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Knowledge acquisition through online learning environments: A structural equation modeling analysis with gender as a moderator

Shakeel Ahmad Sofi[1*], Fayyaz Hussain Qureshi[2], Sarwar Khawaja[3], Shouket Ahmad Tilwani[4], Huda Majeed[5]

[1]*Freelance Research Associate Oxford Business College, England.*
[2,3]*Oxford Business College, England.*
[4,5]*Department of English, College of Science and Humanities, Al-Kharj, Prince Sattam Bin Abdulaziz University, Al-Kharj, 11942, Saudi Arabia.*

Corresponding author: Shakeel Ahmad Sofi (*Email: Shakeel.Ahmad@obc.ac.uk*)

Abstract

This study aims to investigate the effects of online learning on learners, focusing on various psychological, behavioral, and academic outcomes, with gender as a moderating factor. The research employs Structural Equation Modeling (SEM) to analyze the factors influencing knowledge acquisition in online learning environments. The study uses a mixed-methods approach, combining quantitative surveys and qualitative interviews to gather comprehensive data. The findings reveal that online learning platforms offer significant advantages such as flexibility and accessibility, but also present challenges that impact learners' satisfaction. Key determinants of successful knowledge acquisition include mode of learning, instructor support, digital literacy, and cognitive load. Gender differences play a moderating role in these relationships. The study concludes that while online learning environments provide valuable educational opportunities, it is crucial to address the diverse needs of learners to enhance satisfaction and learning outcomes. Gender-specific strategies can help create more inclusive and effective online learning experiences. Educators and policymakers can use the insights from this research to develop targeted interventions that improve online learning environments. By focusing on key factors such as instructor support and digital literacy, and considering gender differences, they can promote equitable educational opportunities for all learners.

Keywords: Knowledge acquisition, Online learning environments, Structural equation and modeling analysis.

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1. Introduction

Technology has dramatically changed the way we learn, leading to the rise of online learning environments. These platforms give learners access to educational resources from anywhere in the world. The shift to online learning has been sped up by events like the COVID-19 pandemic, which forced many to adopt remote learning. This makes it crucial to understand what factors affect knowledge acquisition in these online settings. As more people rely on digital platforms for education, it's important to develop effective online learning strategies that meet diverse needs.

Online learning environments offer a flexible and convenient alternative to traditional classrooms. They allow learners to engage with course materials at their own pace, fostering a self-directed learning approach. However, the success of online learning depends on various factors, such as the mode of learning, instructor support, digital literacy, and cognitive load. These elements can greatly impact learners' satisfaction and overall learning outcomes. Additionally, using interactive tools and multimedia resources in online learning can boost engagement and deepen understanding of the subject matter.

Gender plays a significant role in educational research, affecting how learners interact with and benefit from online learning environments. Studies have shown that there are gender differences in learning preferences, technology use, and cognitive processing. This suggests that gender may influence learners' experiences and satisfaction with online learning. Therefore, it's essential to examine how gender moderates the relationship between different factors and satisfaction with online learning. Understanding these differences can help educators create more inclusive and effective online learning experiences.

Structural Equation Modeling (SEM) is a powerful statistical method that allows researchers to study complex relationships among multiple variables at once. This study uses SEM to analyze the factors that influence knowledge acquisition in online learning environments, focusing on the moderating role of gender. This approach helps us understand how different variables interact and affect learners' satisfaction· SEM's ability to account for measurement errors and latent variables makes it an ideal method for this research.

The findings from this research can guide the design and implementation of online learning environments to better meet the diverse needs of learners. By identifying key factors that contribute to successful knowledge acquisition, educators and policymakers can develop targeted interventions to improve online learning. This can promote equitable educational opportunities for all learners. Additionally, the insights from this study can inform future research on optimizing online learning environments for different demographic groups.

Online Learning Environments: These are digital platforms that deliver educational content and facilitate interactions between instructors and learners. Examples include Learning Management Systems (LMS), Massive Open Online Courses (MOOCs), and virtual classrooms. These environments use technology to offer various learning activities, such as video lectures, discussion forums, and interactive quizzes, to enhance the learning experience.

Satisfaction with Online Learning: This is the dependent variable in the study, representing learners' overall happiness and positive experiences with online learning environments· It includes aspects like perceived usefulness, ease of use, and overall enjoyment of the learning process. Satisfaction with online learning is a key indicator of the effectiveness of online education and can influence learners' motivation and engagement.

Mode of Learning: This independent variable refers to the different formats of online learning, such as synchronous (real-time) and asynchronous (self-paced) learning. The mode of learning can affect learners' engagement and satisfaction with the online learning experience. Synchronous learning allows for real-time interaction with instructors and peers, while asynchronous learning offers flexibility in accessing course materials.

Instructor Support: This independent variable involves the guidance, feedback, and assistance provided by instructors in online learning environments. Effective instructor support can enhance learners' understanding of course materials and foster a positive learning experience. Instructor support can include timely responses to queries, personalized feedback, and additional resources to aid learning.

Level of Digital Literacy: This independent variable represents learners' proficiency in using digital tools and technologies. Higher levels of digital literacy can make it easier to navigate and interact within online learning environments, leading to greater satisfaction. Digital literacy includes skills like using learning management systems, participating in online discussions, and accessing digital resources effectively.

Cognitive Load: This independent variable refers to the mental effort required to process and understand information in online learning environments. High cognitive load can hinder learning and reduce satisfaction, while manageable cognitive load can enhance learning outcomes. Cognitive load theory suggests that instructional design should aim to minimize unnecessary cognitive load to optimize learning efficiency.

The main goal of this study was to investigate the factors that influence satisfaction with online learning environments. By examining the relationships between mode of learning, instructor support, level of digital literacy, cognitive load, and satisfaction, this research aims to identify the key determinants of successful knowledge acquisition in online learning contexts. Understanding these relationships can help educators design more effective online courses that meet learners' needs and preferences.

Another objective was to explore the moderating effect of gender on the relationship between the independent variables and satisfaction with online learning. By analyzing gender differences in learners' experiences and outcomes, this study seeks to provide insights into how online learning environments can be tailored to meet the diverse needs of male and female learners. This analysis will contribute to the development of gender-sensitive educational strategies that promote equitable learning opportunities.

Additionally, this study aimed to contribute to the existing body of literature on online learning by providing empirical evidence on the factors that influence learner satisfaction. The findings can inform the development of best practices for online education and guide future research in this area. By addressing the identified research gaps, this study seeks to advance our understanding of the complexities of online learning environments.

Despite the growing body of literature on online learning, there are still significant gaps in understanding the factors that contribute to learners' satisfaction· Previous studies have often focused on individual variables in isolation, without considering the complex interplay between multiple factors. This research aims to address this gap by employing Structural Equation Modeling to analyze the relationships among various independent variables and their impact on satisfaction with online learning. By adopting a holistic approach, this study seeks to provide a more comprehensive understanding of the factors influencing learner satisfaction.

Additionally, the role of gender as a moderator in online learning environments has been underexplored. While some studies have highlighted gender differences in learning preferences and technology usage, there is a need for more comprehensive research that examines how gender influences the relationships between different variables and satisfaction with online learning. This study seeks to fill this gap by providing a nuanced analysis of gender's moderating effect. Understanding these dynamics can help educators design more inclusive online learning environments that cater to the needs of all learners. Furthermore, there is a lack of research that integrates multiple independent variables to examine their combined effect on learner satisfaction· This study aims to address this gap by considering the mode of learning, instructor support, digital literacy, and cognitive load simultaneously. By doing so, it provides a more holistic view of the factors that contribute to successful online learning experiences.

This research paper is organized into five sections. The first section provides an introduction to the study, outlining the background, definitions, objectives, and research gaps. The second section reviews the relevant literature on online learning environments, satisfaction with online learning, and the moderating role of gender. This literature will highlights key findings from previous studies and identify areas for further investigation.The third section describes the methodology, including the research design, data collection, and analysis techniques. It provides details about the use of Structural Equation Modeling to examine the relationships between the variables and the moderating effect of gender. The fourth section presents the results of the Structural Equation Modeling analysis, highlighting the key findings and their implications. This section includes statistical analyses and visual representations of the data. The final section discusses the conclusions, limitations, and recommendations for future research. It will summarizes the main findings of the study and suggest practical implications for educators and policymakers. Additionally, this sections identifies potential areas for further research to build on the findings of this study.

2· Literature Review

2.1. Cognitive Load and Online Learning Satisfaction

Cognitive load significantly influences online learning satisfaction, as it affects students' ability to process information effectively• Studies have shown that managing cognitive load can enhance short-term learning and student satisfaction in online environments [1]. For instance, a study on accounting students in the Philippines found that teaching quality, learning content quality, and learning management system quality, which represent cognitive load, positively influenced student satisfaction [1]. Similarly, another study confirmed a positive relationship between cognitive load and student satisfaction, emphasizing the importance of instructional design in online learning [2].

Additionally, reducing extraneous cognitive load through clear and concise instructional materials, interactive elements, and timely feedback can further enhance online learning satisfaction• By minimizing unnecessary cognitive demands, students can focus more on understanding and retaining the core content, leading to improved learning outcomes and greater overall satisfaction with the online learning experience• This approach not only supports cognitive processing but also fosters a more engaging and effective learning environment [3].

Gender differences in learning preferences, technology usage, and cognitive processing have been well-documented in educational research· These differences can influence how learners interact with online learning environments and their overall satisfaction· For instance, studies have shown that female learners may place higher importance on perceived playfulness and social interaction in online learning, while male learners may prioritize self-efficacy and performance expectancy [4]. The moderating effect of gender on the relationship between various factors and online learning satisfaction has been explored in several studies· For example, research has found that gender can moderate the impact of cognitive load on learning outcomes, with female learners potentially experiencing higher cognitive load due to multitasking and social responsibilities. Understanding these gender-based differences is crucial for designing inclusive online learning environments that cater to the diverse needs of all learners [4].

$H_{1:}$ Gender differences significantly moderates the relationship between Cognitive Load and the level of Online Learning Satisfaction•

2.2. Mode of Learning and Online Learning Satisfaction

The mode of learning, such as mobile or video-based learning, plays a crucial role in determining online learning satisfaction. Research indicates that mobile learning platforms can significantly improve learner satisfaction and reduce cognitive loads compared to traditional methods [5]. Mobile learning offers the flexibility and convenience that traditional methods often lack, allowing learners to access course materials anytime and anywhere· It has also been found that the presence of an instructor in video lectures can influence cognitive load and learning effectiveness, thereby affecting satisfaction levels [6]. Instructor presence in video-based learning can provide guidance and support, making the learning experience more interactive and engaging. This can help reduce cognitive load by clarifying complex concepts and providing immediate feedback.

Moreover, the flexibility and accessibility offered by mobile learning allow students to engage with course materials at their own pace and convenience, which can lead to higher satisfaction levels· Mobile learning platforms often include features such as notifications, reminders, and progress tracking, which can help learners stay organized and motivated. This personalized approach to learning can enhance overall satisfaction. Video-based learning, particularly when it includes interactive elements and real-time feedback, can create a more immersive and engaging learning experience. Interactive videos can include quizzes, discussion prompts, and other activities that encourage active participation. This mode of learning not only helps in better retention of information but also fosters a sense of connection and support, which are critical for maintaining student motivation and satisfaction in an online learning environment [3].

Additionally, gender differences have been observed in preferences for different modes of learning. For instance, female learners may prefer collaborative and interactive learning environments, while male learners may favor more independent and self-paced learning formats [7]. These preferences can influence how different modes of learning impact overall satisfaction. Understanding these gender-based differences is crucial for designing inclusive online learning environments that cater to the diverse needs of all learners· By considering gender as a moderating factor, educators can tailor online learning experiences to better meet the needs of both male and female learners, ultimately enhancing satisfaction and learning outcomes [8].

$H_{2:}$ Gender differences significantly moderates the relationship between the Mode of Learning and the level of Online Learning Satisfaction•

2.3. Digital Literacy and Online Learning Satisfaction

Digital literacy is a critical factor influencing online learning satisfaction• While the provided papers do not directly address digital literacy, it is implied that higher digital literacy can reduce cognitive load and enhance satisfaction by enabling students to navigate online learning environments more effectively and [9]. The ability to manage digital tools and resources efficiently is essential for minimizing extraneous cognitive load and improving learning outcomes [10]. In addition to reducing cognitive load, digital literacy empowers students to take full advantage of the diverse tools and resources available in online learning platforms• This includes the ability to effectively use search engines, participate in online discussions, and utilize multimedia resources, all of which can enrich the learning experience• Students with higher digital literacy are more likely to engage actively with the content, collaborate with peers, and seek out additional information, leading to a deeper understanding of the subject matter and higher overall satisfaction [11].

Furthermore, digital literacy can enhance students' confidence and autonomy in their learning journey• When students are proficient in using digital tools, they can troubleshoot technical issues independently, customize their learning environment to suit their preferences, and access a wider range of educational materials• This sense of control and self-efficacy not only reduces frustration and anxiety but also fosters a positive attitude towards online learning, ultimately contributing to greater satisfaction and academic success [12].

Gender differences in digital literacy have been well-documented, with studies showing that these differences can influence online learning satisfaction. Research indicates that female learners often face more barriers to developing digital literacy skills, such as limited access to technology and gender biases in tech education [13]. These barriers can impact their ability to navigate online learning environments effectively, potentially leading to lower satisfaction levels. Conversely, male learners may have more opportunities to develop digital literacy skills, which can enhance their online learning experiences· Studies have shown that male learners often report higher levels of confidence in using digital tools and technologies, which can contribute to greater satisfaction with online learning [13]. These gender-based differences in digital literacy can moderate the relationship between digital literacy and online learning satisfaction.

Understanding these gender differences is crucial for designing inclusive online learning environments· By considering gender as a moderating factor, educators can develop targeted interventions to support female learners in building digital literacy skills, thereby enhancing their satisfaction with online learning· For instance, providing additional training and resources for female learners can help bridge the digital literacy gap and promote equitable learning opportunities.

$H_{3:}$ Gender Differences significantly moderate the relationship between the Level of Digital Literacy and Online Learning Satisfaction.

2.4. Instructor Support and Online Learning Satisfaction

Instructor support is vital for enhancing online learning satisfaction. Although not explicitly covered in the provided papers, the role of instructor presence in video lectures suggests that instructor support can reduce cognitive load and improve learning satisfaction. Effective instructor support can help students manage cognitive challenges and foster a more engaging and satisfying learning experience [6].

Instructor support is crucial in creating a positive online learning environment. When instructors provide timely and constructive feedback, it helps students understand their progress and areas for improvement, which can significantly enhance their learning satisfaction. Additionally, instructors who are approachable and responsive to student inquiries can alleviate feelings of isolation and frustration that often accompany online learning• This supportive interaction not only boosts students' confidence but also encourages them to stay engaged and motivated throughout the course [14]. Furthermore, the use of synchronous sessions, such as live lectures and virtual office hours, allows for real-time interaction between instructors and students• These sessions can mimic the immediacy of face-to-face communication, making the online learning experience more personal and effective. Research has shown that students who participate in synchronous activities report higher levels of satisfaction due to the increased sense of connection and support from their instructors [14]. By fostering a supportive and interactive online learning environment, instructors can significantly enhance student satisfaction and learning outcomes.

Gender differences in the perception and impact of instructor support have been observed in educational research. Studies suggest that female learners may place a higher value on instructor support and interaction compared to male learners [15]. Female students often seek more guidance and reassurance from instructors, which can significantly influence their satisfaction with online learning [16]. On the other hand, male learners may prioritize self-efficacy and independent learning, potentially perceiving instructor support differently [17]. Research has found that gender can moderate the relationship between instructor support and online learning satisfaction. For instance, female learners may benefit more from frequent and personalized instructor interactions, leading to higher satisfaction levels [15]. Conversely, male learners might prefer less frequent but more focused interactions that support their independent learning style [17]. Understanding these gender-based differences is crucial for designing inclusive online learning environments that cater to the diverse needs of all learners.

By considering gender as a moderating factor, educators can tailor their support strategies to better meet the needs of both male and female learners. This approach can enhance overall satisfaction and learning outcomes, ensuring that all students receive the support they need to succeed in online learning environments.

$H_{4:}$ Gender Differences significantly moderate the relationship between Instructor Support and the level of Online Learning Satisfaction•

2.5. Conceptual Framework

The conceptual framework for the study is shown below and it consists of independent variables viz. Mode of Learning (MOL) , Level of Digital Awareness (DL), Cognitive Load (Cognitive) and Instructor Support (IS).

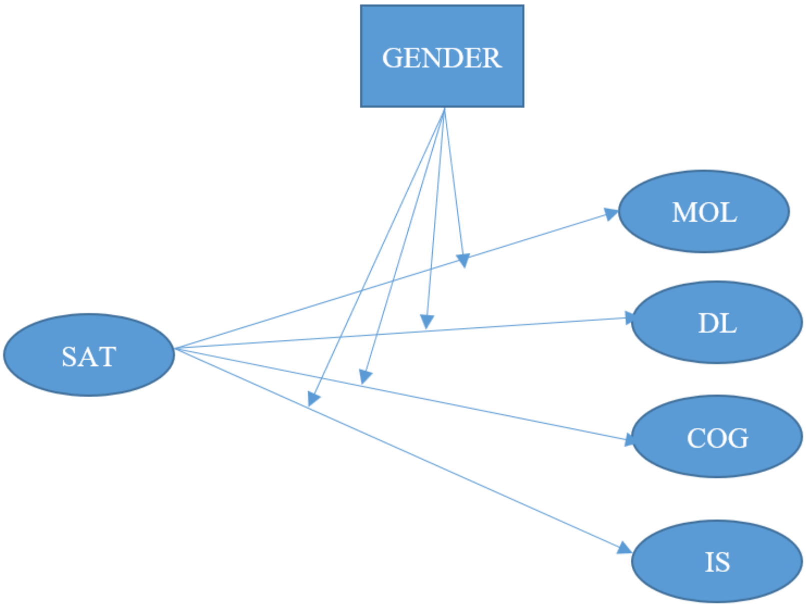

Figure 1.
Conceptual Framework.

The Dependent variables for is Level of Satisfaction with the Online Learning and is represented by SAT. Gender is implied between the independent and dependent variable relationship and is tested as a moderator.

3. Research Methodology

This section details the research methodologies utilized in the present study. The accuracy of the selected methodology is paramount in ensuring the quality of research within educational and psychological disciplines. The core of any research initiative is its methodological approach, especially when investigating human behavior and learning outcomes. This process is inherently complex and necessitates meticulous consideration of specific parameters to mitigate potential challenges.

3.1. Research Design

This study utilized a mixed-methods research design, combining both quantitative and qualitative approaches to achieve a comprehensive understanding of the impact of online learning on learners· The mixed-methods approach facilitates data triangulation, thereby enhancing the validity and reliability of the findings. The quantitative component involved administering structured surveys to collect numerical data, while the qualitative component comprised semi-structured interviews to obtain in-depth insights from participants.

3.2. Sampling Design

The sampling design is a pivotal aspect of the research methodology, encompassing the definition of various parameters essential for conducting a thorough study. It functions as a roadmap or framework that directs the process of reaching the final sample. In the current research, the primary components of the sampling design included the area of study, sample size, sampling technique, sampling frame, and the implementation of the sampling frame.

3.2.1. Area of Study and Sample Frame

The research focused on India, specifically targeting students enrolled in various educational institutions offering online courses. Data collection was facilitated using online tools like Google Forms and Survey Monkey. This method ensured efficient and comprehensive data gathering, resulting in a broad and representative sample. By leveraging these digital tools, the study was able to reach a diverse group of participants, capturing a wide range of experiences and perspectives· This approach not only streamlined the data collection process but also enhanced the overall reliability and validity of the research findings.

3.2.2. Population for the Study

The sample population for this study consisted of individuals aged 18 years and older· A substantial segment of this population included students enrolled in online courses across various educational institutions.

To ensure a thorough analysis, the population was divided into three distinct age groups: Early Adulthood (18-23 years), Middle Adulthood (24-29 years), and Late Adulthood (30-35 years). This categorization facilitated a more detailed understanding of how different age groups experience and perceive online learning. Furthermore, by incorporating a diverse age range, the study aimed to capture a broad spectrum of perspectives, thereby enhancing the generalizability of the findings. This approach also enabled the identification of age-specific trends and challenges within online learning environments.

3.2.3. Sample Size

To determine an appropriate sample size, systematic attributes and reliable procedures were employed. These included:

- Application of the Sample Size Determination Table: Krejcie and Morgan [18] recommended a sample size of 384.
- Ratio-Based Calculation: Using a ratio of 5:1 or 10:1 based on the number of items, sample sizes of 165 or 330 for 33 items were derived [19].
- Rule of Thumb: Additional guidelines for determining sample size were provided by Roscoe [20].

After evaluating various measures and prerequisites, a final sample size of 665 was selected. This comprehensive approach ensured that the sample size was both adequate and representative, thereby enhancing the reliability and validity of the research findings.

3.2.4. Sampling Method (Technique)

Considering the stratified nature of the population, online survey tools like Google Forms and Survey Monkey were selected for data collection through random sampling. Before the final data collection phase, a preliminary sample of 100 respondents was analyzed to evaluate various population measures and identify any potential anomalies. Social media platforms such as Facebook, WhatsApp, and Email were used to reach out to respondents. This approach ensured a comprehensive and representative sample, thereby enhancing the reliability and validity of the research findings. Additionally, leveraging these platforms allowed for efficient communication and follow-up with participants, ensuring higher response rates. The use of digital tools also facilitated real-time data monitoring and analysis, enabling timely adjustments to the survey process if needed. This method not only streamlined data collection but also minimized logistical challenges associated with traditional survey methods. Overall, the integration of online tools and social media platforms proved to be an effective strategy for gathering diverse and reliable data.

3.2.5. Instrument for the Study

The primary instrument for data collection in this study was a carefully crafted questionnaire, specifically designed to address the research problem. The development of both the research problem and the questionnaire was guided by an extensive review of related literature and further refined through consultations with experts in education and psychology. The research instrument focused on key attributes of the study, including cognitive load, mode of learning, digital literacy, and instructor support.

The structured and validated instrument comprised five distinct sections:

Section 1: Learning Satisfaction (Overall Experience, Course Effectiveness)

- The online course met my overall learning expectations.
- I am satisfied with the quality of instructional materials provided.
- The online course was engaging and kept my interest throughout.
- The course content was relevant to my learning needs.
- I would recommend this online course to others.
- The course provided a good balance between theory and practical application.
- The overall structure of the course was easy to follow.
- I received adequate support from the instructor(s) during the course.
- The assessments and assignments reflected the course objectives well.

Section 2: Cognitive Load (Ease or Difficulty in Understanding Content)

- The course content was easy to understand and follow.
- I did not feel overwhelmed by the amount of information provided.
- The course structure helped in reducing cognitive overload.
- The instructions for assignments and assessments were clear and concise.
- The learning materials were presented in a way that minimized confusion.

Section 3: Mode of Online Learning (Synchronous vs. Asynchronous)

- I prefer live (synchronous) online sessions over pre-recorded lectures.
- I find asynchronous learning (pre-recorded lectures, self-paced study) more flexible for my schedule.
- I feel more engaged in synchronous online classes with real-time discussions.
- Asynchronous courses allow me to learn at my own pace without feeling rushed.
- I find it easier to ask questions and get immediate feedback in synchronous sessions.

Section 4: Digital Literacy Level (Basic, Intermediate, Advanced)

- I feel confident navigating online learning platforms (e·g·, Zoom, Google Classroom, Moodle).
- I can easily troubleshoot minor technical issues (e·g·, internet connectivity, software errors).
- I am comfortable using various digital tools such as discussion forums, shared documents, and online quizzes.
- I rarely require technical support while participating in online courses.
- I can effectively use online collaboration tools (e·g·, Google Docs, Microsoft Teams) for group work.
- I find it easy to submit assignments and assessments using online platforms.

Section 5: Instructor Support (Availability, Responsiveness, Engagement)

- My instructor is readily available to answer questions and provide support.
- I receive timely responses to my queries from the instructor.
- The instructor provides clear explanations and feedback on assignments.
- My instructor actively engages students in discussions and activities.
- The instructor uses various teaching methods (e·g·, videos, live discussions, quizzes) to enhance learning.
- I feel comfortable reaching out to my instructor for additional support.
- The instructor provides sufficient guidance to ensure I understand the course content.
- The instructor encourages interaction among students to enhance learning.

3.3. Preliminary Testing

The preliminary investigation aimed to identify inconsistencies and assess various scale attributes. A sample of 100 respondents was selected for this phase. The data collected underwent empirical analysis to estimate different scale properties. The pilot study results demonstrated reliability and validity. Statistical tools such as SPSS and AMOS were utilized for data analysis at this stage. This rigorous preliminary testing ensured the robustness of the research instrument and provided a solid foundation for the subsequent phases of the study.

3.3.1. Assessment of Scale Properties

The assessment of scale properties is crucial both at the preliminary stage and during the main study. The reliability of the questionnaire was primarily evaluated using Overall Cronbach's Alpha, Split-Half Reliability, and Inter-Rater Reliability. The results of these measures indicated high reliability and validity of the instrument.

3.4. Data Collection Procedure

Data collection was carried out over a period of three months. Participants were invited to complete the online questionnaire through email invitations and social media posts. Follow-up reminders were sent to ensure a high response rate. The qualitative data was collected through semi-structured interviews conducted via video conferencing platforms. The interviews were recorded and transcribed for analysis.

3.4. Data Analysis

Multi-group analysis was employed to conduct the moderation analysis, specifically to test the influence of gender on the relationship between the independent variables (mode of learning, instructor support, level of digital literacy, and cognitive load) and the dependent variable (satisfaction with online learning). This statistical technique allows for the comparison of different groups within the sample, in this case, male and female learners, to determine if the relationships between the variables differ significantly across these groups.

By using multi-group analysis, the study was able to identify whether gender acts as a moderating factor, influencing how the independent variables impact online learning satisfaction· This approach provided a nuanced understanding of gender-based differences, ensuring that the findings are robust and applicable to diverse learner populations.

The quantitative data collected through the questionnaires was analyzed using statistical software such as SPSS. Descriptive statistics, correlation analysis, and regression analysis were employed to examine the relationships between the variables. Descriptive statistics provided an overview of the demographic characteristics of the sample and the distribution of responses for each item. Correlation analysis was used to identify the strength and direction of relationships between the independent and dependent variables. Regression analysis helped in determining the predictive power of the independent variables on the dependent variable, online learning satisfaction.

Given the focus on quantitative methods, the study did not incorporate qualitative data analysis· Instead, the emphasis was placed on statistical techniques to ensure objectivity and precision in measuring the impact of cognitive load, mode of learning, digital literacy, and instructor support on online learning satisfaction. This approach allowed for a rigorous examination of the hypothesized relationships and provided robust evidence to support the study's conclusions.

4. Results and Discussion

The "Results and Discussion" section provides a thorough analysis, starting with the demographics of the study participants to establish a foundational understanding of the sample population· This is followed by the results of the Exploratory Factor Analysis (EFA), which uncovers the underlying relationships between the measured variables. Finally, the section explores the findings from the Structural Equation Modeling (SEM), offering insights into the complex interdependencies among the variables and validating the proposed theoretical model. Additionally, Multi-Group Analysis was conducted to examine the moderating effect of gender on the relationships between the independent and dependent variables. This analysis provided a nuanced understanding of how gender influences these relationships, highlighting significant differences between male and female learners. The results from the Multi-Group Analysis further enriched the discussion by identifying gender-specific trends and implications.

4.1. Demographic Section

The demographic information of the respondents is presented in the following sections.

Table 1.
Gender.

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Female	266	40.0	40.0	40.0
	Male	399	60.0	60.0	100.0
	Total	665	100.0	100.0	

The gender distribution of the study participants shows that out of a total of 665 respondents, 40% (266) are female and 60% (399) are male. This indicates a higher representation of males in the sample, with the cumulative percentage reaching 100% for both genders.

Table 2.
Age in Years.

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	18-30	464	69.8	69.8	69.8
	31-35	61	9.2	9.2	78.9
	36-40	70	10.5	10.5	89.5
	41-45	36	5.4	5.4	94.9
	46-50	24	3.6	3.6	98.5
	Above 50	10	1.5	1.5	100.0
	Total	665	100.0	100.0	

The age distribution reveals that the majority of participants (69·8%) are between 18-30 years old, followed by smaller proportions in other age groups: 9·2% are 31-35 years old, 10·5% are 36-40 years old, 5·4% are 41-45 years old, 3·6% are 46-50 years old, and 1·5% are above 50 years old. This suggests a predominantly young sample population.

Table 3.
Marital Status.

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Married	217	32.6	32.6	32.6
	Unmarried	448	67.4	67.4	100.0
	Total	665	100.0	100.0	

Regarding marital status, 32.6% (217) of the respondents are married, while a significant majority of 67.4% (448) are unmarried. This distribution highlights a larger proportion of unmarried individuals in the study.

Table 4.
Types of area which you belong

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Rural	181	27.2	27.2	27.2
	Semi-Urban	93	14.0	14.0	41.2
	Urban	391	58.8	58.8	100.0
	Total	665	100.0	100.0	

The data on the types of areas participants belong to shows that 27.2% (181) are from rural areas, 14.0% (93) from semi-urban areas, and 58.8% (391) from urban areas. This indicates a higher representation of urban residents in the sample.

Table 5.
Monthly Income.

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Above Rs.60000	116	17.4	17.4	17.4
	Below Rs.15,000	282	42.4	42.4	59.8
	Rs.15000 to 30000	144	21.7	21.7	81.5
	Rs.30000 to 45000	63	9.5	9.5	91.0
	Rs.45000-60000	60	9.0	9.0	100.0
	Total	665	100.0	100.0	

The monthly income distribution of the respondents indicates that 42·4% (282) earn below Rs·15,000, 21·7% (144) earn between Rs.15,000 to Rs·30,000, 9·5% (63) earn between Rs.30,000 to Rs.45,000, 9·0% (60) earn between Rs·45,000 to Rs·60,000, and 17·4% (116) earn above Rs.60,000. This shows a diverse range of income levels among the participants, with the largest group earning below Rs·15,000.

4.2. Factor Analysis

Exploratory Factor Analysis was performed on 33 items/questions and results are discussed in the following sections.

Table 6.
KMO and Bartlett's Test.

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		**0.961**
Bartlett's Test of Sphericity	Approx. Chi-Square	12128.583
	Df	528
	Sig.	0.000

The results of the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test of Sphericity indicate that the data is suitable for factor analysis. The KMO value of 0·961 suggests a high level of sampling adequacy, meaning the variables have enough common variance for factor analysis· Bartlett's Test of Sphericity, with an approximate Chi-Square value of 12128·583 and a significance level of 0·000, confirms that the correlations between variables are significantly different from zero, further justifying the use of factor analysis.

Table 7.
Communalities.

	Initial	Extraction
MOL1	1.000	0.642
MOL2	1.000	0.648
MOL3	1.000	0.621
MOL4	1.000	0.522
DL5	1.000	0.596
MOL6	1.000	0.395
DL7	1.000	0.505
DL8	1.000	0.597

DL9	1.000	0.578
DL10	1.000	0.557
DL11	1.000	0.582
SAT12	1.000	0.600
SAT13	1.000	0.568
SAT14	1.000	0.624
SAT15	1.000	0.608
SAT16	1.000	0.557
COG17	1.000	0.484
SAT18	1.000	0.547
SAT19	1.000	0.511
IS20	1.000	0.546
IS21	1.000	0.650
SAT22	1.000	0.583
IS23	1.000	0.592
IS24	1.000	0.634
IS35	1.000	0.615
IS26	1.000	0.664
IS27	1.000	0.586
IS28	1.000	0.602
SAT29	1.000	0.612
COG30	1.000	0.600
COG31	1.000	0.639
COG32	1.000	0.567
COG33	1.000	0.650
Extraction Method: Principal Component Analysis.		

The communalities table shows the proportion of each variable's variance that can be explained by the extracted factors. Initial communalities are all 1·000, indicating that all the variance is considered. After extraction, the communalities range from 0.395 (MOL6) to 0·664 (IS26), suggesting that the extracted factors explain between 39.5% and 66·4% of the variance in these variables. Variables like IS26, IS21, and COG33 have higher extraction values, indicating they are well-represented by the factors, while MOL6 has the lowest, suggesting it is less well-represented. This information helps in understanding the adequacy of the factor model in capturing the underlying structure of the data.

Table 8.
Total Variance Explained.

Component	**Initial Eigenvalues**			**Extraction Sums of Squared Loadings**			**Rotation Sums of Squared Loadings**		
	Total	**% of Variance**	**Cumulative %**	**Total**	**% of Variance**	**Cumulative %**	**Total**	**% of Variance**	**Cumulative %**
1	14.260	43.213	43.213	14.260	43.213	43.213	4.448	13.479	13.479
2	1.548	4.691	47.904	1.548	4.691	47.904	4.376	13.260	26.739
3	1.297	3.929	51.833	1.297	3.929	51.833	3.772	11.429	38.168
4	1.115	3.380	55.213	1.115	3.380	55.213	3.416	10.351	48.518
5	1.062	3.217	58.430	1.062	3.217	58.430	3.271	9.912	58.430
6	0.943	2.858	61.288						
7	.879	2.664	63.952						
8	0.810	2.453	66.405						
9	0.762	2.309	68.714						
10	0.693	2.100	70.815						
11	0.653	1.980	72.795						
12	0.644	1.950	74.745						
13	0.590	1.786	76.531						
14	0.577	1.747	78.278						

15	0.543	1.646	79.924						
16	0.528	1.601	81.525						
17	0.513	1.556	83.081						
18	0.492	1.492	84.573						
19	0.463	1.403	85.976						
20	0.455	1.378	87.354						
21	0.410	1.243	88.597						
22	0.394	1.194	89.791						
23	0.368	1.116	90.906						
24	0.360	1.092	91.998						
25	0.346	1.048	93.046						
26	0.344	1.042	94.088						
27	0.322	.975	95.063						
28	0.300	0.908	95.971						
29	0.294	0.891	96.862						
30	0.285	0.863	97.725						
31	0.268	0.813	98.538						
32	0.259	0.783	99.321						
33	0.224	0.679	100.000						
Extraction Method: Principal Component Analysis.									

The "Total Variance Explained" table provides a detailed breakdown of the variance accounted for by each component in the factor analysis· The initial eigenvalues indicate that the first five components have eigenvalues greater than 1, explaining 43·213%, 4·691%, 3·929%, 3.380%, and 3·217% of the variance respectively, cumulatively accounting for 58·430% of the total variance. After extraction, these components still explain the same amount of variance· However, after rotation, the variance is more evenly distributed among the components, with the first component explaining 13.479% and the fifth component explaining 9·912%, cumulatively accounting for 58·430% of the variance· This rotation helps in achieving a simpler and more interpretable factor structure.

Table 9.
Component Matrix[a].

	Component				
	1	**2**	**3**	**4**	**5**
MOL1	0.600			0.361	
MOL2	0.610	0.353		0.309	
MOL3	0.663	0.313			
MOL4	0.645				
DL5	0.582	0.365			
MOL6	0.569				
DL7	0.651				
DL8	0.581	0.330		-0.322	
DL9	0.656				
DL10	0.634				-0.358
DL11	0.655				
SAT12	0.693			0.310	
SAT13	0.649				
SAT14	0.680				
SAT15	0.704				

SAT16	0.680				
COG17	0.599				
SAT18	0.675				
SAT19	0.673				
IS20	0.694				
IS21	0.733			-0.326	
SAT22	0.744				
IS23	0.709				
IS24	0.622				0.300
IS35	0.664	-0.345			
IS26	0.689				0.322
IS27	0.706				
IS28	0.732				
SAT29	0.684	-0.305			
COG30	0.604		0.381		
COG31	0.531		0.496		
COG32	0.628				
COG33	0.690	-0.315			
Extraction Method: Principal Component Analysis.					

Note: a. 5 components extracted.

The Component Matrix shows the loadings of each variable on the five extracted components· High loadings indicate a strong relationship between the variable and the component. For instance, SAT22 has a high loading of 0.744 on Component 1, suggesting it is strongly associated with this component· Similarly, IS21 has a high loading of 0·733 on Component 1. Some variables, like MOL2 and DL5, load on multiple components, indicating they share variance with more than one factor· The matrix helps in understanding which variables group together, providing insights into the underlying structure of the data.

Table 10.
Rotated Component Matrix[a]

	Component				
	1	**2**	**3**	**4**	**5**
IS24	0.706				
IS26	0.694				
IS35	0.625			0.391	
IS27	0.570		0.359		
IS28	0.568	0.364			
IS23	0.507	0.350	0.408		
IS20	0.488		0.413		
SAT14		0.685			
SAT13		0.622			0.325
SAT15		0.611		0.338	
SAT16		0.600			
SAT12		0.540			0.437
SAT29	0.415	0.466		0.416	
SAT18	0.448	0.464			0.323
SAT19	0.378	0.447	0.355		
SAT22	0.388	0.425	0.312	0.362	
DL8			0.686		
DL9		0.352	0.575		

DL5			0.568		0.446
DL11		0.410	0.547		
IS21	0.487	0.319	0.522		
DL10		0.470	0.483		
DL7		0.361	0.438		0.311
COG31				0.757	
COG30				0.679	
COG33	0.417			0.618	
COG32	0.330			0.604	
COG17			0.384	0.475	
MOL2					0.719
MOL1					0.717
MOL3			0.408		0.575
MOL4			0.372		0.513
MOL6					0.464

Extraction Method: Principal Component Analysis
Rotation Method: Varimax with Kaiser Normalization

Note: a. Rotation converged in 16 iterations.

The Rotated Component Matrix provides a clearer picture of the factor loadings after applying the Varimax rotation method, which simplifies the interpretation by maximizing the variance of squared loadings of a factor across variables. For example, MOL1 and MOL2 load highly on Component 5 with values of 0.717 and 0.719, respectively, indicating a strong association with this component. Similarly, DL8 and DL9 load highly on Component 2 with values of 0·686 and 0·575, respectively. This rotation helps in identifying which variables are most strongly associated with each component, making it easier to interpret the underlying factors.

Table 11.
Component Transformation Matrix.

Component	1	2	3	4	5
1	0.496	0.496	0.438	0.400	0.395
2	-0.454	-0.055	0.537	-0.475	0.525
3	-0.361	-0.500	0.253	0.744	0.048
4	-0.372	0.318	-0.636	0.214	0.556
5	0.528	-0.632	-0.224	-0.125	0.506

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.

The Component Transformation Matrix shows the correlations between the original and rotated components. Each value represents the cosine of the angle between the axes of the original and rotated components.For example, Component 1 has a high correlation with both the original Component 1 (0·496) and Component 2 (0·496), indicating that these components share a significant amount of variance· The matrix helps in understanding how the rotation has redistributed the variance among the components, making the factor structure more interpretable and easier to understand.

4.3. Structure Equation Model

The structural model, as depicted in the Figure 2, presents a compelling conceptual framework for understanding the factors influencing satisfaction with online learning (SAT). The model posits that satisfaction is directly influenced by four key independent variables: Mode of Learning (MOL), Level of Digital Awareness (DL), Cognitive Load (COG), and Instructor Support (IS)· Furthermore, the model incorporates gender as a moderator, suggesting that the relationships between the independent variables and satisfaction may differ based on gender.

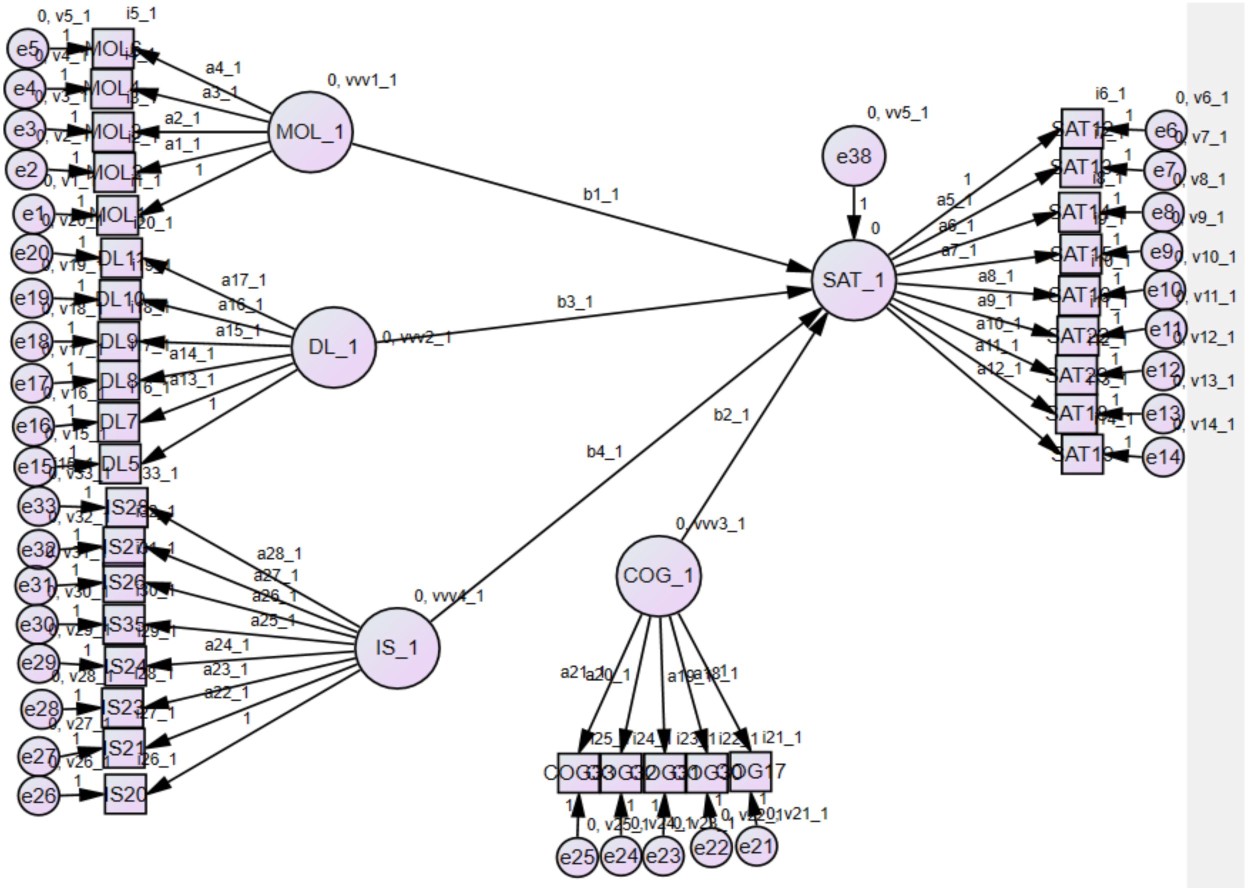

Figure 2.
Male/female model without test.

4.3.1. Strengths of the Model

Comprehensive Variable Selection: The model identifies crucial factors relevant to online learning satisfaction.

Mode of Learning (MOL): Recognizes the impact of different online learning formats (e·g·, synchronous vs· asynchronous, blended learning).

Digital Awareness (DL): Acknowledges the importance of learners' digital literacy and skills in navigating the online learning environment.

Cognitive Load (COG): Addresses the cognitive demands placed on learners in online settings and their impact on satisfaction.

Instructor Support (IS): Highlights the critical role of instructors in facilitating effective online learning and student support.

Direct Relationship Assumption: The model proposes direct paths from each independent variable to satisfaction, suggesting a causal relationship. This allows for the examination of the unique contribution of each factor to online learning satisfaction.

Moderation by Gender: Incorporating gender as a moderator is a significant strength· It acknowledges the potential for differential experiences and perceptions of online learning based on gender, allowing for a more nuanced understanding of the relationships.

Clear Visual Representation: The figure effectively illustrates the hypothesized relationships, making it easy to understand the model's structure and the proposed influences on satisfaction.

4.4. Results of the Model When Tested

4.4.1. Notes for Model (Unconstrained)

Table 12.
Computation of degrees of freedom (Unconstrained).

Number of distinct sample moments:	1188
Number of distinct parameters to be estimated:	206
Degrees of freedom (1188 - 206):	982

4.4.2. Result (Unconstrained)

Minimum was achieved
Chi-square = 4474.152
Degrees of freedom = 982
Probability level = .000

The model was tested under unconstrained conditions, resulting in a chi-square value of 4474·152 with 982 degrees of freedom· The probability level was found to be 0·000, indicating a significant result· The degrees of freedom were calculated by subtracting the number of parameters to be estimated (206) from the number of distinct sample moments (1188), resulting in 982 degrees of freedom. The minimum was successfully achieved in this model and the results indicate that the model tested under unconstrained conditions has a significant fit to the data.

4.4.3. Model Fit Summary

Table 13.
CMIN

Model	NPAR	CMIN	DF	P	CMIN/DF
Unconstrained	206	4474.152	982	0.000	4.556
Measurement weights	178	4518.768	1010	0.000	4.474
Measurement intercepts	145	4564.190	1043	0.000	4.376
Structural weights	141	4566.874	1047	0.000	4.362
Structural covariances	137	4569.305	1051	0.000	4.348
Structural residuals	136	4570.732	1052	0.000	4.345
Measurement residuals	103	4691.430	1085	0.000	4.324
Saturated model	1188	.000	0	0.000	
Independence model	132	13492.061	1056	0.000	12.777

The models with lower CMIN/DF values (closer to 1) indicate a better fit to the data· The Measurement Residuals model has the best fit among the constrained models, while the Independence Model has the worst fit.The Saturated Model has a perfect fit but is not practical due to the high number of parameters.

These results suggest that while the unconstrained model fits the data reasonably well, the constrained models, particularly the Measurement Residuals model, provide a better balance between fit and complexity.

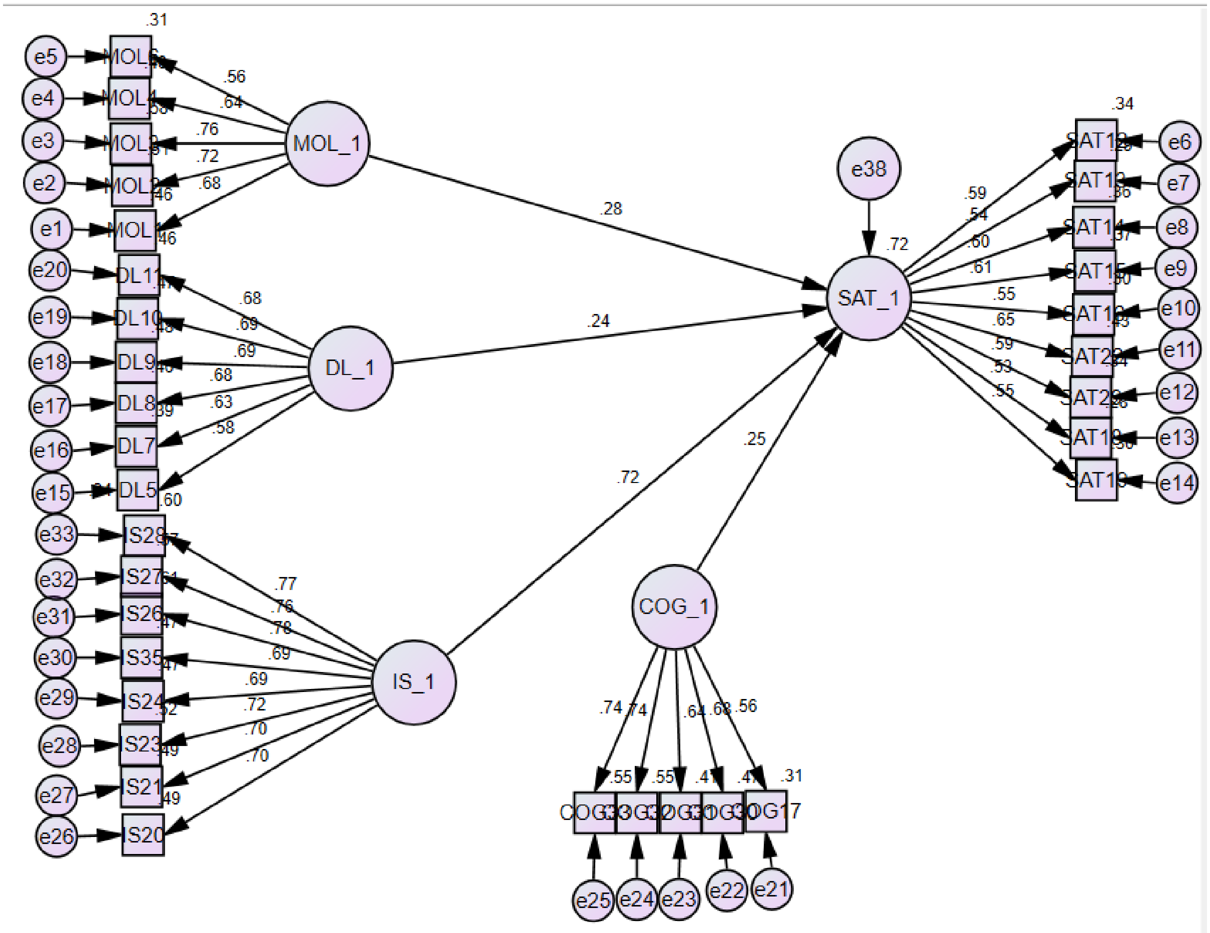

Figure 3.
Male Model.

Interpretation of Findings from the Structural Model of Online Learning Satisfaction

The structural model provides insights into the factors influencing online learning satisfaction (SAT_1), revealing varying degrees of influence from the independent variables. Here's a breakdown based on the path coefficients:

4.5. Effects on Online Learning Satisfaction (SAT_1):

Mode of Learning (MOL_1): The path coefficient of .28 suggests a positive relationship between the mode of learning and satisfaction. This indicates that certain modes of online learning (e·g·, perhaps more interactive or flexible formats) are associated with higher satisfaction levels. However, the effect is relatively moderate compared to other variables.

Digital Awareness (DL_1): With a path coefficient of .24, digital awareness also exhibits a positive influence on satisfaction. Students with higher levels of digital literacy and comfort with technology tend to report greater satisfaction in online learning environments. Again, the effect is moderate.

Cognitive Load (COG_1): Interestingly, the path coefficient for cognitive load is .72, the strongest direct effect in the model. This suggests that cognitive load has a substantial impact on satisfaction.The positive sign implies that higher cognitive load is associated with higher satisfaction.This counterintuitive finding warrants further investigation. It's possible that in this specific context, students who experience a greater cognitive challenge feel more satisfied with their learning outcomes. Alternatively, there might be issues with how cognitive load was measured or interpreted.

Instructor Support (IS_1): Instructor support demonstrates the strongest positive influence on satisfaction, with a path coefficient of .25. This highlights the critical role of instructors in online learning. Students who perceive strong instructor support (e·g., timely feedback, clear communication, accessible instructors) are significantly more satisfied with their online learning experience.

Table 14.
Regression Weights: (MALE - Unconstrained).

			Estimate	S.E.	C.R.	P	Label
SAT_1	<---	MOL_1	0.232	0.057	4.070	***	b1_1
SAT_1	<---	COG_1	0.227	0.060	3.802	***	b2_1
SAT_1	<---	DL_1	0.208	0.063	3.306	***	b3_1
SAT_1	<---	IS_1	0.527	0.061	8.605	***	b4_1

4.6. Regression Weights (Unstandardized):

SAT_1 <--- MOL_1 (Mode of Learning): The unstandardized regression weight is .232. This means that for every one-unit increase in the mode of learning (MOL_1), satisfaction with online learning (SAT_1) is predicted to increase by .232 units, holding other variables constant. The p-value (***) indicates this effect is statistically significant.

SAT_1 <--- COG_1 (Cognitive Load): The unstandardized regression weight is .227. For every one-unit increase in cognitive load (COG_1), satisfaction with online learning is predicted to increase by ·227 units, holding other variables constant. This effect is also statistically significant.

SAT_1 <--- DL_1 (Digital Literacy): The unstandardized regression weight is .208. For every one-unit increase in digital literacy (DL_1), satisfaction with online learning is predicted to increase by .208 units, holding other variables constant.This effect is statistically significant.

SAT_1 <--- IS_1 (Instructor Support): The unstandardized regression weight is .527. For every one-unit increase in instructor support (IS_1), satisfaction with online learning is predicted to increase by .527 units, holding other variables constant. This effect is statistically significant and the strongest among the predictors.

Table 15.
Standardized Regression Weights: (MALE - Unconstrained).

			Estimate
SAT_1	<---	MOL_1	0.282
SAT_1	<---	COG_1	0.252
SAT_1	<---	DL_1	0.245
SAT_1	<---	IS_1	0.720

4.7. Standardized Regression Weights

SAT_1 <--- MOL_1: The standardized regression weight is .282. This indicates that a one standard deviation increase in MOL_1 leads to a .282 standard deviation increase in SAT_1, when controlling for other variables.

SAT_1 <--- COG_1: The standardized regression weight is .252. A one standard deviation increase in COG_1 leads to a .252 standard deviation increase in SAT_1, when controlling for other variables.

SAT_1 <--- DL_1: The standardized regression weight is .245. A one standard deviation increase in DL_1 leads to a .245 standard deviation increase in SAT_1, when controlling for other variables.

SAT_1 <--- IS_1: The standardized regression weight is .720. A one standard deviation increase in IS_1 leads to a .720 standard deviation increase in SAT_1, when controlling for other variables.

Key Observations:

Instructor Support is the Strongest Predictor: Both unstandardized and standardized weights indicate that instructor support (IS_1) has the strongest positive effect on online learning satisfaction (SAT_1) for male students.

All Effects are Statistically Significant: The p-values (***) for all regression weights are highly significant (typically $p < \cdot 001$), indicating that the relationships are unlikely to be due to chance.

Positive Relationships: All regression weights are positive, suggesting that higher levels of mode of learning, cognitive load, digital literacy, and instructor support are associated with higher levels of satisfaction with online learning for male students.

4.8. Important Considerations

Causality: While SEM suggests relationships, it doesn't definitively prove causality. These results indicate associations, but further research is needed to establish causal links.

Male Subgroup: These findings are specific to the male subgroup and may not generalize to other populations.

Model Fit: The output only shows regression weights. A complete SEM analysis would also include measures of model fit to assess how well the model represents the data.

Cognitive Load Paradox: The positive relationship between cognitive load and satisfaction is counterintuitive and warrants further investigation. It's possible that in this specific context, students who experience a greater cognitive challenge feel more satisfied with their learning outcomes. Alternatively, there might be issues with how cognitive load was measured or interpreted.

In summary, this analysis suggests that instructor support is the most influential factor in online learning satisfaction for male students, followed by mode of learning, cognitive load, and digital literacy. The positive relationship with cognitive load is an unexpected finding that requires further exploration.

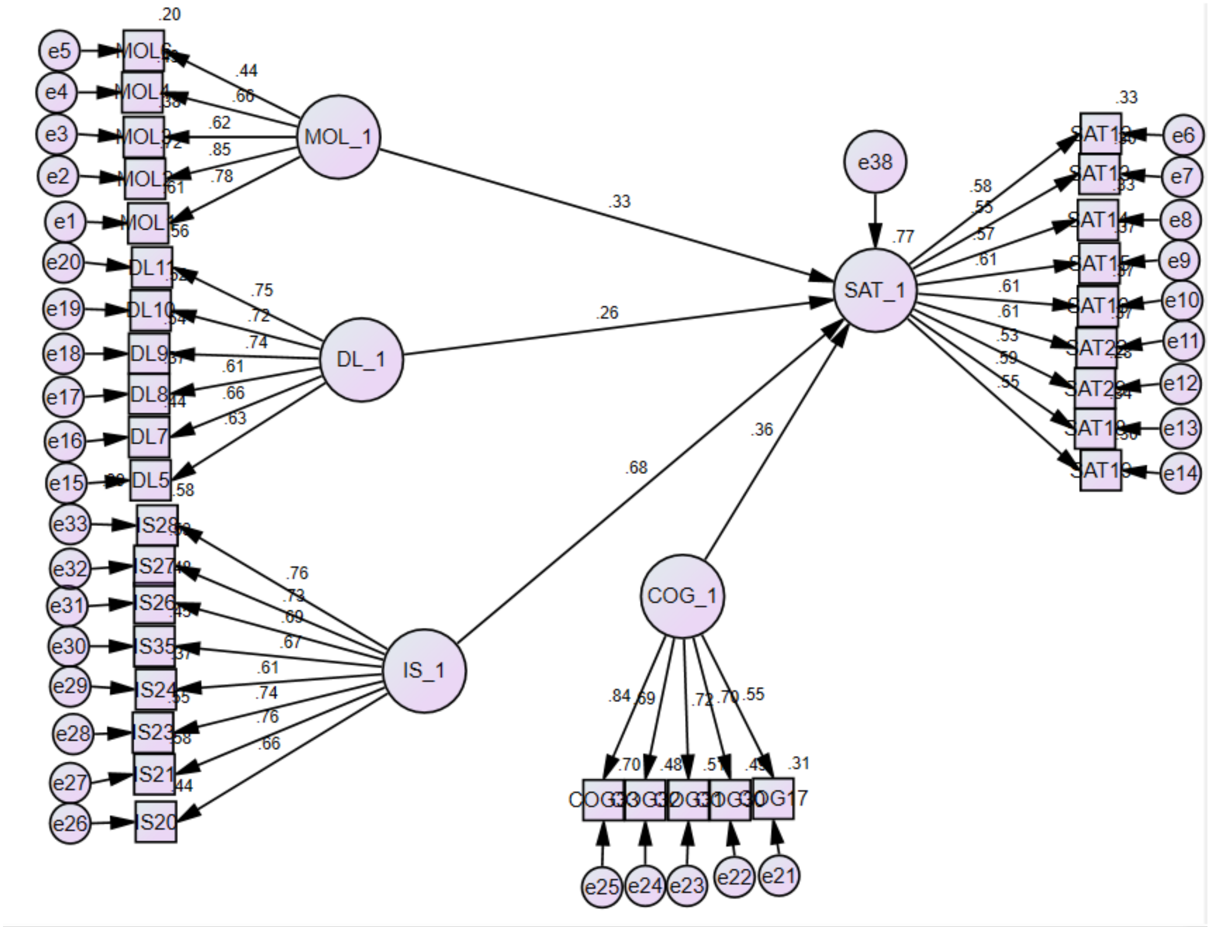

Figure 4.
Female Model.

Path Coefficients (indicating strength and direction of relationships):

MOL_1 -> SAT_1 (·33): This suggests a positive relationship between the mode of learning and satisfaction. A higher score in MOL_1 is associated with a higher satisfaction score. The effect is moderate.

DL_1 -> SAT_1 (.26): Digital awareness also positively influences satisfaction. Students with higher digital awareness tend to be more satisfied, although the effect is relatively weaker than MOL_1.

IS_1 -> SAT_1 (.68): Instructor support has the strongest positive influence on satisfaction. This highlights the critical role of instructors in online learning success and satisfaction.

COG_1 -> SAT_1 (·36): Cognitive load exhibits a positive relationship with satisfaction. This is a less common finding and could suggest that students who experience a suitable level of cognitive challenge are more satisfied. However, it warrants further investigation as excessively high cognitive load is generally considered detrimental.

Table 16.
Regression Weights: (FEMALE - Unconstrained).

			Estimate	**S.E.**	**C.R.**	**P**	**Label**
SAT_1	<---	MOL_1	0.231	0.054	4.303	***	b1_2
SAT_1	<---	COG_1	0.327	0.072	4.527	***	b2_2
SAT_1	<---	DL_1	0.212	0.072	2.938	0.003	b3_2
SAT_1	<---	IS_1	0.470	0.071	6.643	***	b4_2

4.9. Regression Weights (Unstandardized)

SAT_1 <--- MOL_1 (Mode of Learning): The unstandardized regression weight is .231. This means that for every one-unit increase in the mode of learning (MOL_1), satisfaction with online learning (SAT_1) is predicted to increase by .231 units, holding other variables constant. The p-value (***) indicates this effect is statistically significant.

SAT_1 <--- COG_1 (Cognitive Load): The unstandardized regression weight is .327. For every one-unit increase in cognitive load (COG_1), satisfaction with online learning is predicted to increase by ·327 units, holding other variables constant. This effect is also statistically significant.

SAT_1 <--- DL_1 (Digital Literacy): The unstandardized regression weight is .212. For every one-unit increase in digital literacy (DL_1), satisfaction with online learning is predicted to increase by .212 units, holding other variables constant. This effect is statistically significant (p = .003).

SAT_1 <--- IS_1 (Instructor Support): The unstandardized regression weight is .470. For every one-unit increase in instructor support (IS_1), satisfaction with online learning is predicted to increase by .470 units, holding other variables constant. This effect is statistically significant and strong among the predictors.

Table 17.
Standardized Regression Weights: (FEMALE - Unconstrained).

			Estimate
SAT_1	<---	MOL_1	0.328
SAT_1	<---	COG_1	0.362
SAT_1	<---	DL_1	0.261
SAT_1	<---	IS_1	0.682

4.10. Standardized Regression Weights

SAT_1 <--- MOL_1: The standardized regression weight is .32. This indicates that a one standard deviation increase in MOL_1 leads to a .328 standard deviation increase in SAT_1, when controlling for other variables.

SAT_1 <--- COG_1: The standardized regression weight is .362. A one standard deviation increase in COG_1 leads to a .362 standard deviation increase in SAT_1, when controlling for other variables.

SAT_1 <--- DL_1: The standardized regression weight is .261. A one standard deviation increase in DL_1 leads to a .261 standard deviation increase in SAT_1, when controlling for other variables.

SAT_1 <--- IS_1: The standardized regression weight is .682. A one standard deviation increase in IS_1 leads to a .682 standard deviation increase in SAT_1, when controlling for other variables.

Comparison of Male and Female

Based on the provided findings, we can draw some conclusions about how gender has moderated the relationships between the independent variables and online learning satisfaction (SAT_1), although it's crucial to remember that these are based on observed differences and not formal tests of moderation:

Key Observations on Gender Differences:

1·Instructor Support (IS_1): While instructor support is the strongest predictor of satisfaction for both genders, the effect appears slightly stronger for males (.720 standardized weight) compared to females (.682 standardized weight). This suggests that males might be slightly more sensitive to the quality of instructor support in online learning environments. However, it's essential to note that both are very strong effects.

2.Cognitive Load (COG_1): The positive relationship between cognitive load and satisfaction is present for both genders, but the effect seems more pronounced for females (.362 standardized weight) than for males (.252 standardized weight). This implies that females might derive greater satisfaction from online learning experiences that provide a suitable level of cognitive challenge. Again, it's crucial to investigate why cognitive load is positively related to satisfaction.

3.Mode of Learning (MOL_1): The effect of mode of learning on satisfaction is also slightly stronger for females (.328 standardized weight) compared to males (.282 standardized weight). This suggests that females might be more influenced by the specific design and delivery format of online learning.

4.Digital Literacy (DL_1): The effect of digital literacy is somewhat similar across genders, with a slightly stronger effect for males (.245 standardized weight) compared to females (.261 standardized weight). This suggests that both genders benefit from higher digital literacy in online learning.

4.11. Overall Interpretation of Moderation

Quantitative Differences: The results suggest quantitative differences in the relationships between the variables and satisfaction for males and females. The direction of the effects is the same (positive for all predictors), but the strength of the effects varies somewhat.

Potential for Qualitative Differences: While not directly evident, the differences in magnitude hint at the possibility of qualitative differences. For example, perhaps males are more satisfied with direct instructor support, while females are more satisfied with facilitative support. This would require further investigation beyond just the path coefficients.

Need for Formal Moderation Tests: It's important to emphasize that these are just observations based on comparing the subgroups. To definitively conclude that gender moderates these relationships, formal tests of moderation (e·g., multigroup analysis, interaction terms) are necessary. These tests would statistically determine if the differences in path coefficients between males and females are significant.

5. Conclusion

The study on online learning environments, with a focus on the moderating role of gender, provides significant insights into the factors influencing learner satisfaction. The findings indicate that instructor support, cognitive load, mode of learning, and digital literacy are critical determinants of satisfaction in online learning contexts. The structural equation modeling (SEM) analysis revealed that these factors interact in complex ways, with gender playing a moderating role. Specifically, the study found that instructor support had the strongest positive influence on satisfaction for both male and female learners, highlighting the importance of effective instructor engagement in online education. Additionally, the positive relationship between cognitive load and satisfaction suggests that a certain level of cognitive challenge may enhance the learning experience, although this finding warrants further investigation· Overall, the study underscores the need for tailored online learning strategies that consider gender differences and the diverse needs of learners.

The importance of instructor support cannot be overstated. In online learning environments, where face-to-face interaction is limited, the role of the instructor becomes even more crucial. Effective instructor support includes timely feedback, clear communication, and availability for consultations. These elements help create a supportive and interactive learning environment, which is essential for student satisfaction. The study's findings suggest that both male and female learners benefit significantly from strong instructor support, although the effect is slightly stronger for males. This indicates that while all students value instructor engagement, there may be subtle differences in how different genders perceive and benefit from this support.

Cognitive load, another critical factor, was found to have a positive relationship with satisfaction. This finding is somewhat counterintuitive, as high cognitive load is generally considered detrimental to learning· However, the study suggests that a certain level of cognitive challenge may actually enhance the learning experience. This could be because students who are challenged cognitively feel a greater sense of accomplishment and satisfaction when they overcome these challenges. It is also possible that the cognitive load in this study was within a manageable range, allowing students to engage deeply with the material without feeling overwhelmed. Further research is needed to explore this relationship in more detail and to determine the optimal level of cognitive load for different types of learners.

The mode of learning, whether synchronous or asynchronous, also plays a significant role in learner satisfaction. The study found that both male and female learners benefit from a mix of synchronous and asynchronous learning opportunities. Synchronous sessions provide real-time interaction and immediate feedback, which can enhance engagement and motivation. Asynchronous learning, on the other hand, offers flexibility and allows students to learn at their own pace. This combination of learning modes can cater to different learning preferences and help maximize satisfaction. The study's findings suggest that female learners may benefit more from synchronous learning, while male learners may prefer asynchronous options. This highlights the importance of offering a variety of learning modes to meet the diverse needs of learners·

Digital literacy is another important factor influencing satisfaction with online learning· Students with higher levels of digital literacy are better able to navigate online platforms, troubleshoot technical issues, and utilize digital resources effectively. This not only reduces frustration and anxiety but also enhances the overall learning experience. The study found that digital literacy had a positive impact on satisfaction for both male and female learners, although the effect was slightly stronger for males. This suggests that while all students benefit from digital literacy, there may be differences in how different genders develop and utilize these skills.

Providing resources and training to help students improve their digital literacy can therefore enhance satisfaction and learning outcomes.

Gender differences play a moderating role in the relationship between these factors and learner satisfaction. The study found that while the overall trends were similar for both male and female learners, there were some differences in the strength of these relationships. For example, instructor support had a slightly stronger impact on satisfaction for males, while cognitive load had a stronger impact for females. These findings highlight the importance of considering gender when designing online learning environments. By understanding and addressing these differences, educators can create more inclusive and effective online learning experiences.

In conclusion, the study provides valuable insights into the factors influencing satisfaction with online learning environments. Instructor support, cognitive load, mode of learning, and digital literacy are all critical determinants of satisfaction, with gender playing a moderating role. These findings underscore the need for tailored online learning strategies that consider the diverse needs of learners. By enhancing instructor support, optimizing cognitive load, diversifying learning modes, and promoting digital literacy, educators can create more effective and satisfying online learning experiences. Further research is needed to explore these relationships in more detail and to develop best practices for online education.

5.1. Recommendations

1·Enhance Instructor Support: Given the significant impact of instructor support on learner satisfaction, online education providers should prioritize training instructors to effectively engage with students. This includes timely feedback, clear communication, and availability for consultations. Instructors should be equipped with the skills to create a supportive and interactive online learning environment. This can be achieved through professional development programs that focus on online teaching strategies, communication skills, and the use of digital tools. Additionally, institutions should provide ongoing support and resources to help instructors stay updated with the latest trends and best practices in online education.

2·Optimize Cognitive Load: While cognitive load positively influenced satisfaction, it is essential to balance the complexity of course materials to avoid overwhelming students. Instructional designers should focus on creating clear, concise, and well-structured content that challenges learners without causing excessive cognitive strain. Incorporating interactive elements and real-time feedback can help manage cognitive load effectively.For example, breaking down complex topics into smaller, manageable chunks and using multimedia resources to explain difficult concepts can enhance understanding and retention. Regular assessments and feedback can also help students gauge their progress and identify areas for improvement.

3.Diversify Learning Modes: To cater to different learning preferences, online courses should offer a mix of synchronous and asynchronous learning opportunities. Synchronous sessions can provide real-time interaction and immediate feedback, while asynchronous options offer flexibility and self-paced learning. This approach can enhance overall satisfaction by accommodating various learning styles. Institutions should invest in technology and infrastructure to support both types of learning. Additionally, instructors should be trained to effectively facilitate both synchronous and asynchronous sessions, ensuring that all students have a positive and engaging learning experience.

4·Promote Digital Literacy: Enhancing students' digital literacy is crucial for successful online learning. Educational institutions should provide resources and training to help students develop the necessary skills to navigate online platforms effectively. This includes troubleshooting technical issues, using collaboration tools, and accessing digital resources. Workshops, tutorials, and online courses on digital literacy can help students build confidence and competence in using digital tools. Institutions should also provide technical support and resources to assist students with any technical challenges they may encounter during their online learning journey.

5·Gender-Sensitive Approaches: Recognizing the moderating role of gender, online learning environments should be designed to address gender-specific needs. For instance, female learners may benefit from more collaborative and interactive learning experiences, while male learners might prefer self-paced and independent study options. Tailoring online courses to these preferences can improve satisfaction and learning outcomes. Educators should consider conducting regular surveys and feedback sessions to understand the specific needs and preferences of their students. This information can be used to design and implement gender-sensitive teaching strategies and learning activities.

6·Foster a Sense of Community: Building a sense of community in online learning environments can enhance student engagement and satisfaction. Instructors should encourage interaction and collaboration among students through discussion forums, group projects, and virtual study groups. Creating opportunities for social interaction can help students feel connected and supported, reducing feelings of isolation and enhancing their overall learning experience. Institutions should also provide platforms and tools that facilitate communication and collaboration among students, such as virtual meeting rooms and social media groups.

7·Continuous Improvement and Feedback: Institutions should establish mechanisms for continuous improvement and feedback to ensure the quality and effectiveness of online learning programs· Regular evaluations and assessments can help identify areas for improvement and inform the development of new strategies and interventions. Instructors should seek feedback from students on their learning experiences and use this information to make necessary adjustments to their teaching methods and course content. Institutions should also stay updated with the latest research and trends in online education to continuously enhance their programs.

8·Support for Diverse Learners: Online learning environments should be inclusive and accessible to all learners, including those with disabilities and diverse learning needs. Institutions should provide accommodations and support services to ensure that all students have equal opportunities to succeed. This includes providing accessible course materials, offering alternative assessment methods, and providing support services such as tutoring and counseling. Educators should also be trained to recognize and address the diverse needs of their students, creating a supportive and inclusive learning environment.

9·Leverage Technology and Innovation: Institutions should leverage technology and innovation to enhance the online learning experience. This includes using advanced learning management systems, interactive multimedia resources, and adaptive learning technologies that personalize the learning experience for each student. Institutions should also explore emerging technologies such as virtual reality and artificial intelligence to create immersive and engaging learning experiences. By staying at the forefront of technological advancements, institutions can provide high-quality and innovative online learning experiences that meet the evolving needs of learners.

10.Collaboration and Partnerships: Institutions should collaborate with other educational institutions, industry partners, and technology providers to enhance their online learning programs· Partnerships can provide access to additional resources, expertise, and technology, enabling institutions to offer a wider range of courses and learning opportunities. Collaboration with industry partners can also help ensure that online learning programs are aligned with the needs of the job market, providing students with relevant skills and knowledge that enhance their employability.

By implementing these recommendations, educational institutions can create effective and satisfying online learning environments that meet the diverse needs of learners. These strategies can enhance student engagement, satisfaction, and learning outcomes, ultimately contributing to the success of online education. Further research and continuous improvement are essential to ensure that online learning environments remain effective and inclusive in the face of evolving educational needs and technological advancements.

5.2 Limitations and Directions for Future Research

1.Sample Diversity: The study's sample was predominantly young and included a higher proportion of male participants. Future research should aim to include a more diverse sample in terms of age, gender, and socio-economic background to enhance the generalizability of the findings. This will provide a more comprehensive understanding of how different demographic groups experience online learning.

2.Longitudinal Studies: The current study provides a snapshot of learner satisfaction at a single point in time· Longitudinal research is needed to examine how satisfaction and the influencing factors evolve over time. This approach can help identify long-term trends and the sustained impact of online learning strategies on learner outcomes.

By addressing these limitations and exploring new research directions, future studies can build on the findings of this research to further enhance the effectiveness and inclusivity of online learning environments.

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