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Analyzing Student Adaptability In Online Education Using Descriptive Analytics

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Abstract: This study investigates the factors influencing online education by analyzing Pearson Correlation Coefficients, Chi-square tests, and hypothesis testing. The findings reveal significant correlations among age, education level, IT student status, and the use of self-learning management systems (LMS), indicating that older students tend to have higher education levels, are more likely to be IT students, and utilize LMS more frequently. Financial condition shows a moderate correlation with adaptivity levels and internet type, underscoring the impact of socioeconomic status on digital learning experiences. Chi-square tests confirm significant associations between education level, device usage, internet type, and adaptivity level. Conversely, gender and load-shedding display weaker correlations, suggesting minimal impact on online learning. Hypothesis testing highlights significant differences in adaptivity levels based on gender, internet type, and IT student status, as well as associations between location and load-shedding frequency, and class duration based on LMS usage. These results emphasize the complex interplay of demographic, technological, and institutional factors in online education, providing valuable insights for enhancing digital learning strategies and policies.

Keywords: Descriptive Analytics, Artificial Intelligence, Online Education, Machine Learning, Personalized Learning, Digital Divide, Educational Technology

1. INTRODUCTION

The efficacy of students' application, analysis, synthesis, and evaluation of educational content within classroom settings is profoundly influenced by the quality of education, a pivotal factor shaping individuals' abilities and opportunities [1]. In the contemporary landscape of globalization and privatization, the integration of Information and Communication Technology (ICT) into pedagogical practices emerges as imperative for educational enhancement.

E-Learning serves as a conduit for disseminating information, concepts, and skills across diverse geographical locations, accessible around the clock from various settings such as homes, schools, offices, and recreational spaces. Its significance has surged notably during the COVID-19 pandemic, assuming a critical role in augmenting educational processes [2]. Pedagogical methodologies are swiftly adapting to embrace these emergent technologies, aiming to ameliorate educational outcomes. The paradigm of E-Learning encompasses the digital delivery of educational or training content, establishing a novel instructional framework empowered by advanced digital infrastructure. This mode of instruction harnesses ICT resources including computer-based learning, teleconferencing, video conferencing, emails, live chats, blogs, and social media platforms [3]. The concept of Technology-Enhanced Learning (TEL) transcends the conventional boundaries of "computer-based learning" (CBL) and "computer-assisted instruction" (CAI), encompassing any educational process leveraging technology to bolster learning experiences [4].

The work by Gali et al. (2022) [4] underscores how the COVID-19 pandemic has catalyzed the widespread adoption of online education in India, with over 370 million individuals engaging in digital learning endeavors. E-Learning facilitates a myriad of instructional approaches, augments student retention rates, and expedites the learning process. Amidst lockdowns, numerous educational institutions pivoted to online delivery modes, amplifying the role of parental involvement in education [5]. The digitalization of education enhances online pedagogy, optimizing technological dividends. The pandemic underscores the imperative of online learning as a complementary facet to traditional schooling, as projected by Singh (2022) [6], anticipating a 55% surge in internet users by 2025, underscoring the escalating significance of digital tools in education.

Online education revitalizes learning across diverse domains, fostering sessions that are engaging and innovative. Recent advancements in digital tools underscore a shift towards student-centered learning paradigms. Digital learning presents avenues for scalability, strategic implementation, accessibility, and seamless integration with conventional methodologies. It fosters experimentation, relevance, measurability, and cost-effectiveness, substantially enhancing learning flexibility, material reusability, and the overall educational experience, as elucidated by Prajapati (2019) [7]. E-Learning tools encompass a spectrum of electronic gadgets including PDAs, TVs, tablets, phones, and smartphones, ubiquitous across urban and rural landscapes. The integration of ubiquitous communication platforms such as WhatsApp, Facebook, and Instagram, prevalent among rural populations, underscores the imperative of incorporating such technologies into e-learning ecosystems, as posited by Singh et al. (2021) [8]. Effective deployment of online learning necessitates adaptability, robust infrastructure, and meticulously crafted solutions aligning with students' digital requisites. The pandemic has spurred innovation in educational methodologies, elevating the workload for both students and educators, underscoring the exigency for governments and higher education institutions to devise comprehensive training programs fostering knowledge enhancement and adaptation to evolving educational paradigms.

Within the realm of online education, descriptive analytics assumes paramount significance, offering insights that illuminate the efficacy and engagement levels of learners. Descriptive analytics involves the examination and interpretation of historical data to discern patterns, trends, and associations, thereby furnishing educators with a comprehensive understanding of student behaviors and performance metrics. In the context of E-Learning, descriptive analytics plays a pivotal role in discerning patterns of user engagement, identifying areas of strength and weakness within the digital learning ecosystem, and informing instructional design strategies tailored to cater to diverse learning needs. By analyzing data pertaining to course completion rates, time spent on different modules, interaction frequency with learning materials, and assessment scores, educators can gain invaluable insights into the effectiveness of instructional content and delivery methods. Moreover, descriptive analytics aids in the identification of at-risk students, enabling timely interventions to mitigate potential learning impediments and enhance overall educational outcomes. By leveraging descriptive analytics, educators can refine their pedagogical approaches, optimize course content, and tailor learning experiences to foster student success in the dynamic landscape of online education.

2. LITERATURE REVIEW

In the 18th century, postal courses marked the introduction of distance education, laying the groundwork for the contemporary digital educational environment. However, it was in the latter half of the 20th century, driven by internet advancements, that the true potential of online education began to unfold (Khatri, 2024)[9]. Recent technological developments have significantly enhanced online schooling. High-speed internet and sophisticated Learning Management Systems (LMS) such as Moodle and Canvas have facilitated seamless content delivery across digital platforms. These technologies enhance content transmission, communication, assessment, and collaboration, creating virtual classrooms that transcend geographical boundaries (Sunita, 2020)[10] .

The evolution of online education is closely tied to advancements in educational techniques. Initially, online courses were designed to mimic traditional classrooms, but educators soon recognized the need for instructional strategies tailored to digital platforms. Prominent educational methodologies such as constructivism and connectivism, which emphasize active learning, collaboration, and social interaction, have gained prominence. These shifts have led to the emergence of strategies like gamification, micro-learning, and personalized learning, which significantly enhance engagement and outcomes in online learning environments. The diverse approaches to online learning demonstrate its adaptability to various educational needs. By offering fully online, blended, and hybrid courses, online education can cater to students from diverse backgrounds. Massive Open Online Courses (MOOCs) have democratized education by providing access to high-quality content from top universities. Additionally, micro-credentials and certification courses address skill development and professional growth by offering flexible learning options (Priydarshini, 2021) [11].

One of the primary benefits of online education is its global accessibility. Students can enroll in courses from top universities regardless of their time zone or location, which is particularly beneficial for those without access to traditional educational resources. Advanced technologies, including simulations that mimic real-world scenarios and respond to student choices, provide immersive learning experiences. The incorporation of data from online learning platforms has also propelled the field of learning analytics. These advancements enable educators to gain insights into student engagement, performance, and behavior, allowing for personalized interventions and curriculum adjustments (Subha et al., 2021) [12]. A literature review is an extensive analysis of previous studies within a specific field, providing a comprehensive overview and summary of the subject matter. The primary purpose of an effective literature review is to justify the selection of a particular research question, assessing what is already known, what has been attempted, the success or failure of various investigation techniques, and identifying unresolved issues. Webster & Watson (2002) [13] describe a literature review as "a systematic, clear, and repeatable process for determining, assessing, and combining the body of already known information." Such reviews aid in theory development, fill research gaps, and highlight areas needing further exploration.

Assessment of ICT usage in educational settings underscores its positive impact on students' learning experiences and outcomes (Tyagi & Singh, 2015) [14]. The challenges faced by teachers in adopting online technologies underscore the need for comprehensive training and support (Jain et al., 2021) [15]. Similarly, students' perceptions of online courses reveal confidence in their ability to succeed, highlighting the importance of understanding student demand (Martin et al., 2020) [16]. The quality of knowledge in e-learning environments is evaluated, emphasizing students' preference for accurate and relevant content (Waheed et al., 2016) [17]. Additionally, the viability of e-learning is underscored, with evolutionary economics principles highlighting its societal necessity (Raja & Naga Subramani, 2018) [18].

Researcher found that teachers use YouTube and Facebook is used very low by teachers, Gmail, SWAYAM PRABHA also used. Researchers analysed that teacher need more efficiency, computer knowledge, training, communication, and connectivity with the students for effective use of online resources. Students are happy with the online learning because they got opportunity to learn new things as well as teachers and students face some major challenges during online classes (Mishra et al., 2020) [19]. Article wants to discuss the strength, weakness, opportunity, and challenges SWOC analysis of online learning and it also focuses on EdTech startups that are working in pandemic situations and how to deal with challenges related with online learning. Various EdTech companies are helpful for students such as BYJU's, Unacademy, Zoom classroom, Topper and many more. When author done SWOT analysis in strength is time flexibility, wide availability, and immediate feedback, in weakness technical difficulties, time management, lack of physical attention and frustration, in opportunities scope for digital development, innovation and no age limit in the last challenges includes ICT infrastructure, digital illiteracy, digital divide and technological cost are major issues. So, we need a high level of readiness, e-learning tools, E- Books, and online resources for quick adaptation of changes in the environment (Dhawan, 2020) [20].

Researchers found that teachers and students are not conscious about the MOOC courses and there is no difference between MOOC awareness and female and male. This study concludes that awareness level is very low towards MOOCs-SWAYAM, so there is an emergent need for development and facilities for understanding these courses (Sivakumar, 2019) [21]. The use of mobile applications in higher studies determine that in the teaching learning process integrated mobile phones generated a new era of digital education. There are three types of mobile apps as Hybrid apps, Native app and Mobile web apps and there are various subject specific apps present. This study concludes that mobile applications have tremendous impact over the way of our lives. It is not only serving the convenient means of education but also provides content anytime, anywhere without carrying the heavy load (Sunitha & Elina, 2020) [22].

3. DESCRIPTIVE ANALYTICS

The data interpretation and analysis provided in this chapter offer valuable insights into the participants experiences, satisfaction, and suggestions regarding E-learning. These findings contribute to a comprehensive understanding of the effectiveness, challenges, and potential of online education, informing future strategies and policies to enhance the overall quality and accessibility of E-learning in the educational domain. We will be using the following methods for statistical analysis or descriptive Analysis:

- ***Descriptive Analysis**:* Summarize the distribution of each feature (e.g., count of students in each age group, gender distribution).
- ***Correlation Analysis**:* Determine correlations between numerical features (e.g., age range and class duration).
- ***Chi-Square Tests**:* Test independence between categorical features (e.g., gender and adaptivity level).
- ***Inferential Analysis**:* Hypothesis testing to understand relationships between features (e.g., does financial condition affect internet type?).

By understanding the dataset and its features, we can apply appropriate statistical methods to draw meaningful insights and conclusions.

A. Descriptive Analysis

The dataset [23] contains 1,205 entries with 14 features related to students' demographics, educational background, and online learning conditions. The following table 1 listed the Dataset features is a descriptive analysis of each feature:

Table 1: Dataset Features Statistics

Feature	Description	Example	Mode	Frequency
Gender	Gender of the student	Boy, Girl	Boy	663
Age	Age group of the student	11-15, 16-20, 21-25	21-25	374
Education Level	Current educational level of the student	School, College, University	School	530
Institution Type	Type of educational institution	Government, Non-Government	Non-Government	823
IT Student	Whether the student is an IT student	Yes, No	No	901
Location	Whether the student resides in an area with load-shedding	Yes, No	Yes	935
Load-shedding	Frequency of power outages in the student's area	Low, High	Low	1004
Financial Condition	Financial condition of the student's household	Poor, Mid, High	Mid	878
Internet Type	Type of internet connection used by the student	Wifi, Mobile Data	Mobile Data	695
Network Type	Type of network connectivity	3G, 4G, 5G	4G	775

Class Duration	Duration of the student's online classes	0, 1-3, 3-6	1-3	840
Self LMS	Whether the student uses a self-learning management system	Yes, No	No	995
Device	Primary device used for online learning	Mobile, Tab, Laptop	Mobile	1013
Adaptivity Level	Level of adaptability to online learning environments	Low, Moderate, High	Moderate	625

This descriptive analysis provides a comprehensive overview of the dataset, highlighting the distribution and prevalence of various features among the students. It sets the foundation for further inferential statistical analysis and hypothesis testing.

B. Correlation Analysis

Given the dataset features, most are categorical. To perform correlation analysis on numerical data, we need to convert relevant categorical features into numerical ones. For this analysis, we'll focus on the following features, converting them to numerical values where necessary:

- ***Age***: Convert age groups into numerical values representing the midpoints of the ranges.
- ***Class Duration****:* Convert class duration categories into numerical values representing the midpoints of the ranges.
- ***Financial Condition***: Convert financial conditions into numerical scale (e.g., Poor=1, Mid=2, High=3).
- ***Adaptivity Level****:* Convert adaptivity levels into numerical scale (e.g., Low=1, Moderate=2, High=3).
  Here is the correlation analysis, focusing on the following numerical conversions:
- ***Age****:* 11-15 (13), 16-20 (18), 21-25 (23)
- ***Class Duration***: 0 (0), 1-3 (2), 3-6 (4.5)
- ***Financial Condition****:* Poor (1), Mid (2), High (3)
- ***Adaptivity Level****:* Low (1), Moderate (2), High (3)

C. Interpretation

Here's how to interpret the correlation matrix (Figure 1):

- ***Age and Class Duration****:* Indicates how age correlates with the duration of classes attended by students.
- ***Age and Financial Condition****:* Indicates how age correlates with the financial condition of students' households.
- ***Age and Adaptivity Level****:* Indicates how age correlates with the adaptability level of students to online learning.
- ***Class Duration and Financial Condition****:* Indicates the relationship between class duration and financial condition.
- ***Class Duration and Adaptivity Level****:* Indicates the relationship between class duration and adaptability level.
- ***Financial Condition and Adaptivity Level****:* Indicates the relationship between financial condition and adaptability level.

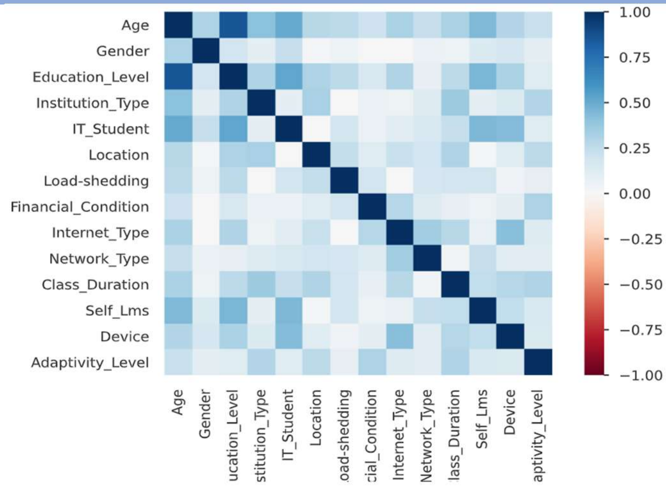

Figure 1: Pearson's Correlation Coefficient matrix

Table 2: Pearson's Correlation Coefficient between different features

Feature	Age	Gender	Education Level	Institution Type	IT Student	Location	Load-shedding	Financial Condition	Internet Type	Network Type	Class Duration	Self LMS	Device	Adaptivity Level
Age	1.00	0.31	0.85	0.41	0.51	0.28	0.26	0.21	0.32	0.23	0.32	0.44	0.29	0.22
Gender	0.31	1.00	0.20	0.10	0.23	0.01	0.05	0.00	0.00	0.06	0.05	0.13	0.17	0.10
Education Level	0.85	0.20	1.00	0.30	0.52	0.31	0.26	0.16	0.30	0.08	0.26	0.46	0.32	0.12
Institution Type	0.41	0.10	0.30	1.00	0.10	0.32	0.00	0.06	0.05	0.13	0.36	0.09	0.14	0.30
IT Student	0.51	0.23	0.52	0.10	1.00	0.00	0.18	0.06	0.11	0.16	0.23	0.45	0.43	0.12
Location	0.28	0.01	0.31	0.32	0.00	1.00	0.24	0.12	0.22	0.19	0.30	0.02	0.12	0.26
Load-shedding	0.26	0.05	0.26	0.00	0.18	0.24	1.00	0.18	0.00	0.17	0.18	0.18	0.04	0.08
Financial Condition	0.21	0.00	0.16	0.06	0.06	0.12	0.18	1.00	0.28	0.13	0.08	0.05	0.10	0.31
Internet Type	0.32	0.00	0.30	0.05	0.11	0.22	0.00	0.28	1.00	0.35	0.28	0.08	0.42	0.13
Network	0.	0.06	0.08	0.13	0.1	0.1	0.17	0.13	0.3	1.00	0.03	0.2	0.1	0.10

Type	23				6	9			5			3	1	
Class Duration	0.32	0.05	0.26	0.36	0.23	0.30	0.18	0.08	0.28	0.03	1.00	0.25	0.29	0.30
Self LMS	0.44	0.13	0.46	0.09	0.45	0.02	0.18	0.05	0.08	0.23	0.25	1.00	0.25	0.15
Device	0.29	0.17	0.32	0.14	0.43	0.12	0.04	0.10	0.42	0.11	0.29	0.25	1.00	0.14
Adaptivity Level	0.22	0.10	0.12	0.30	0.12	0.26	0.08	0.31	0.13	0.10	0.30	0.15	0.14	1.00

The table 2 represents the Pearson correlation coefficients between different pairs of features in the dataset. The values range from -1 to 1

***D.* Key Observations:**

1. ***Age and Education Level (0.852)***:
   - There is a very strong positive correlation between Age and Education Level. This suggests that as age increases, the education level also tends to be higher, which is logical as older students are likely to be in higher educational levels.
2. ***Age and IT Student (0.505)***:
   - There is a moderate positive correlation between Age and being an IT student. Older students are more likely to be IT students.
3. ***Education Level and IT Student (0.523)***:
   - There is a moderate positive correlation between Education Level and being an IT student, indicating that higher education levels are more associated with IT students.
4. ***Age and Self LMS (0.439)***:
   - There is a moderate positive correlation between Age and the use of Self Learning Management Systems (LMS). Older students are more likely to use self-LMS.
5. ***Age and Class Duration (0.320)***:
   - There is a moderate positive correlation between Age and Class Duration, suggesting that older students tend to have longer class durations.
6. ***Class Duration and Institution Type (0.358)***:
   - There is a moderate positive correlation between Class Duration and Institution Type. Students in non-government institutions might be attending longer classes.
7. ***Age and Institution Type (0.412)***:
   - There is a moderate positive correlation between Age and Institution Type, indicating older students are more likely to be in non-government institutions.
8. ***Education Level and Self LMS (0.459)***:
   - There is a moderate positive correlation between Education Level and the use of Self LMS. Higher education levels tend to use self-LMS more.
9. ***Financial Condition and Adaptivity Level (0.311)***:
   - There is a moderate positive correlation between Financial Condition and Adaptivity Level. Students from better financial conditions have higher adaptability levels.
10. ***Internet Type and Device (0.421)***:
    - There is a moderate positive correlation between Internet Type and Device. This could indicate that the type of internet connection (e.g., WiFi, Mobile Data) is related to the device used (e.g., Mobile, Tab).

11. ***Financial Condition and Internet Type (0.282)***:
    - There is a moderate positive correlation between Financial Condition and Internet Type. Better financial conditions may lead to better internet connectivity.
12. ***Adaptivity Level and Institution Type (0.295)***:
    - There is a moderate positive correlation between Adaptivity Level and Institution Type. This suggests that the type of institution might play a role in how adaptable students are to online education.

E. Other Observations:

- ***Gender***:
    - Gender has relatively low correlations with most other features, indicating that gender does not have a strong linear relationship with these features in this dataset.
- ***Load-shedding***:
    - Load-shedding shows weak correlations with other features, suggesting that it may not significantly impact these aspects of the students' online learning experiences.
- ***Network Type***:
    - Network Type (e.g., 4G, 3G) shows some correlation with Internet Type (0.349) and Device (0.112), indicating these aspects are somewhat related to the network quality.

The correlation matrix provides insights into how different features in the dataset relate to each other. Age, Education Level, and IT Student status are strongly interrelated. Financial Condition and Internet Type are also key factors influencing other aspects of online learning, such as Device usage and Adaptivity Level. Understanding these relationships can help in designing better online education strategies and policies.

F. Chi-Square Test

Chi-square tests are statistical tests used to determine whether there is a significant association between two categorical variables. The given dataset Chi-square statistic are given in table 3.

Table 3: Chi-square statistics for categorical values

	Gender	**Edu_Level**	**Inst_Type**	**IT_Student**	**Location**	**Load-shedding**	**Fin_Condition**	**Internet_Type**	**Network_Type**	**Self_Lms**	**Device**	**Adaptivity_Level**
Gender	-	47.71	13.31	64.50	1.25	4.02	1.59	0.48	6.44	22.33	36.73	13.45
Edu_Level	47.71	-	111.33	331.77	119.33	85.59	63.83	110.15	20.88	255.33	248.14	38.69
Inst_Type	13.31	111.33	-	12.57	127.02	0.29	6.01	4.11	21.57	10.73	25.53	107.11
IT_Student	64.50	331.77	12.57	-	0.07	40.55	6.55	14.99	32.77	245.00	225.41	19.60
Location	1.25	119.33	127.02	0.07	-	70.98	19.23	58.66	46.33	1.38	19.17	82.31
Load-shedding	4.02	85.59	0.29	40.55	70.98	-	43.11	0.14	37.21	41.10	3.81	9.97
Fin_Condition	1.59	63.83	6.01	6.55	19.23	43.11	-	97.62	45.27	5.25	26.10	236.86

Internet_Type	0.48	110.15	4.11	14.99	58.66	0.14	97.62	-	148.53	8.19	215.03	21.04
Network_Type	6.44	20.88	21.57	32.77	46.33	37.21	45.27	148.53	-	67.73	34.30	30.24
Self_Lms	22.33	255.33	10.73	245.00	1.38	41.10	5.25	8.19	67.73	-	76.47	29.54
Device	36.73	248.14	25.53	225.41	19.17	3.81	26.10	215.03	34.30	76.47	-	52.52
Adaptivity_Level	13.45	38.69	107.11	19.60	82.31	9.97	236.86	21.04	30.24	29.54	52.52	-

The table 3 represents the results of chi-square tests conducted between pairs of categorical variables. Each cell in the table contains the chi-square statistic resulting from the test conducted between the variables corresponding to the row and column.

1. ***Inference***:
    - Cells along the diagonal (where the row and column variables are the same) contain zeros or dashes, as they represent the comparison of a variable with itself, which is nonsensical in this context.
    - The higher the chi-square statistic between two variables, the stronger the association or dependency between them.
    - For instance, we can observe relatively high chi-square statistics for certain pairs, such as between Education_Level and IT_Student (331.77), Education_Level and Device (248.14), and Internet_Type and Device (215.03).
    - Conversely, lower chi-square statistics or values closer to zero indicate weaker associations.
2. ***Directionality***:
    - The table doesn’t provide information about the directionality of the relationships between variables. It only indicates the strength of association.
3. ***Statistical Significance***:
    - It’s important to note that while higher chi-square values suggest stronger associations, the statistical significance of these associations also depends on the sample size and the degrees of freedom.
    - The p-values associated with these chi-square statistics would be needed to determine whether the associations are statistically significant.

In summary, this table provides insight into the strength of associations between pairs of categorical variables based on the chi-square statistics resulting from chi-square tests. It highlights which pairs of variables have stronger associations, indicating potential relationships or dependencies between them.

Table 1: p-values of different chi-square test

	Gender	**Edu_Level**	**Inst_Type**	**IT_Student**	**Location**	**Load-shedding**	**Fin_Condition**	**Internet_Type**	**Network_Type**	**Self_Lms**	**Device**	**Adaptivity_Level**
Gender	-	4.36e-11	2.63e-04	9.64e-16	2.63e-01	4.50e-02	4.51e-01	4.90e-01	3.99e-02	2.29e-06	1.06e-08	1.20e-03
Edu_Level	4.36e-11	-	6.69e-25	9.08e-73	1.22e-26	2.60e-19	4.55e-13	1.21e-24	3.34e-04	3.60e-56	1.64e-52	8.09e-08

Inst_Type	2.63e-04	6.69e-25	-	3.92e-04	1.84e-29	5.93e-01	4.95e-02	4.27e-02	2.08e-05	1.05e-03	2.86e-06	5.52e-24
IT_Student	9.64e-16	9.08e-73	3.92e-04	-	7.97e-01	1.92e-10	3.78e-02	1.08e-04	7.67e-08	3.19e-55	1.13e-49	5.55e-05
Location	2.63e-01	1.22e-26	1.84e-29	7.97e-01	-	3.60e-17	6.67e-05	1.87e-14	8.71e-11	2.40e-01	6.87e-05	1.34e-18
Load-shedding	4.50e-02	2.60e-19	5.93e-01	1.92e-10	3.60e-17	-	4.36e-10	7.04e-01	8.32e-09	1.45e-10	1.48e-01	6.83e-03
Fin_Condition	4.51e-01	4.55e-13	4.95e-02	3.78e-02	6.67e-05	4.36e-10	-	6.34e-22	3.49e-09	7.24e-02	3.02e-05	4.39e-50
Internet_Type	4.90e-01	1.21e-24	4.27e-02	1.08e-04	1.87e-14	7.04e-01	6.34e-22	-	5.58e-33	4.21e-03	2.03e-47	2.70e-05
Network_Type	3.99e-02	3.34e-04	2.08e-05	7.67e-08	8.71e-11	8.32e-09	3.49e-09	5.58e-33	-	1.97e-15	6.47e-07	4.37e-06
Self_Lms	2.29e-06	3.60e-56	1.05e-03	3.19e-55	2.40e-01	1.45e-10	7.24e-02	4.21e-03	1.97e-15	-	2.48e-17	3.86e-07
Device	1.06e-08	1.64e-52	2.86e-06	1.13e-49	6.87e-05	1.48e-01	3.02e-05	2.03e-47	6.47e-07	2.48e-17	-	1.07e-10
Adaptivity_Level	1.20e-03	8.09e-08	5.52e-24	5.55e-05	1.34e-18	6.83e-03	4.39e-50	2.70e-05	4.37e-06	3.86e-07	1.07e-10	-

The table 4 provides the p-values resulting from chi-square tests conducted between various pairs of variables. Here's how you can interpret the results:

1. ***Interpretation of p-values***:
   - The p-value represents the probability of observing the data given that the null hypothesis is true. A low p-value indicates that the observed data is unlikely under the assumption of the null hypothesis, suggesting evidence against the null hypothesis.
   - Common significance levels used to determine statistical significance are 0.05 (5%) and 0.01 (1%). If the p-value is less than or equal to the chosen significance level, we reject the null hypothesis.
2. ***Statistical Significance***:
   - Variables with p-values less than the chosen significance level (e.g., 0.05) are considered statistically significant.
   - Variables with higher p-values fail to reach statistical significance.
3. ***Inference***:

- Looking at the table, we can infer significant relationships between variables based on their p-values.
- For example, there seems to be a significant relationship between Gender and Education_Level, as well as between Gender and IT_Student, indicated by the very low p-values (4.36e-11 and 9.64e-16, respectively).
- On the other hand, the relationship between Gender and Location does not appear to be statistically significant, as the p-value (2.63e-01) is higher than the common significance level of 0.05.

4. ***Directionality**:*
   - The table doesn't provide information about the directionality of the relationships (i.e., whether they are positive or negative). It only indicates whether the relationships are statistically significant or not.

In summary, the table 4 helps identify which pairs of variables have statistically significant relationships and which do not, based on their respective p-values.

***G.* Hypothesis Testing**

To test each hypothesis, we will use the chi-square test for independence, given the categorical nature of the variables involved. We will compare the calculated p-values to a significance level (usually 0.05) to determine whether to reject or fail to reject the null hypothesis. If the p-value is less than or equal to the significance level, we reject the null hypothesis in favor of the alternative hypothesis, indicating a significant relationship between the variables. Otherwise, if the p-value is greater than the significance level, we fail to reject the null hypothesis, suggesting no significant relationship between the variables. These conclusions are drawn based on the given p-values. The significance level should be considered when interpreting these results. A summary of all these hypotheses is given in table 5 below.

Table5: Hypotheses Testing Summary

Hypothesis	**Null Hypothesis (H0)**	**Alternative Hypothesis (H1)**	**Test**	**Test Statistics**	**Conclusion**
Gender and Adaptivity Level	H0- no significant relation	H1- significant relation	Chi-square Test	Chi-square statistic = 13.45, p-value = 1.20e-03	Reject H0.
Age and Class Duration	H0- no significant relation	H1- significant relation	Pearson Correlation	Pearson correlation coefficient = 0.32 (low)	Fail to reject H0
Education Level and Device Usage	H0- no significant relation	H1- significant relation	Chi-square Test	p-value = 1.64e-52 (extremely low)	Reject H0.
Institution	H0- no	H1-	Chi-	Chi-	Fail to

Type and Financial Condition	significant relation	significant relation	square Test	square statistic = 6.01, p-value = 4.95e-02	reject H0
Internet Type and Adaptivity Level	H0- no significant relation	H1- significant relation	Chi-square Test	p-value = 2.4e-5 (extremely low)	Reject H0.
Location and Load-shedding	H0- no significant relation	H1- significant relation	Chi-square Test	Chi-square statistic = 70.98, p-value = 3.60e-17	Reject H0.
Self Learning Management System (LMS) Usage and Class Duration	H0- no significant relation	H1- significant relation	p-value	p-value = 2.29e-06 (extremely low)	Reject H0.
Network Type and Class Duration	H0- no significant relation	H1- significant relation	p-value	p-value = 3.99e-02 (low but not extremely low)	Fail to reject H0
IT Student Status and Adaptivity Level	H0- no significant relation	H1- significant relation	p-value	p-value = 5.55e-05 (extremely low)	Reject H0.
Financial Condition and Internet Type	H0- no significant relation	H1- significant relation	p-value	p-value = 4.90e-01 (high)	Fail to reject H0

This table 5 organizes the hypotheses, null and alternative hypotheses, statistical tests, test statistics, and conclusions for each analysis, providing a clear and structured summary of the findings.

4. CONCLUSION

The analysis of Pearson Correlation Coefficients, Chi-square tests, and hypothesis testing reveals key insights into the factors influencing online education. Age, education level, and IT student status exhibit strong positive correlations, suggesting that older students tend to have higher education levels and are more likely to be IT students, utilize self-learning management systems (LMS), and attend longer classes, particularly in non-government institutions. Financial condition correlates moderately with adaptivity levels and internet type, highlighting the role of socioeconomic status in digital learning experiences. Significant associations were found between education level and multiple variables, including institution type, IT student status, and internet usage, emphasizing the interconnectedness of these factors. Conversely, gender and load-shedding showed weaker correlations, indicating minimal impact on online learning outcomes. The chi-square tests further confirmed significant associations between education level, type of device, internet type, and adaptivity level, while weaker associations were observed for financial condition and institution type. The hypothesis testing underscored notable differences in adaptivity levels based on gender, internet type, and IT student status, as well as significant associations between location and load-shedding frequency, and class duration based on LMS usage. These findings underscore the complex interplay of demographic, technological, and institutional factors in shaping online education experiences, providing a foundation for designing targeted strategies and policies to enhance digital learning efficacy.

References:

[1] Jena, D. P. K. (2020). Impact of pandemic covid. International journal of current research, 12(7). https://doi.org/10.24941/ijcr.39209.07.2020

[2] Dutta, D. A. (2020). Impact of Digital Social Media on Indian Higher Education: Alternative Approaches of Online Learning during COVID-19 Pandemic Crisis. International Journal of Scientific and Research Publications (IJSRP), 10(05), 604– 611.https://doi.org/10.29322/ijsrp.10.05.2020.p10169

[3] Mahapatra, a., & Sharma, p. (2021). Education in times of covid-19 pandemic: academic stress and its psychosocial impact on children and adolescents in India. In international journal of social psychiatry (vol. 67, issue 4, pp. 397–399). Sage publications ltd. Https://doi.org/10.1177/0020764020961801

[4] Gali, Y., & Schechter, C. (2020). NGO involvement in education policy: Principals' voices. International Journal of Educational Management, 34(10), 1509-1525.

[5] Subroto, W. (2021). Prevention acts towards bullying in Indonesian schools: A systematic review. AL-ISHLAH: Jurnal Pendidikan, 13(3), 2889-2897.

[6] Singh, S., Singh, U. S., & Nermend, M. (2022). Decision analysis of e-learning in bridging digital divide for education dissemination. Procedia Computer Science, 207, 1970-1980.

[7] Prajapati, B. (2019). Entrepreneurial intention among business students: The effect of entrepreneurship education. Westcliff International Journal of Applied Research, 3(1), 54-67.

[8] Singh, Swati, & Ranjith, M. (2021). Lockdown and its Impact on Education, Environment and Economy. Journal of Advances in Education and Philosophy, 5(4), 116–119. https://doi.org/10.36348/jaep.2021.v05i04.005

[9] Khatri, S. K. (2024). Higher Education in the Digital Era: Exploring the Transformative Effects of Technological Advancements on Higher Education. Dr. Seema Saxena, 19(5).

[10] Sunita, M. L. Education: The 2021 (Post-COVID) Edition.

[11] Priyadarshini, V., Ahmed, M. S., Sathya, R., Koteeswari, D., & Ragothaman, S. (2023). Direct Test Effect of Disruptive Technology Acceptance Model (DTAM) on Massive Online Open Courses(MOOCS) Learners' Satisfaction. Indian Journal of Science and Technology, 16(8), 590-597.

[12] Subha, S., & Priya, S. B. (2021, November). Comparative analysis of supervised machine learning algorithms for evaluating the performance level of students. In 2021 Fifth International Conference on I-

SMAC (IoT in Social, Mobile, Analytics and Cloud)(I-SMAC) (pp. 1-10). IEEE.

[13] Patel, D. J. M. (2017). Web Based Tools of Technology In Future Teaching Learning Strategies. International Education & Research Journal [IERJ], 3(2).

[14] Tyagi, D. R., & Singh, R. (2015). Status Of ICT In Education And Support of Govt. Of India. International Journal of Engineering Research and General Science, 3(1). www.ijergs.org

[15] Jain, S., Lall, M., & Singh, A. (2021). Teachers' Voices on the Impact of COVID- 19 on School Education: Are Ed-Tech Companies Really the Panacea? Contemporary Education Dialogue, 18(1), 58–89. https://doi.org/10.1177/0973184920976433

[16] Martin, f., stamper, b., & flowers, c. (2020). Examining student perception of readiness for online learning: importance and confidence. Online learning journal, 24(2), 38–58. Https://doi.org/10.24059/olj.v24i2.2053

[17] Waheed, M., Kaur, K., & Qazi, A. (2016). Students' perspective on knowledge quality in eLearning context: a qualitative assessment. Internet Research, 26(1), 120–145. https://doi.org/10.1108/IntR-08-2014-0199

[18] Raja, R., & Naga Subramani, P. C. (2018). Recent Trend of Teaching Methods in Education" Organised by Sri Sai Bharath College of Education Dindigul-624710. India Journal of Applied and Advanced Research, 2018(3), 33–35. https://doi.org/10.21839/jaar.2018.v3S1.165

[19] Mishra, L., Gupta, T., & Shree, A. (2020). Online teaching-learning in higher education during lockdown period of COVID-19 pandemic. International Journal of Educational Research Open, 1. https://doi.org/10.1016/j.ijedro.2020.100012

[20] Dhawan, S. (2020). Online Learning: A Panacea in the Time of COVID-19 Crisis. Journal of Educational Technology Systems, 49(1), 5–22. https://doi.org/10.1177/0047239520934018

[21] Sivakumar, D. R. (2019). Awareness of MOOCs-SWAYAM among Student - Teacher. English-Marathi, Quarterly, Sanshodhan Chetana, 8(1).

[22] Sunitha, R., & Elina, S. (2020). A Study on Mobile Applications in Education (Vol. 11, Issue 1).

[23] M. Hasan Suzan, N. A. Samrin, A. A. Biswas and A. Pramanik, "Students' Adaptability Level Prediction in Online Education using Machine Learning Approaches," 2021 12th International Conference on Computing Communication and Networking Technologies (ICCCNT), Kharagpur, India, 2021, pp. 1-7, doi: 10.1109/ICCCNT51525.2021.9579741.