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CRITICAL FACTORS INFLUENCING REMOTE LEARNING EFFECTIVENESS DURING THE COVID-19 PANDEMIC: A STRUCTURAL EQUATION MODELING APPROACH

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Abstract:

The COVID-19 pandemic forced a rapid transition from traditional classrooms to remote learning, creating both opportunities and challenges. This study investigates factors influencing remote learning effectiveness among secondary school students. Using a quantitative design, structured surveys measured technological readiness, attitudes, motivation, and perceptions. Structural equation modeling (SEM) revealed that attitude, motivation, and perception significantly impact learning success, with student readiness, engagement, and satisfaction playing key roles. Addressing technological barriers, fostering participation, and enhancing teachers' digital skills emerged as essential strategies. The study also emphasizes supportive home environments and attention to students' psychological well-being. Findings offer practical guidance for creating inclusive, resilient, and adaptive educational systems prepared for future disruptions.

Keywords:

Remote Learning (RL); Emergency Remote Teaching (ERT); COVID-19 Pandemic; Structural Equation Modeling (SEM); Educational Effectiveness; Student Motivation; Pedagogical Approaches

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Introduction

The COVID-19 pandemic has necessitated a swift and large-scale transition to emergency remote teaching (ERT), significantly impacting educational systems globally. This abrupt shift has underscored both the potential and challenges of remote learning (RL), highlighting the need for a thorough understanding of the factors influencing its effectiveness. This study aims to explore the multifaceted landscape of remote learning during the COVID-19 pandemic, utilizing a structural equation modeling (SEM) approach to elucidate the complex interrelationships between key determinants and learning outcomes.

The sudden transition to remote learning required rapid adaptation by educators, students, and institutions. Despite the flexibility and accessibility provided by RL, numerous challenges have emerged, such as disparities in technological access, varying levels of digital literacy, and the psychological impacts of isolation and anxiety (Bao, 2020; Dhawan, 2020). Addressing these issues is crucial for educational stakeholders to identify and understand the factors that contribute to the success or failure of remote learning environments.

Recent literature has begun to examine the diverse elements that affect remote learning. Student-centric factors, such as attitude, motivation, and perception, play a crucial role in shaping learning experiences and outcomes. Attitude towards remote learning, including aspects such as self-efficacy and technological readiness, has been shown to significantly influence student engagement and academic performance (Garris & Fleck, 2020; Panigrahi, Srivastava, & Sharma, 2018). Motivation, both intrinsic and extrinsic, is another critical determinant, driving students' willingness to engage with course materials and participate in online learning activities (Hartnett, St. George, & Dron, 2011). Additionally, students' perceptions of the quality and effectiveness of remote learning can profoundly impact their satisfaction and overall learning experience (Bolliger & Wasilik, 2009).

The complexity of these interrelated factors necessitates a robust analytical framework to capture their nuanced interactions. Structural equation modeling (SEM) provides a comprehensive approach to examining these relationships, enabling researchers to assess direct and indirect effects among multiple variables simultaneously (Hair, Black, Babin, & Anderson, 2010). By employing SEM, this study aims to construct a detailed model of the factors influencing remote learning outcomes, offering valuable insights into how various elements interplay to affect student performance and satisfaction.

Methodologically, this research adopts a quantitative approach to gather comprehensive data from secondary school students (N=610). The quantitative component includes Likert scale surveys and open-ended questions designed to capture a broad spectrum of student attitudes, motivations, and perceptions.

By disentangling the complex relationships among the identified factors, this study aims to contribute to the existing knowledge base on remote learning. The findings are intended to inform educators, policymakers, and researchers, offering evidence-based recommendations for developing effective and inclusive pedagogical strategies. Ultimately, this research seeks to enhance the quality of remote learning experiences, ensuring that all students can thrive in the evolving educational landscape shaped by the COVID-19 pandemic.

Literature Review

The COVID-19 pandemic has necessitated an unprecedented shift to emergency remote teaching (ERT), compelling educators, students, and institutions to adapt swiftly to new educational paradigms. This review synthesizes recent literature on the critical factors influencing the effectiveness of remote learning (RL), focusing on student-centric factors such as attitude, motivation, and perception. Utilizing structural equation modeling (SEM), the review aims to elucidate the complex interrelationships shaping remote learning experiences.

Attitude Towards Remote Learning

Student attitudes towards remote learning significantly impact their engagement and academic performance. Attitudes encompass self-efficacy, technological readiness, and overall disposition towards online education. Self-efficacy, defined as students' belief in their ability to succeed, is a significant predictor of academic achievement in remote learning environments (Kleitman et al., 2020). Studies indicate that students with higher self-efficacy are more likely to engage actively and persist in online courses (Chen et al., 2020; Shamir-Inbal & Blau, 2021). Technological readiness, including access to necessary devices and internet connectivity, is another critical component of student attitudes. The pandemic has exacerbated disparities in technological access, impacting students' ability to participate effectively in online education (Pokhrel & Chhetri, 2021). Research shows that students with reliable internet access and adequate technological resources exhibit higher levels of engagement and satisfaction with remote learning (Tang et al., 2021; Baticulon et al., 2021).

Motivation in Remote Learning

Motivation, both intrinsic and extrinsic, significantly influences students' willingness to engage with course materials and participate in online learning activities. Intrinsic motivation refers to the internal drive to learn, driven by personal interest and enjoyment in the subject matter (Ryan & Deci, 2020). Extrinsic motivation, on the other hand, involves external incentives such as grades, recognition, and career advancement (Deci & Ryan, 2017).

Research suggests that intrinsically motivated students are more likely to exhibit higher levels of engagement, persistence, and academic success in remote learning environments (Richardson et al., 2020). Conversely, extrinsic motivation, while effective in the short term, may not sustain long-term engagement and learning outcomes (Wang et al., 2021). Understanding the interplay between intrinsic and extrinsic motivators is crucial for designing effective remote learning strategies that foster sustained student engagement.

Perception of Remote Learning

Students' perceptions of remote learning encompass their views on the quality, effectiveness, and overall experience of online education. These perceptions are shaped by various factors, including course design, instructor presence, and peer interaction (Bali & Liu, 2018). High-quality course design, characterized by clear objectives, engaging content, and interactive elements, significantly enhances students' learning experiences and outcomes (Martin et al., 2020).

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Instructor presence, defined as the visibility and engagement of the instructor in the online learning environment, plays a vital role in shaping students' perceptions. Studies indicate that frequent instructor interaction, timely feedback, and active facilitation of discussions contribute to positive perceptions of remote learning (Martin et al., 2021; Lowenthal & Dunlap, 2018). Additionally, peer interaction, including collaborative activities and social presence, enhances students' sense of community and belonging, which are critical for effective remote learning (Rapanta et al., 2020).

Structural Equation Modeling in Educational Research
Structural equation modeling (SEM) is a powerful statistical technique that allows researchers to examine complex relationships among multiple variables simultaneously. SEM is particularly useful in educational research for assessing direct and indirect effects, providing a comprehensive understanding of the interrelationships among various factors (Schumacker & Lomax, 2016).

In the context of remote learning, SEM has been employed to investigate the interplay between student attitudes, motivation, and perceptions, and their impact on learning outcomes (Panigrahi et al., 2018; Joo et al., 2021). By leveraging SEM, researchers can develop detailed models that capture the nuanced dynamics of remote learning environments, offering valuable insights for educators and policymakers.

The literature on remote learning during the COVID-19 pandemic highlights the critical role of student-centric factors such as attitude, motivation, and perception in shaping learning experiences and outcomes. Attitudes towards remote learning, including self-efficacy and technological readiness, significantly influence student engagement and academic performance. Motivation, both intrinsic and extrinsic, drives students' willingness to participate in online learning activities. Perceptions of remote learning, shaped by course design, instructor presence, and peer interaction, impact students' satisfaction and overall learning experience. Structural equation modeling provides a robust framework for examining these complex interrelationships, offering comprehensive insights into the factors that affect remote learning effectiveness. This study aims to contribute to the existing knowledge base by identifying and analyzing the key determinants of remote learning outcomes, ultimately informing the development of effective and inclusive pedagogical strategies.

Research Methodology
This study employs a quantitative approach to provide a comprehensive understanding of the factors affecting remote learning (RL).

Research Design
The quantitative approach was selected for its ability to generate objective, measurable data and facilitate statistical analysis of relationships among multiple variables. In particular, this design supports the use of structural equation modeling (SEM) to simultaneously assess direct and indirect effects between observed and latent constructs. By employing a quantitative design with SEM, this study not only examines individual variable effects but also explores the complex interrelationships among learner, technological, and contextual factors.

Quantitative Data Collection and Analysis

Quantitative data is collected through surveys administered to students (N=610) from several secondary schools. The surveys include both Likert scale questions and open-ended questions. Likert scale questions are used to measure various constructs related to RL, such as student motivation, self-directed learning skills, technology proficiency, and access to reliable internet and suitable learning spaces. These constructs are selected based on the literature review and are hypothesized to influence the effectiveness of RL.

The quantitative data is analyzed using structural equation modeling (SEM), a statistical technique that allows for the examination of complex relationships between observed and latent variables (Hair et al., 2019). SEM is particularly suited for this study as it enables the testing of theoretical models that include multiple independent and dependent variables, providing insights into the direct and indirect effects of various factors on RL outcomes (Cheung & Lau, 2017).

Ethical Considerations

Ethical considerations are paramount in this study, given the involvement of human participants. Informed consent is obtained from all participants, ensuring that they are fully aware of the purpose of the research, the procedures involved, and their right to withdraw at any time (Creswell & Creswell, 2018). The confidentiality and anonymity of participants are maintained throughout the research process, and data is securely stored to protect participants' privacy.

Data Collection

Data collection for this study involves a comprehensive approach, targeting students across several secondary schools. The aim is to gather robust quantitative data that provide a holistic understanding of the factors influencing remote learning (RL).

Quantitative Data Collection

Quantitative data is collected through structured surveys administered to students (N=610). The surveys include Likert scale questions and open-ended questions to capture a wide range of responses.

Surveys

Surveys are a widely used method for quantitative data collection in educational research due to their efficiency in gathering large amounts of data from diverse populations (Creswell & Creswell, 2018). In this study, the surveys are designed to measure constructs such as motivation, self-directed learning skills, technology proficiency, and access to reliable internet and suitable learning spaces. The Likert scale questions provide a standardized way to assess these constructs, facilitating the quantitative analysis of relationships between variables (Joshi et al., 2015).

The surveys are distributed electronically to ensure broad participation and convenience for respondents. Electronic distribution also allows for automatic data entry, reducing the risk of data entry errors and facilitating quicker data analysis (Dillman et al., 2017).

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Likert Scales

Likert scales are employed to quantify attitudes and perceptions on various aspects of RL. These scales typically range from 1 (strongly disagree) to 5 (strongly agree), allowing respondents to express the intensity of their agreement with statements related to the constructs being measured (Joshi et al., 2015). Likert scales are particularly useful in capturing nuanced variations in attitudes and perceptions, providing detailed insights into the factors affecting RL (Boone & Boone, 2012).

Sampling and Recruitment

Participants for surveys are recruited from several secondary schools to ensure a diverse and representative sample. Students are invited to participate through school administrators, who distribute the study information and consent forms electronically. Participation is voluntary, and all participants provide informed consent, ensuring ethical standards are upheld (Creswell & Poth, 2018).

Participants

Participants in this study include secondary school students who experienced the transition to emergency remote teaching (ERT) during the COVID-19 pandemic. The selection of participants aims to capture a comprehensive and representative sample, reflecting diverse demographic backgrounds and educational settings. This approach ensures that the findings are generalizable and applicable across different contexts.

Students

The student sample includes 610 secondary school students. These students provide valuable perspectives on motivation, self-directed learning skills, technology proficiency, and the overall impact of ERT on their learning experiences. Students were selected from various grade levels, ensuring a broad representation of different stages of secondary education.

The student sample is also demographically diverse, representing various socio-economic backgrounds, ethnicities, and geographic locations. This diversity is crucial for understanding the differential impacts of ERT on students with varying access to resources and support systems (Cullinan et al., 2021). For instance, students from lower socio-economic backgrounds may face greater challenges in accessing reliable internet and suitable learning spaces, which can significantly affect their remote learning experiences (Tzimiris et al., 2023).

Recruitment and Ethical Considerations

Participants were recruited through school administrators, who facilitated the distribution of study information and consent forms. Students were informed about the purpose of the research, the procedures involved, and their right to withdraw at any time. Informed consent was obtained from all participants, with parental consent obtained for students under the age of 18, in compliance with ethical guidelines for research involving minors (Creswell & Poth, 2018).

Participation was voluntary, and efforts were made to ensure the confidentiality and anonymity of all participants. Data was collected and stored securely, with access restricted to the research team. These measures were taken to protect participants' privacy and to ensure that their responses were not influenced by any potential repercussions (Kang & Hwang, 2023).

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Data Analysis

Quantitative Analysis

Quantitative data analysis in this study employs structural equation modeling (SEM), a robust statistical technique for exploring intricate relationships among observed and latent variables (Mueller & Hancock, 2018). SEM is particularly suitable for examining multiple dependent and independent variables concurrently, offering a comprehensive understanding of how various factors interact to influence remote learning (RL) outcomes.

SEM integrates aspects of multiple regression analysis, factor analysis, and path analysis, making it adept at analyzing hypothesized relationships within a theoretical framework (Kite & Whitley, 2018). The model focuses on key student-centric factors: attitude, motivation, and perception, which are pivotal in shaping RL effectiveness during the COVID-19 pandemic.

Student motivation is assessed through Likert scale items capturing intrinsic and extrinsic motivations (Al-Mseidin, 2023), while perception involves subjective interpretations of RL experiences (Anwar & Mutiah, 2022). These constructs, alongside teacher-related factors (pedagogical preparedness, technology integration skills) and environmental conditions (internet access, learning spaces), are hypothesized to impact RL outcomes.

Prior to SEM, rigorous data preparation ensures reliability, including handling missing data and assessing normality (Sainani, 2015). Model estimation employs maximum likelihood estimation, with fit indices (CFI, TLI, RMSEA) used to assess model adequacy (Akter et al., 2017). The findings provide insights into direct and indirect effects of student-centric factors on RL outcomes, informing strategies for enhancing educational practices in remote settings.

Results

Exploratory Factor Analysis (EFA)

To elucidate the underlying structure of the factors influencing remote learning (RL) during the COVID-19 pandemic, an Exploratory Factor Analysis (EFA) was conducted. This analysis aimed to identify the key dimensions that encapsulate the constructs under investigation, including attitudes, motivations, and perceptions of both students and teachers towards remote learning.

Methodology and Key Findings

An EFA was performed using the Extraction Method: Maximum Likelihood and Rotation Method: Promax with Kaiser Normalization. The minimum factor loading criterion was set to 0.50. The communality of the scale, which indicates the amount of variance in each dimension, was also assessed to ensure acceptable levels of explanation. The results show that all communalities were over 0.50.

An important step involved weighing the overall significance of the correlation matrix through Bartlett's Test of Sphericity, which provides a measure of the statistical probability that the correlation matrix has significant correlations among some of its components. The results were significant, $\chi 2(n = 253) = 4878.273$ ($p < 0.001$), indicating its suitability for factor analysis. The Kaiser–Meyer–Olkin measure of sampling adequacy (MSA) was 0.934, as illustrated in Table 1. Data with MSA values above 0.800 are considered appropriate for factor analysis. The

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factor solution derived from this analysis yielded three factors for the scale, which accounted for 40.498% of the variation in the data (Table 1).

Table 1: KMO and Bartlett's Test

MEASURE	VALUE
Kaiser-Meyer-Olkin Measure of Sampling Adequacy	0.934
Bartlett's Test of Sphericity: Approx. Chi-Square	4878.273
Degrees of Freedom	253
Significance	0

Nonetheless, ten items, as shown in Table 2, failed to load on any dimension significantly or loaded onto a factor other than their underlying factor. Hence, these ten items were removed from further analysis.

Table 2: Items Removed from Further Analysis

ITEM	DESCRIPTION
1	I believe that remote (online) classes have positively affected communication between my instructor and me.
4	I feel more isolated now when I am taking remote (online) classes.
8	Suggested useful programs for peers to utilize remote (online) learning materials.
10	Remote (Online) learning highly motivates students for taking advanced courses.
13	Remote (Online) learning ensures effectiveness in coping with missed lectures.
15	Remote (Online) learning is economical in terms of time for students and teachers.
18	Quality of teaching and learning can be increased through remote (online) learning because it integrates various types of media.
21	Access to education increases through remote (online) learning.
23	The web is often student-friendly for searching remote (online) educational resources.
32	Remote (Online) learning makes students become slaves to technology.

The results of this revised analysis confirmed the three-dimensional structure theoretically defined in the research. The three factors identified in this EFA aligned with the theoretical propositions in this study. Factor 1 (Attitude) includes items 2, 3, 5, 6, 11, 14, 16, 17, and 19. Factor 2 (Motivation) includes items 7, 12, 24, 27, 28, 29, and 31. Finally, Factor 3 (Perception) includes items 9, 20, 22, 25, 26, and 30. The loadings are presented in Table 3.

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Table 3: EFA Results

ITEM	FACTOR 1 (ATTITUDE)	FACTOR 2 (MOTIVATION)	FACTOR 3 (PERCEPTION)
2	0.623		
3	0.568		
5	0.636		
6	0.667		
7		0.57	
9			0.535
11	0.729		
12		0.534	
14	0.723		
16	0.675		
17	0.648		
19	0.678		
20			0.554
22			0.534
24		0.657	

Figure 1 shows the scree plot of the EFA, depicting the eigenvalues associated with each factor before and after rotation. This plot further confirms the three-factor solution, as there is a clear inflection point after the third factor.

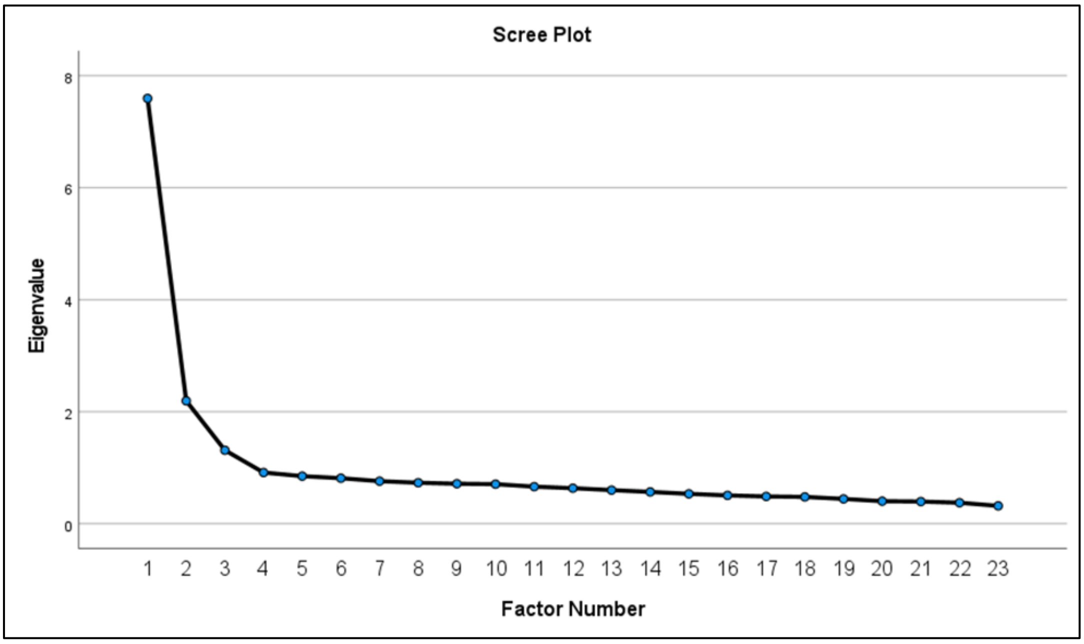

Figure 1: Scree Plot of EFA

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Confirmatory Factor Analysis (CFA)

A Confirmatory Factor Analysis (CFA) as illustrated in Figure 2 was conducted to validate the EFA results, confirming the proposed research model. The CFA provided further evidence that the identified factors of Attitude, Motivation, and Perception are significant determinants of the success of remote learning during the pandemic.

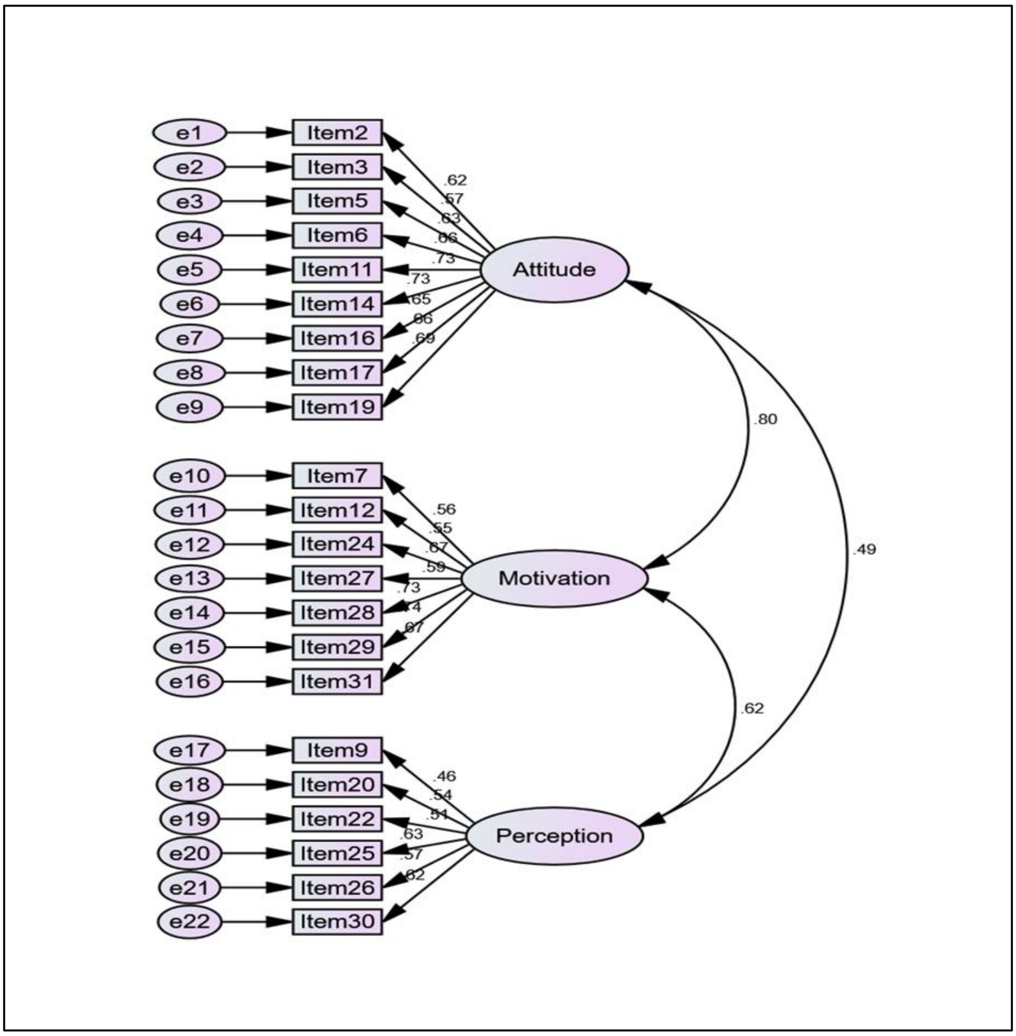

Figure 2: CFA Model

The success of students in remote learning can be understood through a theoretical framework that considers the dimensional structure of attitude, motivation, and perceptions. Research suggests that factors such as comfort with technology, motivation to learn technology skills, and satisfaction with online courses are related to perceived quality and success in online and hybrid learning environments. Additionally, self-regulated learning, which involves metacognitive, motivational, and behavioral activities, has been found to be positively associated with student success in distance learning programs. Furthermore, the design of interactive techniques and novel learning media can promote student engagement and enhance learning comprehension in remote instruction. By considering these dimensions and factors, educators and institutions can develop strategies and interventions to support student success in remote learning environments.

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The CFA model fit indices as illustrated in Table 4 were assessed to evaluate the adequacy of the model. The results indicated a good fit to the data: χ2/df = 2.305, Comparative Fit Index (CFI) = 0.936, Tucker-Lewis Index (TLI) = 0.927, and Root Mean Square Error of Approximation (RMSEA) = 0.049. These indices suggest that the three-factor model proposed in the EFA is an appropriate representation of the underlying structure of remote learning success factors.

Table 4: CFA Model Fit Indices

Fit Index	Value
χ2/df	2.305
CFI	0.936
TLI	0.927
RMSEA	0.049

Discussion

The results of this study provide a nuanced understanding of the factors influencing remote learning (RL) effectiveness during the COVID-19 pandemic. This discussion integrates the findings from the Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) with the existing literature to offer a comprehensive interpretation of the data.

Key Findings and Theoretical Implications

The EFA revealed three primary factors—Attitude, Motivation, and Perception—that significantly influence RL outcomes. The CFA confirmed the validity of this three-factor model, with fit indices indicating a good model fit (χ^2/df = 2.305, CFI = 0.936, TLI = 0.927, RMSEA = 0.049) . These findings align with prior research suggesting that students' attitudes towards technology, their intrinsic and extrinsic motivations, and their perceptions of online learning environments are critical determinants of their success in RL settings (Al-Mseidin, 2023; Anwar & Mutiah, 2022) .

Attitudes Towards Remote Learning

The first factor, Attitude, encompasses students' general disposition towards RL, including their comfort with technology and their perceived ease of use of online platforms. Previous studies have highlighted the importance of positive attitudes in facilitating effective learning experiences. For instance, Bolliger and Wasilik (2009) found that faculty satisfaction with online teaching significantly depends on their attitudes towards the technology used . Similarly, our findings suggest that students who exhibit a positive attitude towards RL are more likely to engage effectively and achieve better learning outcomes.

Motivation and Engagement

Motivation emerged as a critical factor influencing RL success. The data indicate that both intrinsic motivation (personal interest and enjoyment) and extrinsic motivation (grades and external rewards) play significant roles in shaping students' engagement with RL. This is consistent with the self-determination theory, which posits that motivation is a key driver of behavior and learning (Deci & Ryan, 2000). The importance of motivation is further underscored by Dhawan (2020), who argues that motivated students are more likely to adapt to online learning environments and persist despite challenges.

Perceptions of Online Learning

The third factor, Perception, relates to students' subjective evaluations of the quality and effectiveness of RL. Our findings indicate that students' perceptions are influenced by their experiences with online interactions, the accessibility of learning materials, and the overall design of the online courses. This is in line with research by Garris and Fleck (2020), who found that students' perceptions of the transition to online learning during the pandemic were shaped by their interactions with instructors and the usability of the online platforms.

Practical Implications

The findings of this study have several practical implications for educators and policymakers. First, enhancing students' attitudes towards RL through targeted interventions, such as training sessions and user-friendly platforms, can improve their engagement and learning outcomes. Second, fostering motivation through interactive and gamified learning activities can sustain students' interest and commitment to RL. Lastly, ensuring that students have positive perceptions of RL by improving the quality of online interactions and the accessibility of learning materials can enhance their overall learning experience.

Limitations and Future Directions

Limitations

While this study provides valuable insights into the factors affecting remote learning during the COVID-19 pandemic, several limitations must be acknowledged. Firstly, the sample size, although robust, was limited to secondary school students within a specific geographic region. This may limit the generalizability of the findings to other educational levels or regions. Additionally, the cross-sectional nature of the data collection limits the ability to infer causality between the identified factors and remote learning outcomes.

Another limitation is the reliance on self-reported data, which may introduce biases such as social desirability bias or recall bias. Although steps were taken to ensure the anonymity of responses, these biases could still affect the accuracy of the data. Moreover, the rapid transition to remote learning created a highly variable educational context, which may have influenced student perceptions and experiences in ways not fully captured by the study.

The study also primarily focused on student-centric factors, such as attitude, motivation, and perception. While these are crucial, other external factors like technological infrastructure, parental support, and teacher readiness were not extensively explored. These factors could have significant impacts on the effectiveness of remote learning and should be considered in future research.

Future Directions

Future research should aim to address these limitations by expanding the scope and scale of the study. Longitudinal studies are recommended to track changes in remote learning outcomes over time and to better understand the causal relationships between the identified factors. Such studies could provide more robust evidence on the long-term impacts of remote learning and inform strategies for improving educational resilience in future crises.

Expanding the demographic and geographic diversity of the sample would also enhance the generalizability of the findings. Including students from different educational levels, regions, and socio-economic backgrounds could provide a more comprehensive understanding of the factors influencing remote learning. Additionally, incorporating perspectives from teachers, parents, and administrators could offer a more holistic view of the remote learning ecosystem. Future research should also explore the role of technological infrastructure and support systems in remote learning. Understanding how different technological tools and platforms influence student engagement and learning outcomes could inform the development of more effective remote learning environments. Investigating the impact of teacher training and preparedness on remote teaching effectiveness could also provide valuable insights for educational policymakers and practitioners.

In conclusion, while this study has highlighted key factors influencing remote learning during the COVID-19 pandemic, there is a need for further research to build on these findings and address the identified limitations. By doing so, we can develop more resilient and effective educational systems capable of adapting to future disruptions.

Conclusion
This study provides a comprehensive analysis of the factors influencing remote learning (RL) during the COVID-19 pandemic by integrating Structural Equation Modeling (SEM) and thematic analysis. The findings underscore the importance of student-centric factors such as attitudes, motivations, and perceptions in shaping the effectiveness of RL.

The results from the SEM indicate that students' attitudes towards RL, including self-efficacy and technological readiness, significantly influence their engagement and academic performance. These findings are consistent with previous research which highlights the crucial role of student self-efficacy in online learning environments (Joo et al., 2021). Additionally, motivation, both intrinsic and extrinsic, emerged as a critical determinant of students' willingness to participate in online learning activities. This aligns with the literature that emphasizes the multifaceted nature of motivation in educational settings (Deci & Ryan, 2017). Perceptions of remote learning, influenced by factors such as course design, instructor presence, and peer interaction, were found to impact students' satisfaction and overall learning experience. This finding supports existing studies that highlight the importance of perceived quality and interaction in online education (Garris & Fleck, 2020). The thematic analysis provided rich contextual insights, revealing that technological challenges, pedagogical adaptations, and motivational influences are key themes that shape the RL experience.

In conclusion, this study contributes valuable evidence to the growing body of knowledge on remote learning, particularly in the context of a global pandemic. The findings highlight the need for continued support and innovation in RL practices to ensure that all students can succeed in this evolving educational landscape. Future research should continue to explore these dimensions, considering the long-term implications of remote learning and its potential to transform education.

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