for enhancing their resilience and adaptability.

In another work, [21] investigates the factors that negatively influence students' transition from traditional classroom learning to ERT. It highlights the role of personal realities such as the student's generation, emotional state, tech skills, technological infrastructure, place of study, and perspectives regarding this change. The study found that students' emotional states negatively influence their feelings about ERT and that the measuring factors influence optimism and awareness of learning. The paper suggests that institutions should offer innovative distance learning strategies, identify students' needs for the Internet and devices, and provide psychological support to aid the student's emotional state.

In [30], the authors investigated the impact of ERT and the requirement to teach synchronously online through video-conferencing software on the motivation of university teachers in Hong Kong. It also reveals two distinct groups of teachers who thrived or survived the ERT semester and discusses the factors that influenced their experiences.

Similar to our findings, these studies highlight the significant impact of the sudden shift to ERT on students' motivation levels and emotional states. However, our study extends this line of research by examining these effects over an entire semester, providing a more comprehensive understanding of the persistent influence of ERT. In addition, our study focused on programming classes, providing a specialized investigation that contributes valuable insights into the distinctive challenges and adaptations within this technical discipline. This targeted exploration enhances the applicability of our findings to the unique context of programming education, further enriching the existing literature on Emergency Remote Teaching (ERT) in higher education.

ROLE OF TECHNOLOGICAL INFRASTRUCTURE IN ERT

The importance of technological infrastructure in ERT has been a common theme in previous research.

The work of [31] presents a narrative synthesis of 32 studies that focused on higher education teachers' perspectives on technology use and changes in the relationship between teachers and students during ERT. The article suggests that various factors interact to shape academics' technology use in ERT across different contexts and highlights the importance of teachers' resilience, resourcefulness, and ethics of care.

In another work, the authors of [32] reports a quantitative study of 735 K-12 teachers in Israel, exploring the factors that contribute to their sense of success and self-efficacy for integrating technology in ERT. The research uses decision-tree models to reveal the influence of experience, emotional difficulties, leadership roles, and subject domains on teachers' outcomes. The paper also provides recommendations for enhancing school-based teaching and learning.

In [33], the authors review 29 studies that examined the educational effects of ERT practices on students and teachers during the COVID-19 pandemic. The article identifies four main themes: academic performance, engagement and motivation, psychological well-being, and pedagogical approaches. The article discusses the challenges and opportunities of ERT and suggests directions for future research and practice.

Consistent with our findings, these studies underscore the significant role of technological infrastructure in shaping students' perceptions of ERT. Our study contributes to this body of work by demonstrating this effect even as in-person teaching gradually resumes.

ADAPTABILITY OF TEACHING METHODS IN POST-CRISIS EDUCATIONAL LANDSCAPES

Research on the adaptability of teaching methods in post-crisis educational landscapes is still emerging.

For example, in [34], a framework for adaptability that outlines examples of flexible and equitable adaptation to change is presented. The authors define adaptability as the ability of educational systems to respond to rapidly changing circumstances while maintaining stability, promoting equality, and expanding substantive freedoms and well-being.

In another work, [35] discusses the challenges and opportunities of ERT and suggests directions for future research and practice. It reveals that the 'forced' experience of teaching with digital technologies as part of ERT can gradually give place to a harmonious integration of physical and digital tools and methods for the sake of more active, flexible and meaningful learning.

Our study contributes to this field by offering actionable insights and recommendations for educational institutions and instructors navigating the aftermath of the pandemic.

GAP IDENTIFICATION

While these studies provide valuable insights, there remains a gap in the literature concerning the experiences of computer science students during the ERT period and the lasting impact on their motivation, emotional states, and perspectives. Our research aims to fill this gap by conducting a retrospective analysis, reflecting on the enduring effects and lessons learned from this transformative period.

By addressing this gap, our study contributes to the ongoing discourse on technology, education, and human experience, emphasizing the need for educators to consider the emotional and motivational dimensions when implementing changes in educational delivery modes, even as we emerge from the immediate crisis of the pandemic.

RESEARCH METHODS

RESEARCH MODEL AND PROCEDURES

In this quantitative study, we used three questionnaires administered at different stages of the academic semester to measure factors influencing undergraduate programming students' perspectives and feelings about the shift in their educational methodology. We used a within-subject design and created the surveys on the Google Forms platform.

RESEARCH CONTEXT AND SAMPLE

Due to the 2020 pandemic, the higher education institute (HEI) local of this study had to shift its teaching methodology to emergency remote classes, which presented a considerable challenge for a university with mostly low-income students. The academic calendar was delayed, and emergency remote education was implemented. The entire community received virtual classes to learn how to use the e-learning platform adopted by the institution, Google Education. Some students received financial support to contract an internet plan and buy a tablet, but this aid was insufficient due to a lack of investment.

We invited over 100 programming students to participate in our study, with 52 accepting and completing the first questionnaire (pre-) on September 15th, 2020. The second questionnaire (mid-) was available to those who completed the first, but only 27 students responded. The final questionnaire (post-) was sent on December 21st, and 21 students who answered all three questionnaires were included in our analysis. No filters were applied to participants to reach a diverse group regarding social class, age, gender, semester enrolled, and digital skills.

In conducting this research, we acknowledge the importance of ethical considerations in academic studies. It is essential to note that when this research was conducted, our institution did not have a formalized ethics committee protocol in place. However, we want to emphasize that we followed rigorous ethical principles and procedures throughout the study.

Our commitment to ethical research practices included obtaining informed consent from all participants, ensuring anonymity and confidentiality, and adhering to the principles outlined in widely accepted ethical guidelines for academic research. While we did not have a formal ethics committee review, we approached this study with the utmost integrity and diligence to safeguard the rights and well-being of our participants.

It is important to mention that the university semester lasts five months.

SURVEY DESIGN

Measuring factors:

The applied survey is divided into seven (7) sections. Section one, presented after obtaining student consent, collects background information such as age, gender, and enrollment details. Sections two to six, presented at the three study moments, assess emotional state and measure the four factors of interest: technological infrastructure (TI), local of study (LS), perspectives about programming subject (PP), and perspectives regarding ERT (PE).

In summary, section three consisted of five questions related to the TI factor, section four had three questions that measured the LS factor, and section five had four questions that measured the PP factor. Finally, section six had five questions to identify the student's PE. The questions in sections three to six are presented in [36] (Appendix_1 - Pre-questionnaire) and underwent minor changes in how we presented them in the middle and post-questionnaires, with participants asked to indicate their current perception of each evaluated factor. The questions are available in [36] (Appendix_2 - Mid-Post-questionnaire). Section seven, which was only used in the post-questionnaire, had six questions to measure the student's acceptance of the ERT. The questions presented are in [36] (Appendix_3 - Feelings ERT post-questionnaire).

Additionally, a 5-point Likert scale was included as the last question in each survey to measure the participants' motivation to study programming in the ERT modality. Three professors reviewed and adjusted the questionnaire to clarify unclear content or misleading items as necessary.

Emotional State:

In section two, we measured students' emotional state to examine its correlation with their motivation to study programming in the ERT. We used the PANAS questionnaire ([37]), which has scores ranging from 10 to 50 for positive and negative affect on 17 questions. Lower scores indicate lower levels, while higher scores indicate higher levels.

DATA PREPARATION AND STATISTICAL ANALYSIS

Before the statistical analysis, a score was determined by three professors for each option based on the benefits the option brings to the student. For example, a student who does not have to share the devices will have one more point in the LS factor than a student who does have to share. Thus, a factor score variable was created to classify each participant's TI, LS, PP, PE, and FE values. So, considering this score, it was possible to note that participants with higher values of a specific measuring factor may have a better infrastructure or higher levels of perspectives in that factor. In the [36] (Appendix_1 - Pre-questionnaire), it is possible to see the score given for each option.

We performed the Shapiro-Wilk test to check for normality in our data set, enabling us to use the paired-sample t-test to compare differences between measuring factors, motivation levels, and emotional states across the pre-, mid-, and post-surveys. We also used One-way ANOVA to compare differences in motivation levels and measuring factors across the three questionnaires, followed by Tukey post hoc tests when significant differences were found. The bivariate Pearson Correlation was used to assess linear relationships between measuring factors, feelings toward ERT, and Linear regression to predict feelings based on the measuring factors. A 5% statistical significance level was considered throughout the tests, i.e., p values of ≤ 0.05.

RESULTS

DEMOGRAPHIC DATA:

Out of the 52 participants who completed the pre-questionnaire, 34 were male (65.4%, mean age 24.71 years old, SD = 7.00), and 18 were female (34.6%, mean age 24.11 years old, SD = 12.03). Most (24) were enrolled in six subjects, with algorithms and programming being the most popular. Additionally, 36 (69.2%) were freshmen, 38 (73.1%) did not study programming in other institutions, and 43 (82.7%) had prior knowledge of the systems used in the ERT (Google Classroom, Meet and Forms).

In the mid-survey, 27 out of 52 participants responded, with 16 males (65.4%, mean age 25.56 years old, SD = 9.06) and 11 females (40.7%, mean age 27.00 years old, SD = 16.95). 16 were enrolled in six subjects, with algorithms and programming having the highest number of students. Plus, 19 (70.4%) were freshmen, 6 (22.2%) had taken programming courses outside the university, and 6 (22.2%) had completed online courses on the ERT systems. At the end of the semester, we sent a post-questionnaire to 27 participants. 21 students (12 male and 9 female) filled out the survey. The average age of male participants was 26.58 years old with an SD = 12.20, while the average age of female participants was 27.78 years old with an SD = 17.80. Most (14) were enrolled in algorithms and programming subjects. 53.4% were freshmen at the university, 28.5% started off-university programming courses, and 38.1% finished internet courses about the systems used in the ERT. More information can be found in [36] (Appendix_3 - Descriptive data questionnaires).

MEASURING FACTORS:

Table 1 shows the differences found among each measuring factor between each questionnaire. It is possible to note that the statistical differences were found in the technological infrastructure factor between the answers of mid- and post-questionnaires ($t(20) = -2.353$, $p = 0.029$) and the perspective programming between pre- and mid-questionnaires ($t(20) = 2.259$, $p = 0.035$).

Table 1. Differences among the measuring factors between the questionnaires.

	Mean Difference Between the Questionnaires					
Measuring Factor	Pre-Mid		Pre-Post		Mid-Post	
	t	p	t	p	t	p
Technological Infrastructure	-0.849	0.406	-2.067	0.052	-2.353	0.029*
Local of Study	-0.373	0.713	-0.856	0.402	-1.335	0.197
Perspective Programming	2.259	0.035*	1.600	0.125	-1.057	0.303
Perspective ERT	-0.872	0.393	-0.355	0.726	0.576	0.571
*p <0.05						

MOTIVATION TO STUDY PROGRAMMING IN ERT:

Motivation is a pivotal aspect of education, influencing students' engagement, persistence, and, ultimately, their academic success. In the context of ERT in programming courses, understanding how students' motivation evolves throughout the academic semester is paramount. To gain insights into this crucial aspect, we conducted a comparative analysis of students' motivation levels between the beginning and end of the semester.

In Table 2, it is possible to note that the statistical differences were found in the participants' motivation between the beginning and end of the semester ($t(20) = 2.588$, $p = 0.018$). The last column of the table indicates that the highest mean score for motivation was obtained at the beginning of the semester; meanwhile, the lowest mean score was obtained at the end.

Table 2. Differences in participant motivation to study programming during the semester.

	Mean Differences						
	Pre-Mid		Pre-Post		Mid-Post		Interpretation
	t	p	t	p	t	p	
Motivation level	1.92	0.69	2.588	0.018*	0.196	0.846	Pre>Mid; Mid>Post

MOTIVATION LEVEL AND THE MEASURING FACTORS:

We conducted a comparative analysis to discern the influence of measuring factors on students' motivation levels throughout the semester. Specifically, we examined the relationship between motivation levels and each of the measuring factors.

The One-way ANOVA showed statistical differences between the motivation level and measuring factors in at least one factor of each questionnaire. In the pre-questionnaire, no participant pointed out motivation levels 1 or 2, only 3 to 5. Statistical differences were found between the motivation level and programming perspective in the ERT factors ($F(2, 18) = 5.880$, $p = 0.011$). The Tukey post hoc test identified significant differences in perspective programming between motivation levels 3 and 5 ($p = 0.017$) and between levels 4 and 5 ($p = 0.024$). Table 3 presents the mean factor score (sum of options given) for each factor by the level of motivation, such as the TI factor with the highest mean factor score (3.03) obtained by students with motivation level 4 in the pre-questionnaire.

More participants had a low motivation level than in the pre-questionnaire concerning the mid-questionnaire. Statistical differences were found between the motivation levels with the TI ($F(4, 16) = 3.447$, $p = 0.033$) and PP ($F(4, 16) = 3.547$, $p = 0.030$). The Tukey post hoc test shows that the differences are between the students with motivation levels 2 and 5 ($p = 0.020$) to TI factor and between levels 1 and 5 ($p = 0.050$) and 2 and 5 ($p = 0.047$) to PP factor.

Finally, differences between the participants' motivation levels with the PP ($F(4, 16) = 4.527$, $p = 0.012$) and PE ($F(4, 16) = 4.366$, $p = 0.043$) were found in the post-questionnaire. The Tukey post hoc test shows that the differences are between the students with motivation levels 1 and 5 (p =

0.016), and 2 and 5 (p = 0.026) to PP factor, and between levels 1 and 5 (p = 0.011), and 2 and 5 (p = 0.012) to PE factor.

EMOTIONAL STATE IMPLICATIONS:

The observed fluctuations in students' emotional states at different stages of the academic semester prompt a closer examination of the implications of these variations. In this context, we delve into the impact of emotional states on students' ERT experiences.

Students presented a higher positive emotional state at the beginning (57.1%) of the academic semester compared to the middle (28.6%) and end (38.1%). On the other hand, this behavior was not the same for the negative Affects, in which the students presented higher negative feelings in the middle (81%) and end (76.2%) of the academic semester. [36] (Appendix 5) shows the descriptive analysis of students' emotional states.

Table 4 shows that the statistical differences were found in the participants' positive Affects between the answers of pre- and mid-questionnaires ($t(20) = 2.439$, $p = 0.024$). Regarding the negative, statistical differences were found between the pre- and mid ($t(20) = -3.056$, $p = 0.006$) and pre- and post-surveys ($t(20) = -2.177$, $p = 0.042$). The last column indicated that the higher mean score for the positive Affects was obtained at the beginning of the semester; meanwhile, for the negative Affects, the higher mean score was at the mid-semester.

Finally, in Table 5, it is possible to note the statistical differences between the student's motivation level and the positive Affects at the pre-questionnaire ($F(2, 18) = 6.976$, $p = 0.014$). The Tukey post hoc test shows which motivation level presented statistically significant differences in the emotional state between the motivation levels pointed out by the participants. Regarding the test, the differences are between the students with motivation levels 3 and 5 ($p = 0.013$) for the positive emotional state.

Table 3. Participants' motivation level differences with the measuring factors by questionnaires.

Measuring Factor	Pre-questionnaire Motivation - Level							
	1	2	3	4	5			
	Mean(SD)	Mean(SD)	Mean(SD)	Mean(SD)	Mean(SD)	F	p	Partial Eta Squared
Technological Infrastructure	0	0	2.96(0.80)	3.03(0.80)	2.68(0.66)	0.391	0.682	0.042
Local of Study	0	0	1.72(0.59)	1.90(0.48)	2.03(0.61)	0.447	0.647	0.047
Perspective Programming	0	0	2.18(0.40)	2.36(0.40)	3.11(0.69)	5.880	0.011*	0.395

Perspective ERT	0	0	3.62(1.10)	3.43(0.78)	3.38(1.24)	0.860	0.918	0.009
			Mid-questionnaire					
			Motivation - Level					
	1	2	3	4	5			
	Mean(SD)	Mean(SD)	Mean(SD)	Mean(SD)	Mean(SD)	F	p	Partial Eta Squared
Technological Infrastructure	2.70(0.96)	2.37(0.70)	3(0.78)	3.06(0.20)	3.76(0.15)	3.447	0.033*	0.463
Local of Study	1.53(0.41)	1.60(0.49)	1.97(0.52)	1.78(0.62)	2.56(0.37)	2.987	0.051	0.428
Perspective Programming	1.60(0.26)	1.70(0.69)	1.92(0.85)	2.20(0.53)	3.04(0.65)	3.547	0.030*	0.470
Perspective ERT	3.66(1.66)	3.25(0.51)	3.50(1.06)	3.34(0.45)	4.38(0.77)	1.191	0.352	0.229
			Post-questionnaire					
			Motivation - Level					
	1	2	3	4	5			
	Mean(SD)	Mean(SD)	Mean(SD)	Mean(SD)	Mean(SD)	F	p	Partial Eta Squared
Technological Infrastructure	2.97(0.88)	2.93(0.97)	2.72(0.72)	3.24(0.37)	3.88(0.27)	2.178	0.118	0.353
Local of Study	1.90(0.62)	1.93(0.75)	1.82(0.39)	2.04(0.65)	2.22(092)	0.216	0.925	0.051
Perspective Programming	1.62(1.00)	1.60(0.65)	2.20(0.72)	2.48(0.34)	3.22(0.46)	4.527	0.012*	0.531
Perspective ERT	2.77(1.13)	2.63(1.85)	3.27(0.46)	3.88(0.75)	4.64(0.53)	3.156	0.043*	0.441
*p <0.05								

Table 4. Differences in the student's emotional state during the semester.

Mean Difference Between the Questionnaires							
Emotional State	Pre-Mid		Pre-Post		Mid-Post		Interpretation
	t	p	t	p	t	p	
Positive	2.439	0.024*	1.845	0.080	-1.149	0.264	Pre>Mid; Pre>Post; Post>Mid
Negative	-3.056	0.006*	-2.177	0.042*	0.882	0.388	Mid>Pre; Mid>Post; Post>Pre
*p <0.05							

From the data obtained in the middle of the academic semester, the differences were obtained between the student's motivation level and the positive Affects ($F(4, 16) = 6.976$, $p = 0.002$). The Tukey post hoc test shows that the differences are between the students with motivation levels 1 and 5 ($p = 0.011$), 2 and 4 ($p = 0.035$), and 2 and 5 ($p = 0.003$) for the positive emotional state.

Concerning the post-questionnaire, no statistical differences were found. Appendix_5. Descriptive emotional state shows the participants' emotional state levels by gender and at each phase of the semester ([36]).

Table 5. Differences between participants' motivation and emotional state level by questionnaires.

			Pre-questionnaire					
Emotional State			Motivation - Level					
	1	2	3	4	5			
	Mean(SD)	Mean(SD)	Mean(SD)	Mean(SD)	Mean(SD)	F	p	Partial Eta Squared
Positive	0	0	2.26(6.50)	29.30(3.83)	32(4.85)	5.451	0.014*	0.377
Negative	0	0	19(8.00)	19.40(8.23)	16.67(8.23)	0.210	0.812	0.230
			Mid-questionnaire					
			Motivation - Level					
	1	2	3	4	5			
	Mean(SD)	Mean(SD)	Mean(SD)	Mean(SD)	Mean(SD)	F	p	Partial Eta Squared
Positive	16.67(6.65)	15.75(3.77)	22(4.96)	27.20(4.55)	31.40(6.18)	6.976	0.002*	0.636
Negative	26(16.09)	28(4.08)	19.50(10.78)	21.80(7.29)	21.20(7.59)	0.586	0.677	0.128
			Post-questionnaire					
			Motivation - Level					
	1	2	3	4	5			
	Mean(SD)	Mean(SD)	Mean(SD)	Mean(SD)	Mean(SD)	F	p	Partial Eta Squared
Positive	16.25(7.18)	21(7.00)	25.50(3.87)	29.20(4.43)	28.80(12.71)	2.011	0.141	0.335
Negative	30(5.83)	16.67(6.02)	24.25(10.68)	15.80(2.35)	22.60(9.18)	1.959	0.150	0.329
*p <0.05								

FEELINGS (OPTIMISM AND AWARENESS OF LEARNING) CONCERNING THE ERT:

Participants' feelings about ERT obtained a mean of 3.17 (SD = 1.49), the lowest scoring at 0.80 and the highest at 6. Then, to verify which factor obtained the higher mean at the end of the semester, the mean obtained from each factor in each questionnaire was summed (e.g., the score of the TI factor at pre-, mid- and post-survey). In this sense, we had five final score variables for each measuring factor, with the lowest mean obtained in the local study factor (5.82, SD = 1.60) and the highest for perspective about the ERT (10.6, SD = 2.50). Appendix_6 - Mean and final factors score, shows the values obtained ([36]).

The Pearson correlation to the post-questionnaire data found a low, positive, and statistically significant correlation between TI and feelings about ERT ($r(21) = .435$, $p = .049$). No correlation was found for other factors. A bivariate regression showed that TI could predict 18.9% of the variance in feelings level, with a weak relationship ($r2 = 0.189$). The regression equation to predict feelings level from TI was $Y = 0.908X + 0.271$, indicating that for each unit of TI increased, the feelings level increased by about 0.006 to 1.8 points.

DISCUSSION

Although most students mentioned knowledge about the systems used in the ERT in the pre-questionnaire, they took courses on these systems during the semester. It shows that the student's knowledge was insufficient for the ERT; however, they realized that acquiring more knowledge about the systems was necessary.

MEASURING FACTORS

The study monitored the factors throughout the semester and found differences in TI from the middle to end-semester and PP from before to mid-semester. The differences in TI may be because participants either bought new equipment or realized their existing infrastructure was sufficient for the ERT. The difference in PP may be because of high initial expectations about learning programming that was not sustained. Overall, the study found evidence that TI and perspectives on learning programming were affected during the semester, while other elements (Local of study and Perspective on ERT) remained unchanged (answering our RQ1).

MOTIVATION TO STUDY PROGRAMMING IN ERT

We found that students were more motivated before the semester began, which is a common trend when transitioning to e-learning [38]. However, our study showed a decrease in student motivation throughout the semester. This could be due to several factors, including inadequate e-learning resources (such as internet, equipment, and study environment), a lack of motivational activities during the semester, insufficient preparation of instructors to teach programming in an e-learning environment, the need for social interaction, and distractions such as television, games, mobile phones, and family obligations.

Our data showed that the mean evaluations with the highest level of motivation were in the post-questionnaire, and the difference in motivation level was between the pre- and post-questionnaire. In this sense, we can see that the motivation to learn programming grew during the semester; however, not a big difference between the beginning and the middle of the semester, nor from the middle of the semester to the end. With that, we can answer our RQ2.

MOTIVATION LEVEL AND THE MEASURING FACTORS

From the results of the measuring factors, it can be observed that perspectives on learning programming served as intrinsic sources influencing motivation levels before, during, and at the end of the semester. Based on our experience in programming disciplines, we believe that students' perspectives on learning programming in the early and mid-semester can be based on prior programming experience. For example, students who know the programming world will have a greater perspective of their learning in ERT by presenting a greater motivation, while students unfamiliar with programming will think otherwise. Prior programming knowledge also can be a factor in influencing exam scores and lecture attendance [39].

Students' perspectives on the ERT appeared to influence their motivation levels, particularly in the post-questionnaire. It may have happened because those who initially believed they would not perform well with the platforms and programs used by professors reported increased motivation after successfully completing programming challenges throughout the semester.

We believe that the extrinsic technological infrastructure (TI) element had a mid-semester effect on motivation because some participants perceived that their infrastructure supported the ERT. Conversely, we think this effect did not occur before the semester because students may not have known if their TI would support the new methodology. Additionally, this element did not significantly influence motivation at the end of the semester because students had become more familiar with their TI and the learning environment. Our findings suggest that several measurement elements, such as perspectives on learning programming, technological infrastructure, and perspectives on ERT, may influence students' motivation levels. However, further investigation is necessary to explore these factors more comprehensively (answering the RQ3).

EMOTIONAL STATE IMPLICATIONS

We posit that students' initial positive behavior at the beginning of the semester may be attributed to their expectations about remote education. However, this positive level decreased by 50%, while the high negative level peaked in the mid-semester. We believe this occurred because students faced challenges such as internet connectivity issues, difficulties with professors, and daily life interruptions during synchronous and asynchronous meetings. In the final questionnaire, we observed a slight improvement in students' emotional states, which we attribute to their increased ability to cope with the challenges they encountered throughout the semester. Specifically, we suggest that these problems were no longer surprising and students had developed strategies for managing them.

In addition, we posit that the disparity between the pre- and mid-semester surveys may be attributed to students' optimistic expectations regarding the programming subject they had yet to undertake. As for the high negative emotional state, we believe that the challenges students encountered during the semester had a more significant impact than anticipated at the beginning. Nevertheless, we observed improved students' emotional well-being after the mid-semester, which we attribute to a better alignment of expectations and demands between professors and students. This included adjustments in deadlines and improved management of classes, ultimately reducing negative emotions experienced by students.

We found evidence that the level of motivation felt before and in the middle of the semester is influenced by the student's level of positive emotional state. This behavior coincides with the works of [40, 41], which suggest that positive emotions influence motivation. However, we believe that there were no differences at the end of the semester because students were less motivated, and the positive Affects were also reduced. Furthermore, the negative emotional state did not differ in terms of motivation levels may demonstrate that negative emotions are not strong predictors of motivation, as described in [42].

Although it is difficult to affirm that the change of teaching mode influenced the emotional state level (the pandemic situation may also influence it), we could observe a variance in the emotional levels during the academic semester. In this sense, we can partially answer our RQ4, saying that the abrupt change of teaching mode may influence the student's emotional state level.

FEELINGS (OPTIMISM AND AWARENESS OF LEARNING) CONCERNING THE ERT

The results of our study suggest that the technological infrastructure significantly correlates with students' perceptions of how the ERT was conducted. This finding is not surprising and reinforces the notion that access to the internet, devices, and equipment is crucial for optimal performance in remote learning. Thus, we can answer our final research question by stating that students' technological infrastructure is a critical factor influencing their perceptions of this educational methodology shift based on the measured elements.

CONCLUSION

INFERENCES OF THE STUDY:

In conclusion, we observed changes in two key factors over the course of the semester: students' technological infrastructure and their perspective on learning programming in the ERT. These changes may be attributed to a shift in perception or the acquisition of new equipment and services, such as improved internet connectivity. It is important for educational institutions to identify and address their students' technological needs to support those who require assistance. Moreover, programming subjects are often responsible for the high failure and drop-out rates in computer courses, so preparing programming students for their challenges is essential. We recommend that institutions create projects to disseminate information on how programming content and practical classes will be approached in the ERT, including laboratory classes, to reduce the likelihood of failure and drop-outs.

Our study revealed a decline in the motivation levels of students enrolled in programming disciplines throughout the semester. To mitigate this issue, professors should incorporate innovative activities that stimulate and maintain student motivation. Our findings suggest that motivation was influenced by two key factors: technology infrastructure and perspective on learning programming. We believe that a student's programming perspective relates to their technological infrastructure. In other words, students who perceive their infrastructure as insufficient for remote learning tend to have a lower perspective on their ability to learn programming in this modality. Thus, our results emphasize the need for projects that identify and improve students' technological infrastructure and clarify the ideal infrastructure required for keeping up with programming classes. By addressing this issue, we can increase students' motivation for programming studies in remote environments, enabling them to absorb better and learn the content.

Another crucial factor for a successful transition to ERT that affects student motivation is their emotional state. Our study found that positive affects were higher at the beginning of the semester but decreased as the semester progressed. Similarly, negative affects were higher in the middle of the semester. These fluctuations in emotional states likely impacted student motivation to study. Therefore, institutes and professors should research strategies and techniques to maintain students' emotional well-being. It is recommended that institutes provide access to psychologists or other mental health services to help students manage their emotional states.

We evaluated several essential factors for successfully transitioning to an unfamiliar teaching modality. While all factors are crucial, we found that technological infrastructure strongly correlated with students' feelings towards ERT. This is unsurprising since access to reliable internet and proper computer equipment is necessary for quality remote education. Therefore, we recommend that institutions inform their communities about the minimum requirements for quality ERT and provide assistance to those who need it through donation campaigns, incentives, or loans of resources. This would enable everyone to overcome technical difficulties and have positive feelings about remote learning, leading to a smoother transition and better learning outcomes.

Finally, professors' and students' learning during this pandemic will be greatly valuable when we return to traditional classes. The practices and tools adopted and adapted for distance learning can be utilized to enhance classroom learning. Our study, which monitored students throughout an academic semester, identified the key factors influencing students' success in a remote learning environment. We hope our research will guide educational institutions in improving their online programs, ensuring that students feel motivated, engaged, and adequately supported in their online learning experience.

LIMITATIONS AND FUTURE RESEARCH:

Some limitations regarding the literature review and population focus were faced in this study. The first limitation is the population used and their perception of the situation. In other words, one person's perception of an element can differ. For example, one person may perceive the technological infrastructure as ideal for ERT, and another may not think it is ideal. Another limitation was the lack of participants who completed the pre-questionnaire and did not complete the others. Because of that, we had to disregard the data of those participants in the final analysis.

Further investigations can be carried out on students in different courses and financial and personal situations to compare whether the same pattern of behavior is found. Plus, it is possible to measure other factors that may influence the adaptation of undergraduate students, such as family support, lifestyle and environment. Finally, some suggestions have been made in this document that can be implemented in future studies to investigate whether there is an improvement in students' adaptability, perspectives, emotional state and level of motivation.

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