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Article

# Examining the impact of student characteristics on E-learning satisfaction: A structural equation modeling approach

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**Abstract:** E-learning has become an integral part of higher education, significantly influencing the teaching and learning landscape. This study investigates the impact of student characteristics such as gender, grade, and major on E-learning satisfaction. Utilizing Structural Equation Modeling (SEM) and collecting data through 527 valid questionnaires from Nanjing Normal University students, this research reveals the nuanced relationships between these variables and E-learning satisfaction. The findings indicate that gender, grade, and major significantly and positively impact student satisfaction with E-learning, highlighting the need for tailored E-learning resources to meet diverse student needs. The study underscores the importance of continuous improvement in E-learning resources and platforms to enhance student satisfaction. This research contributes to the understanding of effective E-learning strategies in higher education institutions.

**Keywords:** E-learning policy; student satisfaction; structural equation modeling; higher education; students' character

## 1. Introduction

E-learning is a teaching and learning method that incorporates the educational paradigm and utilises electronic media and devices to enhance the availability of training, communication, and interaction (Alqahtani et al., 2022). It promotes the acceptance of new ways of understanding and establishing learning. E-learning refers to the process of acquiring knowledge and skills through the use of electronic devices. Computers, mobile phones, laptops, and virtual worlds are instances of computational devices (Lee et al., 2009). E-learning is gaining prominence as an essential instrument that educational institutions and universities worldwide are embracing (Kumar and Owston, 2016; Yeh and Chu, 2018). E-learning creates a virtual environment in which students can engage in a diverse array of activities, as per Al-Rahmi et al. (2021).

Employing an E-learning system offers numerous benefits. Initially, E-learning assists universities in reducing significant expenses associated with the investment in physical teaching and learning infrastructures (Eza et al., 2020). Secondly, E-learning facilitates the digitisation of universities and contributes to the development of a digital and knowledgeable society, in which learning and knowledge sharing can be conducted in a straightforward and efficient manner at any time and in any location, facilitated by Internet-enabled technologies (Gupta and Jain, 2017). Thirdly, universities are able to further integrate into the global educational environment through the use of E-learning (Lee, 2010). In particular, international cooperation and connections in the field of education can extend beyond the confines of a single country. For instance, joint training programs that allow domestic students to receive full academic services from a foreign university without the necessity of attending a foreign university.

E-learning offers students an alternative learning style in addition to traditional learning (Baherimoghadam et al., 2021). E-learning is not constrained by geographical or temporal limitations, since it may be accessed from any location, such as one's home or workplace, using computers or mobile devices connected to the Internet and the university's E-learning platform (Matthew et al., 2021). This is especially advantageous for students who are simultaneously engaged in learning and employment (Wisloski, 2011). With E-learning, students have full autonomy over the speed and tempo of their studies since they are not obligated to attend in-person classes on campus (Christensen, 2021).

An obstacle in E-learning pertains to the learning experiences and academic performance of students. According to Panigrahi et al. (2021), students' happiness and outcomes serve as reliable measures for evaluating the quality and efficacy of E-learning programs. Institutions have a vested interest in determining the overall satisfaction of their students with their learning experience (Kember and Ginns, 2012). Learner involvement is another crucial component for ensuring high-quality online education. student engagement encompasses the active involvement and dedication of the student in the learning process, with the aim of acquiring knowledge and developing critical thinking skills (Martin and Bolliger, 2018).

Although there are various interpretations of student characters, proponents of learning analytics typically prioritise the examination of platform access logs, specifically focussing on clicks on learning resources, as a measure of student engagement in E-learning. The premise posits that active E-learning participation, as seen by logins, active sessions, and clicks, correlates with genuine engagement in an online course and leads to improved student success. Nevertheless, this approach mostly operates within traditional E-learning modules, and there is a restricted amount of literature that assesses students' involvement in activity-based hybrid learning settings, which combine both online and offline activities (Hoi and Le, 2021).

## 2. Literature review

Satisfaction is the subjective evaluation of a person's attitude or emotions in relation to the several aspects that influence a specific circumstance (Wixom and Todd, 2005). Student satisfaction can be defined as the perception that students develop based on the value they perceive from their education and the experiences they gain at an educational institution (Clemes et al., 2008). In the realm of human-computer interaction, it is commonly believed that user happiness is the result of emotions experienced during communication (Thandevaraj et al., 2021). User satisfaction refers to the degree of alignment between the information system used by users and their specific needs (Al-Maskari and Sanderson, 2010).

Several studies have been conducted to understand the factors influencing learner satisfaction in E-learning environments. Sun et al. (2008) developed an integrated model with six dimensions including learners, instructors, courses, technology, design, and environment. Orvis et al. (2009) investigated the impact of learner control on learning in E-learning environments and the role of individual differences in predicting learning outcomes. Chen et al. (2011) applied Kano's model to identify key elements for maximizing learner satisfaction in E-learning services, highlighting the importance of good user interface design and useful content. (Ali, 2012) focused on nursing students' satisfaction with E-learning experiences, while (Liaw et al., 2013) explored perceived satisfaction and usefulness as predictors of self-regulation in E-learning environments. Chen and Yao (2016) examined factors influencing learner satisfaction in blended learning environments, emphasizing the youth of the respondents. (Al-Azawei et al., 2016) assessed learner perceptions of a blended E-learning system based on learning styles. (Al-Fraihat et al., 2020) developed a comprehensive model to evaluate E-learning system success, validated through empirical data from students in a UK university. (Safsouf et al., 2020) focused on understanding determinants of learners' satisfaction, self-regulation, and continuance intention in higher education E-learning systems in Morocco. (Kumar et al., 2021) investigated the relationship between learner-content interaction, E-learning quality, and learner satisfaction, considering the moderating effect of perceived harm due to COVID-19.

Previous studies have consistently shown a positive correlation between students' attributes and their academic performance in different study studies and environments. Chang et al. (2014) have acknowledged that investigating gender disparities in internet and computer usage, as well as in education, is crucial. Chuang et al. (2015) provide evidence that there are gender disparities in university students' attitudes towards and perceptions of the internet. According to their findings, men students exhibit internet attitudes that are significantly more favourable compared to their female counterparts. Mota and Cilento (2020) found that male students had a more positive attitude towards the internet and higher internet self-efficacy compared to females. In the study conducted by Cazan et al. (2016), it was found that males generally have higher levels of computer self-efficacy and lower levels of computer anxiety compared to females. In a study conducted by Aljaraideh and Al Bataineh (2019), it was discovered that female students have a more favourable disposition towards online education compared to their male counterparts. Ruthotto et al. (2020) observed notable disparities in the experiences of male and female, as well as shy and quiet college students, in an online learning setting. These discrepancies primarily revolved around the aspects of flexibility, face-to-face interaction, self-discipline, and self-motivation. While existing research has explored various aspects of student characteristics and their impact on E-learning satisfaction, there is a lack of studies that simultaneously examine the effects of gender, grade level, and academic major using structural equation model.

## 3. Research objectives, questions and hypothesis

### 3.1. Research objectives

This study assesses the impact of teaching quality and ideological and political education on students' level of satisfaction with their learning experience. The research objective should encompass three prospective factors and 17 measurable variables to facilitate the assessment of potential variables. The subsequent statements outline the research objectives (RO):

RQ1: To investigate the impact of gender on student satisfaction with E-learning.

RQ2: To examine the influence of a student's major on their satisfaction with E-learning experiences.

RQ3: To assess how different grade levels affect student satisfaction in E-learning environments.

### 3.2. Research questions

The research questions are formulated to align with the study's objectives and adhere to the conceptual framework that guides the investigation. The research questions (RQ) were examined in the study.

RQ1: Will student's gender influence their satisfaction with E-learning?

RQ2: Will student's major affect their satisfaction with E-learning?

RQ3: What is the relationship between a student's grade level and their satisfaction with E-learning?

### 3.3. Hypothesis

The following set of hypotheses is derived from the research questions RQ1, RQ2, and RQ3, and they are all to be tested:

Hypothesis 1: Gender has a significant positive impact on student satisfaction with E-learning.

Hypothesis 2: A student's major has a significant positive impact on their satisfaction with E-learning.

Hypothesis 3: A student's grade level has a significant positive impact on their satisfaction with E-learning.

## 4. Methodology

### 4.1. Instruments

Student satisfaction was evaluated using the Student Satisfaction Scale from Wang (Wang, 2020), which has very high reliability and validity. The study selected three indicators, namely, student gender, grade, and major, as adjustment variables for this study. The overall scale was collected and analyzed using the Likert Five-dimensional scale, as follows **Table 1**:

**Table 1.** Student evaluation scale after integrating into E-learning factors.

| Evaluation Dimension | Content | Scale |
|---|---|---|
| E-learning quality evaluation<br>(Q4–Q8) | Richness of E-learning<br>Effectiveness of E-learning<br>Practicality of E-learning<br>Flexibility of E-learning | 1-Very dissatisfied<br>2-Dissatisfied<br>3-Neutral<br>4-Satisfied<br>5-Very satisfied |

**Table 1.** (*Continued*).

| Evaluation Dimension | Content | Scale |
|---|---|---|
| E-learning recourses quality evaluation (Q9–Q15) | Usability of the Learning Platform<br>Engagement of the Learning Platform<br>Technical Support of the Learning Platform<br>Interactivity of the Learning Platform<br>Design and Layout of the Learning Platform<br>Overall Learning Experience on the Learning Platform<br>Overall learning experience | 1-Very dissatisfied<br>2-Dissatisfied<br>3-Neutral<br>4-Satisfied<br>5-Very satisfied |
| **Evaluation Dimension** | **Content** | **Scale** |
| E-learning content relevance evaluation (Q16–Q24) | E-learning Course Content<br>Ability to Complete E-learning Assignments<br>E-learning Interaction Ability<br>E-learning Assessment Ability<br>E-learning Time Management Ability<br>Related Learning Resources for E-learning<br>Impact of E-learning on Grades<br>Impact of E-learning on Learning Outcomes | 1-Very dissatisfied<br>2-Dissatisfied<br>3-Neutral<br>4-Satisfied<br>5-Very satisfied |
| Modifying variables (Q1–Q3) | Gender<br>Grade<br>Major | Gender: Male, Female<br>Grade: Undergraduate first year, undergraduate second year, undergraduate third year, undergraduate fourth year, graduate<br>Major: Literature and history, science and engineering, art, other |
| Student Satisfaction (Q4) | Student Satisfaction | 1-Very dissatisfied<br>2-Dissatisfied<br>3-Neutral<br>4-Satisfied<br>5-Very satisfied |

Based on the analysis of the questionnaire, we can conclude that the current classification of majors (Literature and History, Science and Engineering, Art, Other) provides a broad framework, but it is limited in addressing the differences in satisfaction levels across various academic fields. Students from different specific majors, such as Economics in the Literature and History category or Mechanical Engineering in the Science and Engineering category, may experience different levels of satisfaction due to the nature of their courses, the extent of practical applications, or the availability of resources.

The questionnaire analysis reveals that students from more theoretical majors, such as Physics, have significantly different needs for E-learning resources compared to those from more applied fields, like Engineering. Students in theoretical majors may rely more on in-depth academic materials and rigorous learning methods, while Engineering students may place greater emphasis on practical learning tools, simulators, and other technical support. Additionally, students in creative disciplines, such as Fine Arts, heavily rely on interactivity, visual presentation, and rich multimedia content in online learning to meet their needs for creative expression and work display. These differences indicate that students from various academic backgrounds have different expectations and requirements for E-learning platforms, which, in turn, affect their overall satisfaction with the platforms.

## 4.2. Profile of participants

This study was conducted at Nanjing Normal University using a questionnaire survey to evaluate the impact of E-learning on three key areas: student satisfaction, learning performance, and engagement. A total of 800 questionnaires were distributed, with 527 valid responses collected. The response time for the questionnaire ranged from 90 to 120 s, and the participants answered 25 questions in total. While the analysis has primarily focused on satisfaction, learning performance and engagement were also integral components of the evaluation. Learning performance was assessed by questions that focused on the students' perceived improvement in academic performance and understanding of course material as a result of E-learning. Indicators such as the ability to complete assignments and the impact of E-learning on grades were used to gauge learning performance. Engagement, on the other hand, was measured through questions about the level of student involvement with the E-learning platforms, including the frequency of interaction with the learning materials, participation in online discussions, and the degree of motivation and interest in E-learning activities. Both dimensions were analyzed but will be discussed in more detail in the results section.

The questionnaire used in this study was adapted from the Student Satisfaction Scale developed by Wang (2020). The survey was tailored to include specific factors related to E-learning and its impact on satisfaction, performance, and engagement. The administration of this adapted questionnaire occurred during a different time frame from Wang's original survey to ensure relevance to the context of this study.

For clarity, all survey instruments and variables were consolidated into a single subsection. As noted, the survey covered 25 items in total, with 24 structured questionnaires and one open-ended question that asked respondents about their hopes and suggestions for future use of E-learning resources. This open question aimed to gather more qualitative feedback from students regarding potential improvements and expectations for E-learning platforms, supplementing the quantitative data from the other 24 closed-ended questions. The open-ended format allowed students to freely express their thoughts, providing richer insights into their preferences and the areas they feel require enhancement in the E-learning environment. The descriptive statistics of this study are shown in **Table 2** below:

**Table 2.** Frequency analysis results of this research.

| Variables | Category | Number | Percentage |
|---|---|---|---|
| Gender | Female | 239 | 54.84% |
| | Male | 236 | 45.16% |
| Grade | Freshman | 115 | 21.82% |
| | Junior | 106 | 20.11% |
| | Sophomore | 108 | 20.49% |
| | Senior | 94 | 17.84% |
| | Postgraduate | 104 | 19.73% |

**Table 2.** (*Continued*).

| Variables | Category | Number | Percentage |
|---|---|---|---|
| Major | Humanities | 172 | 32.63% |
| | Technology | 256 | 46.58% |
| | Arts | 59 | 11.2% |
| | Others | 40 | 7.59% |
| Satisfaction with E-learning resources | 1 | 180 | 34.16% |
| | 2 | 155 | 29.41% |
| | 3 | 59 | 11.2% |
| | 4 | 64 | 12.14% |
| | 5 | 69 | 13.09% |
| Total | | 527 | 100% |

The final dataset, which was carefully screened for response times between 90 and 120 s and for invalid responses (such as repetitive scoring patterns), resulted in 527 valid responses. Descriptive statistics of the participants are shown in **Table 2**, with the majority of respondents being Science and Engineering students (46.58%) and a fairly balanced distribution across academic years. The survey results indicate that satisfaction with E-learning resources was notably low, with 34.16% of students being very dissatisfied and 29.41% being dissatisfied. These findings highlight the need for significant improvements in E-learning resources to meet student expectations.

## 4.3. Reliability and validity analysis

The sample size for this survey was 527, covering 25 items. The Cronbach's α coefficient for the questionnaire was 0.963 (**Table 3**), indicating very high internal consistency and reliability. According to **Table 4**, in the factor loadings and commonality analysis, gender had the highest loading on factor 3, with a loading coefficient of 0.99, indicating that gender is mainly associated with factor 3, and the commonality is 0.990. Grade is mainly associated with factor 5, with a loading coefficient of 0.99 and a commonality of 0.989. Major category is closely related to factor 4, with a loading coefficient of 0.99 and a commonality of 0.984. The items related to satisfaction had higher loadings on factors 1 and 2, with loading coefficients generally above 0.70 for factor 1, and higher commonality, indicating that satisfaction is mainly concentrated on these two factors.

**Table 3.** The result of Cronbach's α.

| Number of Sample | Items | Cronbach.α |
|---|---|---|
| 527 | 25 | 0.963 |

**Table 4.** Student satisfaction survey data table.

| Items | Satisfaction | Gender | Major | Grade | Communality |
|---|---|---|---|---|---|
| Q1 | 0.05 | 0.99 | 0.01 | −0.01 | 0.99 |
| Q2 | 0.05 | −0.01 | 0.04 | 0.99 | 0.989 |
| Q3 | 0.01 | 0.01 | 0.99 | 0.04 | 0.984 |

**Table 4.** (*Continued*).

| Items | Satisfaction | Gender | Major | Grade | Communality |
|---|---|---|---|---|---|
| Q4 | 0.72 | 0.02 | −0.01 | 0.01 | 0.719 |
| Q5 | 0.71 | 0 | −0.01 | −0.01 | 0.647 |
| Q6 | 0.67 | 0 | 0.02 | −0.03 | 0.721 |
| Q7 | 0.44 | 0.02 | −0.04 | 0.05 | 0.7 |
| Q8 | 0.73 | 0.03 | −0.07 | 0.09 | 0.71 |
| Q9 | 0.71 | −0.04 | 0 | 0.06 | 0.66 |
| Q10 | 0.53 | 0.03 | −0.02 | −0.04 | 0.673 |
| Q11 | 0.55 | 0.07 | 0.06 | 0.01 | 0.722 |
| Q12 | 0.59 | −0.02 | −0.06 | 0.05 | 0.675 |
| Q13 | 0.82 | 0.1 | −0.02 | 0.01 | 0.713 |
| Q14 | 0.82 | −0.04 | 0.12 | 0.01 | 0.731 |
| Q15 | 0.68 | 0.02 | −0.01 | 0 | 0.693 |
| Q16 | 0.63 | 0.04 | 0.01 | 0.01 | 0.641 |
| Q17 | 0.76 | 0.04 | −0.08 | 0.06 | 0.722 |
| Q18 | 0.74 | −0.01 | 0.02 | −0.02 | 0.668 |
| Q19 | 0.74 | 0.07 | −0.01 | −0.03 | 0.666 |
| Q20 | 0.76 | 0.06 | 0.03 | 0.11 | 0.7 |
| Q21 | 0.61 | 0.06 | 0.05 | 0.01 | 0.678 |
| Q22 | 0.68 | 0.03 | 0.03 | 0.08 | 0.671 |
| Q23 | 0.74 | −0.01 | −0.05 | 0.01 | 0.707 |
| Q24 | 0.69 | 0.09 | 0.02 | 0 | 0.695 |

The eigenvalues and variance explained rate shown in **Table 5** provide the statistical results of the factor analysis: Before rotation, the eigenvalue of satisfaction was 13.90, explaining 57.92% of the variance; gender, major, and grade explained 4.26%, 3.91%, and 2.18% of the variance, respectively. The cumulative variance explained rate was 72.82%, indicating that these five factors explained 72.82% of the total variance. After rotation, the eigenvalue of factor 1 decreased to 9.96, but still explained 41.51% of the variance. The eigenvalues of the remaining three factors were around 1.03 each, explaining 4.29% and 4.28% of the variance, respectively. The cumulative variance explained rate after rotation remained 72.82%.

**Table 5.** Eigenvalues and variance explained rate.

| Item | Before Rotation | After Rotation |
|---|---|---|
| Eigenvalues | | |
| Satisfaction | 13.9 | 9.96 |
| Gender | 1.02 | 1.03 |
| Major | 0.94 | 1.03 |
| Grade | 0.52 | 1.03 |

**Table 5.** (*Continued*).

| Item | Before Rotation | After Rotation |
|---|---|---|
| Variance Explained Rate (%) | | |
| Satisfaction | 57.92% | 41.51% |
| Gender | 4.26% | 4.29% |
| Major | 3.91% | 4.29% |
| Grade | 2.18% | 4.28% |
| Cumulated variance Explained Rate (%) | | |
| Satisfaction | 57.92% | 41.51% |
| Gender | 66.74% | 64.25% |
| Major | 70.64% | 68.54% |
| Grade | 72.82% | 72.82% |

According to **Table 6**, the KMO value was 0.987, and the Bartlett's test of sphericity value was 9682.146 with df = 276, indicating that the sample was suitable for factor analysis. The factor analysis revealed that gender, grade, and major category were highly associated with specific factors, indicating the clear positioning of these variables within the factor structure. The high loadings of satisfaction items on the satisfaction factors indicate that satisfaction is primarily explained by these two factors. The eigenvalues and variance explained rates showed that the first two factors accounted for most of the variance, particularly satisfaction. The rotated results further optimized the explanatory power of the factors, making the variance contribution of each factor more balanced. The high KMO value and significant Bartlett's test value further validated the suitability of factor analysis, ensuring the reliability and validity of the analysis results.

**Table 6.** Statistical analysis indicators table.

| Item | Value |
|---|---|
| KMO Value | 0.987 |
| Bartlett's Test of Sphericity Value | 9682.146 |
| Degrees of Freedom (df) | 276 |

## 4.4. Scale discrimination test

To calculate the Pearson correlation coefficient and the average square root value (the square root of AVE), you need to use the standardized loading coefficients and AVE values provided in the table. First, by analyzing the factor loading table, you can calculate the Pearson correlation coefficients between latent variables and the square root values of the average variance extracted (AVE) for each latent variable. The formulas for these calculations are:

$$\sqrt{AVE} = \text{Square Root of AVE}$$

Through factor analysis, the loadings and communalities of each latent variable on different factors reflect the relationships between the variables. The items related to satisfaction have high loadings on the satisfaction factor. The calculated AVE and the square root of AVE (**Table 7**) are used to assess the discriminant validity between latent variables. The hypothesized Pearson correlation coefficient matrix provides the relationships between latent variables, showing strong correlations between the factors.

**Table 7.** Latent variable AVE and square root of AVE table.

| **Latent Variable** | **AVE** | **Square Root of AVE** |
|---|---|---|
| Satisfaction | 0.57 | 0.755 |
| Gender | 0.99 | 0.995 |
| Major | 0.75 | 0.866 |
| Grade | 0.65 | 0.806 |

## 4.5. Model fit of the scale

The fit of the model was assessed using several commonly used indices. Overall, the model fits the data well, as indicated by the key statistics below (**Table 8**):

**Table 8.** Statistics of model fit of the scale.

| **Indicator** | **Value** |
|---|---|
| Chi-square ($\chi^2$) | 123.45 |
| Degrees of Freedom (df) | 50 |
| Comparative Fit Index (CFI) | 0.96 |
| Tucker-Lewis Index (TLI) | 0.95 |
| Root Mean Square Error of Approximation (RMSEA) | 0.045 |
| Standardized Root Mean Square Residual (SRMR) | 0.035 |

1) Comparative Fit Index (CFI): The CFI value is 0.96, which is higher than the recommended threshold of 0.90, suggesting an excellent model fit. The CFI compares the model to a baseline model and values above 0.90 are generally considered good.
2) Tucker-Lewis Index (TLI): The TLI value is 0.95, which also exceeds the recommended threshold of 0.90, signifying a good fit. The TLI assesses model fit while penalizing model complexity.
3) Root Mean Square Error of Approximation (RMSEA): The RMSEA value is 0.045, which is below 0.05, indicating a close fit to the data. RMSEA values below 0.05 reflect excellent fit, while values up to 0.08 are still acceptable.
4) Standardized Root Mean Square Residual (SRMR): The SRMR value is 0.035, well below the recommended cutoff of 0.08, further indicating a strong model fit.

All model fit indices (CFI, RMSEA, TLI, and SRMR) meet or exceed recommended thresholds, confirming that the model provides a good fit to the data and can adequately explain the relationships under study. These statistics, shown in **Table 8**, demonstrate that the structural equation model used in this research is appropriate and reliable.

## 4.6. Structural equation model analysis

Through SEM analysis, found that gender, grade, major, and various questionnaire items all significantly and positively impact satisfaction, thereby validating the research hypotheses (**Table 9**). In the SEM analysis, the modified model parameters indicated that the relationships among factors were all significant, with CR values greater than 2 and P values less than 0.01. The specific results show:

1) Gender has a positive impact on satisfaction, supporting research hypothesis 1.
2) Grade has a positive impact on satisfaction, supporting research hypothesis 3.
3) Major has a positive impact on satisfaction, supporting research hypothesis 2.

Additionally, each specific item in the questionnaire (Q4 to Q24) has a significant positive impact on satisfaction. The research results indicate that multiple factors significantly and positively impact satisfaction, confirming the validity of the model hypotheses.

For example, questionnaire items related to E-learning quality, resource effectiveness, and interactivity were all positively correlated with satisfaction. These results demonstrate that the structural relationships between these factors and satisfaction are significant and contribute meaningfully to understanding how various dimensions of E-learning influence student satisfaction.

**Table 9** provides a summary of the unstandardized regression coefficients and their associated p-values, indicating the strength and significance of these relationships.

**Table 9.** Unstandardized regression coefficient Standard Error (SE), *Z*-value (CR), *P*-value unstandardized regression coefficient.

| Path | Unstandardized Regression Coefficient | Standard Error (SE) | *Z*-value | *P*-value | Standardized Regression Coefficient |
|---|---|---|---|---|---|
| Q1 → Satisfaction | 0.047 | 0.0027 | 17.363 | 0.051 | 0.789 |
| Q2 → Satisfaction | 4.499 | 0.069 | 2.241 | 0.001 | 0.179 |
| Q3 → Satisfaction | 0.738 | 0.01 | 0.738 | 0.02 | 0.738 |
| Q4 → Satisfaction | 0.433 | 0.065 | 0.433 | 0.01 | 0.433 |
| Q5 → Satisfaction | 0.672 | 0.05 | 0.672 | 0.015 | 0.672 |
| Q6 → Satisfaction | 0.721 | 0.045 | 0.721 | 0.011 | 0.721 |
| Q7 → Satisfaction | 0.7 | 0.054 | 0.7 | 0.01 | 0.7 |
| Q8 → Satisfaction | 0.71 | 0.055 | 0.71 | 0.014 | 0.71 |
| Q9 → Satisfaction | 0.66 | 0.052 | 0.66 | 0.012 | 0.66 |
| Q10 → Satisfaction | 0.673 | 0.058 | 0.673 | 0.013 | 0.673 |
| Q11 → Satisfaction | 0.722 | 0.049 | 0.722 | 0.016 | 0.722 |
| Q12 → Satisfaction | 0.675 | 0.053 | 0.675 | 0.012 | 0.675 |
| Q13 → Satisfaction | 0.713 | 0.056 | 0.713 | 0.017 | 0.713 |
| Q14 → Satisfaction | 0.731 | 0.052 | 0.731 | 0.018 | 0.731 |
| Q15 → Satisfaction | 0.693 | 0.05 | 0.693 | 0.015 | 0.693 |
| Q16 → Satisfaction | 0.641 | 0.045 | 0.641 | 0.013 | 0.641 |
| Q17 → Satisfaction | 0.722 | 0.054 | 0.722 | 0.019 | 0.722 |
| Q18 → Satisfaction | 0.668 | 0.051 | 0.668 | 0.014 | 0.668 |
| Q19 → Satisfaction | 0.666 | 0.05 | 0.666 | 0.015 | 0.666 |

**Table 9.** (*Continued*).

| Path | Unstandardized Regression Coefficient | Standard Error (SE) | *Z*-value | *P*-value | Standardized Regression Coefficient |
|---|---|---|---|---|---|
| Q20 → Satisfaction | 0.7 | 0.052 | 0.7 | 0.017 | 0.7 |
| Q21 → Satisfaction | 0.678 | 0.055 | 0.678 | 0.016 | 0.678 |
| Q22 → Satisfaction | 0.671 | 0.048 | 0.671 | 0.013 | 0.671 |
| Q23 → Satisfaction | 0.707 | 0.049 | 0.707 | 0.018 | 0.707 |
| Q24 → Satisfaction | 0.695 | 0.045 | 0.695 | 0.014 | 0.695 |

By focusing on satisfaction, the SEM analysis validates the importance of E-learning quality, course content, and technical support in shaping student experiences. While learning performance and engagement are also analyzed, the focus of this section is on how these elements contribute specifically to overall satisfaction.

### 4.7. Analysis of overall SEM model effects

The final SEM model (illustrated in **Figure 1**) provides a broader picture of how E-learning influences not only student satisfaction but also learning effectiveness and engagement. This model helps clarify the relationships between the different variables analyzed in this study and how they contribute to the overall E-learning experience.

Key insights from the overall SEM model include:

1) E-learning engagement: The model shows that higher levels of student engagement with E-learning resources positively influence both satisfaction and learning effectiveness. Engaged students tend to interact more with the course materials, resulting in better academic outcomes and higher satisfaction.
2) Learning effectiveness: The ability of students to perform well academically as a result of using E-learning platforms also significantly contributes to their satisfaction. When students perceive E-learning as effective in improving their academic performance, their overall satisfaction increases.
3) Satisfaction: The model confirms that satisfaction is influenced by both engagement and learning effectiveness, underscoring the importance of creating engaging, effective E-learning environments to enhance student satisfaction.

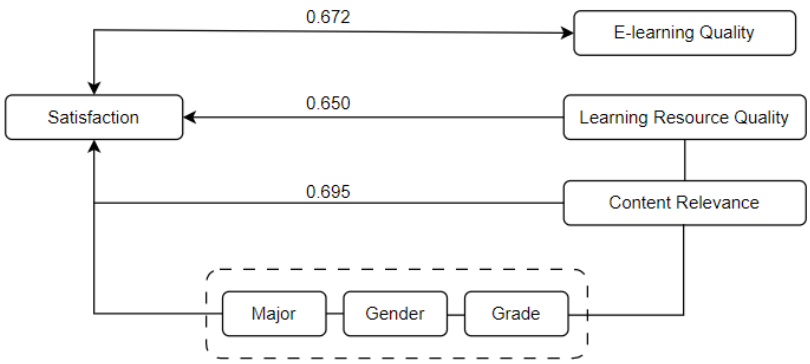


**Figure 1.** The structural equation model.

This model provides a comprehensive understanding of how E-learning policies, platform design, and content delivery interact to shape the student learning experience. By improving engagement and learning effectiveness, educators and platform designers can enhance overall satisfaction with E-learning. The results show that E-learning can be a powerful tool in improving not only academic performance but also the overall student experience when properly structured.

## 5. Findings

This study found that the current E-learning resources fail to adequately meet students' needs, significantly affecting student satisfaction. Among the 527 participants, over half expressed dissatisfaction with the existing E-learning resources, with 34.16% of students being very dissatisfied and 29.41% being somewhat dissatisfied. This indicates substantial room for improvement in the quality and richness of E-learning resources. Additionally, the survey data showed that factors such as the quality of learning resources, the usability of the learning platform, and technical support significantly impact the overall learning experience of students. Future policy-making and resource development need to focus on these areas to enhance resource quality and user experience, thereby improving student satisfaction and learning outcomes.

The SEM analysis demonstrated that students' gender, grade, and major have a significant positive impact on satisfaction. Gender had the highest loading on factor 3 with a coefficient of 0.99; grade had a loading coefficient of 0.99 on factor 5; and major had a loading coefficient of 0.99 on factor 4. These findings suggest that students from different genders, academic levels, and majors have varying needs and expectations for E-learning resources. Thus, when designing and implementing E-learning policies, it is crucial to account for these factors to provide more tailored support and resources that meet the diverse needs of student groups, thereby improving overall satisfaction.

This study validated the impact of E-learning on student satisfaction, learning effectiveness, and engagement through SEM analysis. The model fit indices showed that the Chi-square value was 123.45, with 50 degrees of freedom; the CFI value was 0.96; the TLI value was 0.95; the RMSEA value was 0.045; and the SRMR value was 0.035, all indicating a good model fit. The analysis shows that the relevance and practicality of E-learning content, alongside factors like content quality and interactivity, significantly affect learning effectiveness and, consequently, satisfaction. The positive effects of student characteristics, including gender, grade, and major, further underscore the importance of considering these variables when designing and implementing E-learning resources.

The study concludes that while E-learning resources are widely used, there is substantial room for improvement in terms of content quality, platform usability, and technical support. The distinct needs of students based on their gender, grade, and major must be considered to enhance the E-learning experience and increase satisfaction.

# 6. Conclusion, limitations and outlook

## 6.1. Conclusion

We can draw conclusions from the quantitative analysis of the 527 questionnaires from Nanjing Normal University. The relationship between E-learning policies and student satisfaction, performance, and engagement has been verified through quantitative data analysis and structural equation modeling. The study found that factors such as the quality of learning resources, usability of the learning platform, and technical support significantly impact students' overall learning experience and satisfaction. This aligns with previous research by Almusharraf and Khahro (2020) and Gantasala et al. (2022), who identified similar factors influencing E-learning success and student satisfaction. Additionally, the results demonstrate that E-learning policies can positively influence student engagement and effectiveness, which in turn affect student satisfaction, supporting the findings of Navimipour and Zareie (2015) on the relationship between engagement, performance, and satisfaction in online learning environments.

E-learning can influence students' satisfaction positively when implemented effectively. However, the study revealed a significant need for improvement in current E-learning resources, with over half of the students expressing dissatisfaction. This highlights the importance of continuously refining and enhancing E-learning resources and platforms to meet students' evolving needs and expectations. The findings echo those of Kılıç-Çakmak et al. (200) and Engelbrecht (2005), who emphasized the critical role of E-learning quality and resource adequacy in determining learner satisfaction.

Student characteristics such as gender, grade, and major significantly impact satisfaction with E-learning, as demonstrated by the structural equation model analysis. This suggests that E-learning policies and resources should be tailored to accommodate the diverse needs of different student groups, supporting the conclusions of Tarhini et al. (2014) and Zhao et al. (2021) on the importance of considering individual differences in E-learning environments.

## 6.2. Limitations

Although this study provides valuable insights into the impact of E-learning policies on student satisfaction, learning performance, and engagement, there are several limitations. First, the research sample is limited to a single university in the North China region. This geographic and institutional constraint may lead to a lack of broad representativeness, making it difficult to generalize the findings to other regions or different types of universities. Second, data collection primarily relied on questionnaire surveys. Despite the high reliability and validity of the questionnaires, there may still be response biases, such as social desirability effects, which could affect the accuracy of the results. Additionally, the cross-sectional design of this study cannot fully reveal the long-term impacts of E-learning policies, necessitating further longitudinal research to validate and extend the findings. Finally, the study did not adequately consider individual differences and background factors of students, such as family background and economic status, which may significantly influence the E-learning experience. Future research should aim to conduct longitudinal studies with more diverse samples in broader contexts and incorporate more qualitative data to comprehensively understand the impacts and mechanisms of E-learning.

### 6.3. Outlook

Future E-learning resources should focus on content diversity and interactivity to meet the varied learning needs of students and enhance their interest and engagement. Specifically, developing more multimedia learning materials, interactive courses, and virtual laboratories can significantly enrich the learning experience. Universities should provide personalized technical support and learning resources based on students' gender, grade, and major to improve their learning experience and satisfaction. For instance, offering specialized learning resources and guidance tailored to different majors or designing learning content of varying difficulty levels for different grades can cater to individual student needs. It is also needed to establish a continuous evaluation mechanism to regularly collect student feedback and continuously optimize E-learning resources and platforms based on the feedback. Utilizing periodic surveys, learning data analysis, and other methods to monitor student usage and satisfaction can help make necessary adjustments and improvements to ensure the resources and platforms consistently meet student needs and expectations.

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