Does the Duration of Online Learning Matter? Examining Its Effect on Knowledge Mastery, Creative Thinking, and Expression across Gender and Ethnicity

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Abstract

The COVID-19 pandemic has sped up the integration of online learning into higher education systems, raising concerns about the long-term sustainability and fairness of digital education. While existing studies often focus on short-term results, less attention has been given to how long students are engaged in online learning and its cumulative effects on their development. This study examines how the duration of online learning impacts three key educational outcomes: knowledge mastery, expressive ability, and creative thinking, and whether these impacts vary across gender and ethnic groups. Using survey data from a comprehensive Chinese university, we apply Generalized Estimating Equations (GEE) and quantile regression to evaluate both average and distributional effects. Our results show that extended online learning affects student abilities differently, with female and ethnic minority students facing unique challenges. These findings emphasize the need to develop inclusive and resilient digital education systems, especially in supporting Sustainable Development Goal 4. The study adds to the growing research on education for sustainable development by demonstrating how digital learning methods intersect with social identities to influence learning paths.

Keywords

Online learning duration, Educational sustainability, Gender and ethnicity, Creative thinking, Generalized Estimating Equations

Introduction

The COVID-19 pandemic triggered an unprecedented global shift in higher education, forcing universities to transition quickly to online learning [1]. Although initially introduced as an emergency measure, online learning has increasingly become a semi-permanent part of many academic institutions' pedagogical frameworks. As countries move beyond the acute phase of the pandemic, understanding the long-term effects of ongoing online learning is becoming more urgent - not just regarding educational quality but in terms of equity and inclusion within higher education systems [2,3]. Earlier research on online education mainly focused on short-term outcomes such as student satisfaction, course completion, and immediate academic performance [4,5]. However, the amount of time spent in digital learning environments is a crucial yet underexplored factor. Extended online learning may gradually affect students' cognitive engagement, creative development, and ability to express ideas, especially in situations where face-to-face learning traditionally played a key role in intellectual socialization [6]. In this context, the sustainability of online learning should be evaluated not only by technological access or flexibility but also by its cumulative impact on educational outcomes over time.

Furthermore, the impacts of extended digital instruction are not experienced equally. Factors such as gender and ethnicity continue to shape learning experiences across different formats. Studies indicate that female students often report lower confidence in online settings and face increased emotional and cognitive challenges [7]. Likewise, ethnic minority students may face issues related to digital marginalization, reduced peer engagement, and structural inequalities in access to learning resources [8]. These disparities are especially important in discussions of sustainable education, as highlighted by the United Nations' Sustainable Development Goal 4, which promotes inclusive, equitable, and high-quality lifelong learning opportunities for everyone [9].

Against this context, the present study investigates how the length of online learning impacts student academic outcomes and how these effects are shaped by gender and ethnicity. Using survey data from a large university in China, we analyze three key learning outcomes by employing Generalized Estimating Equations (GEE) and quantile regression techniques: knowledge mastery, expressive ability, and creative thinking. This approach allows us to measure both average effects and differences across various performance levels. In doing so, we contribute to the growing research on sustainable digital education and offer empirical insights into the relationship between online learning, identity, and educational equity in post-pandemic academic systems.

Literature review

The impact of online teaching on student learning

A substantial body of literature has explored how online teaching shapes student learning experiences and outcomes. Many studies suggest that when effectively designed, online learning environments can enhance students' autonomy, promote engagement, and support higher-order thinking [10,11]. In particular, asynchronous instruction models have been found to improve self-paced knowledge acquisition and facilitate flexible learning strategies [12]. These affordances are especially beneficial for students who prefer structured independence, such as female learners, who have consistently shown stronger self-regulated learning performance [13].

But the promise of online learning is not universally realized. Several studies have found that students enrolled in online-only courses tend to receive lower grades than their counterparts in traditional or blended classes [14]. These performance gaps are often attributed to reduced interaction with instructors, delayed feedback cycles, and weaker classroom community, all of which may diminish cognitive engagement and motivation [15]. Some evidence also suggests that the novelty of online learning platforms may induce temporary motivation, but this effect tends to decay over time if instructional design lacks interactivity [16,17]. Thus, while online teaching expands access, its effectiveness depends heavily on pedagogical quality, instructor presence, and platform usability [18,19].

The diversity in learning outcomes across studies further highlights the importance of student characteristics, such as gender, ethnicity, and prior digital experience. As online learning removes some traditional structural barriers, it may amplify others - such as digital exclusion or motivational inequity - which disproportionately affect marginalized groups [20].

Indicators of student performance: Beyond test scores

While creativity and expressive competence are less frequently isolated as primary outcomes, several studies now emphasize their relevance in online learning contexts. For example, data mining models have identified linguistic features and discussion dynamics as proxies for expressive ability [21].

Taken together, these studies support the inclusion of knowledge expression, creative thinking, and mastery of foundational knowledge as multidimensional indicators of student performance.

Gender and ethnic disparities: Patterns, contradictions, and intersections

The effects of online learning are neither monolithic nor evenly distributed across all student groups. Gender and ethnicity, in particular, shape how students experience, adapt to, and succeed in digital environments. Interestingly, while some studies suggest minimal gender-based performance gaps, others highlight that female students often demonstrate stronger engagement, higher self-efficacy, and greater satisfaction in asynchronous learning settings [22]. This may be related to socialized learning behaviors and a greater willingness to follow learning schedules [23,24].

In contrast, the picture is more consistently troubling for ethnic minority students. Research has shown that Black, Hispanic, and Native American students - especially males are more likely to struggle in fully online environments due to a combination of structural barriers and cultural disconnects [25,26]. These challenges are often compounded by limited access to high-speed internet, fewer social support networks, and lower digital fluency [27,28].

Moreover, intersectional perspectives reveal that gender and ethnicity rarely act alone. For example, while females may outperform males in online learning overall, this trend does not always hold within specific racial or socioeconomic groups [29,30]. Studies of South Asian adolescent girls, for instance, show that sociocultural constraints may override the benefits of digital flexibility, leading to mixed academic outcomes despite higher intrinsic motivation [31]. These insights emphasize the need to move beyond additive models of demographic analysis and consider how identity categories interact to shape educational experiences [32,33].

Finally, it is worth noting that differences in outcomes are not always academic. Minority and female students are more likely to report feelings of isolation, reduced interaction, and lower institutional support in online settings. These affective variables, while harder to quantify, have tangible effects on persistence, engagement, and long-term educational attainment [34,35].

Summary and research gap

In sum, the literature demonstrates that online learning can support a wide range of student outcomes, but its effectiveness is contingent upon both instructional design and student characteristics. While previous research has examined the effects of online pedagogy, digital tools, and demographic factors, few studies have systematically explored how the duration of online learning influences students' development across cognitive, expressive, and creative domains [36].

Even fewer have investigated how this relationship varies across gender and ethnic groups, or how intersectional factors interact with online learning structures to shape academic outcomes. This study addresses this gap by focusing on three underexplored but interconnected outcome variables: knowledge mastery, creative thinking, and knowledge expression. It examines how these are impacted by differential durations of online learning, with gender and ethnicity as key moderating factors.

Methodology and data

Research framework

This study explores whether prior exposure to online learning - lasting 0, 1, or 2 academic years has lasting effects on students' later academic performance. Specifically, we look at three learning outcomes: knowledge mastery, creative thinking, and knowledge expression, using data collected during a subsequent face-to-face instruction semester. Although all students were enrolled in a traditional offline course when data was collected, their previous online learning exposure varied across cohorts because of institutional scheduling. This natural variation provides a quasiexperimental basis for studying the long-term educational effects of sustained online learning, especially concerning equity and skill development. Research framework is shown in Figure 1.

The research is carried out in three main phases:

Phase 1: Text mining and expert-based parameter calibration were applied to offline learning interaction data to measure three learning outcomes: knowledge mastery, knowledge expression, and creative thinking. The latter was derived using lexical diversity (TTR) and novelty (TF-IDF) metrics.

Phase 2: Generalized Estimating Equations (GEE) were applied to estimate the average effects of online learning duration, gender, and ethnicity, including both two-way and three-way interaction terms.

Phase 3: Quantile regression was employed to investigate how these effects vary across students at different performance levels (e.g., low, median, and high achievers), enabling us to identify potential inequalities that are masked in average models [37].

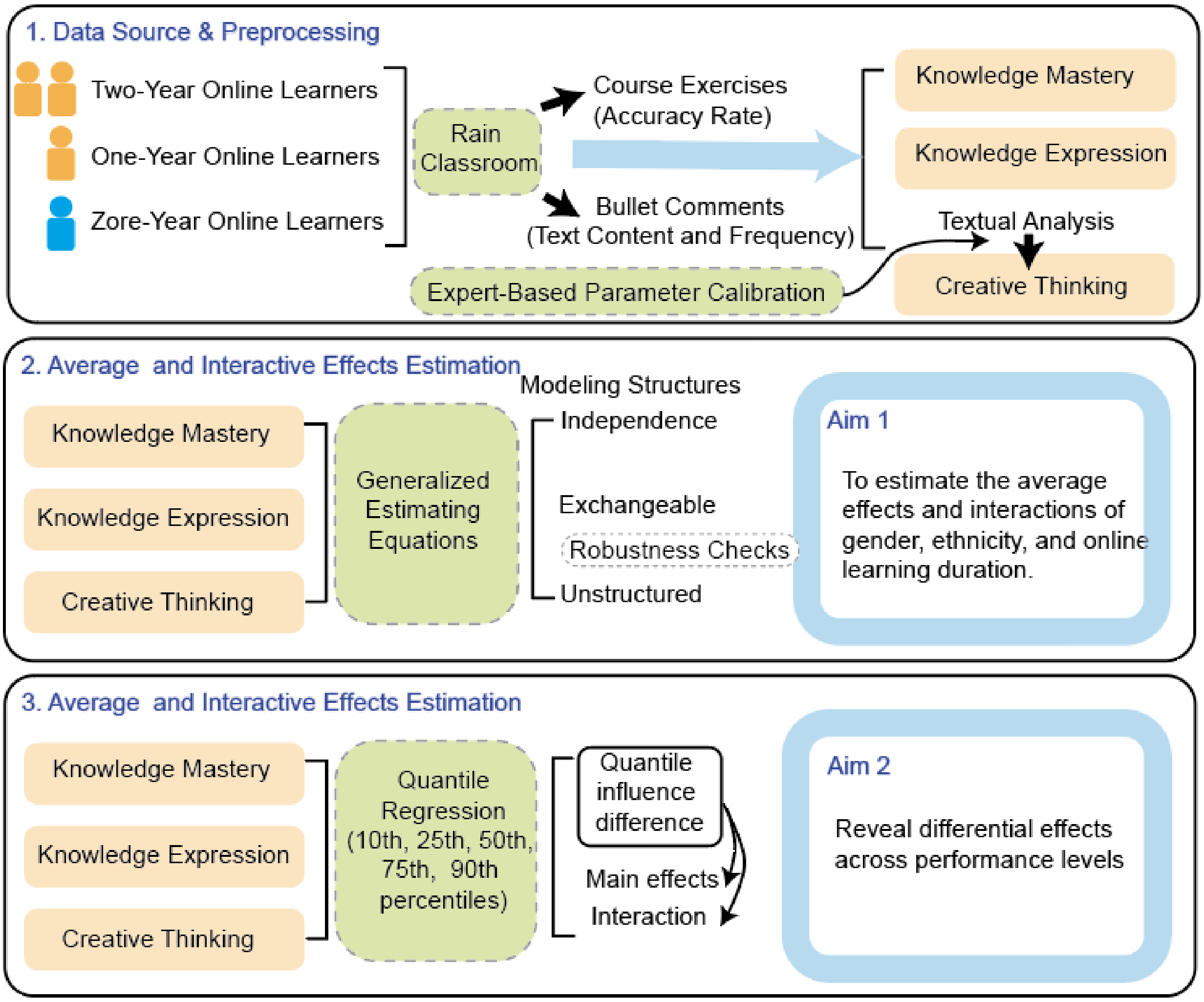

Figure 1. Research framework.

Quantification of students' learning outcomes

To comprehensively quantify students' learning outcomes, this study adopts three key dimensions: knowledge mastery, creative thinking, and knowledge expression. Each dimension's indicator data comes from students' behavioral and textual data on the learning platform.

(1) Knowledge mastery

Knowledge mastery refers to students' proficiency in grasping fundamental course content. It is measured directly through students' average accuracy rate on course exercises:

$$\text{Mastery}_\text{i} = \frac{\text{Number of correct answers}_\text{i}}{\text{Total number of exercise questions}} \quad (1)$$

(2) Knowledge expression

Knowledge expression captures students' willingness and capacity to articulate their understanding and ideas. This dimension is quantified by the frequency of bullet comments (real-time comments during online classes):

$$\text{Expression}_i = \text{Total number of bullet comments by student } i \quad (2)$$

This simple frequency indicator directly reflects students' active verbal engagement and participation in knowledge-sharing activities during online classes.

(3) Creative thinking

Creative thinking refers to students' ability to generate original, diverse, and meaningful ideas during the learning process. This construct is quantified through textual analysis of students' bullet comment content. The measurement process comprises three major steps: text pre-processing, indicator computation, and expert-based parameter calibration.

Text pre-processing: In the first step, all bullet comments are processed using standard natural language processing techniques. This includes tokenization (splitting the text into individual words), removal of stop words (such as "is", "and", "of"), and normalization (converting words to a standard form, e.g., lowercase). Emoji and image-based expressions are preserved by uniformly converting them to the placeholder token "enoji" to ensure that all content types are included in the analysis.

Indicator computation: Two key indicators are computed to reflect different dimensions of creative expression. Lexical diversity is captured using the Type-Token Ratio (TTR), calculated as:

$$\text{TTR}_i = \frac{\text{Number of unique words}_i}{\text{Total number of words}_i} \quad (3)$$

A higher TTR indicates more varied vocabulary usage. Novelty is assessed using Term Frequency-Inverse Document Frequency (TF-IDF) values. For each student, the average TF-IDF across all their comments is computed to capture how uncommon their language is compared to others. Words that are frequent in one student's comments but rare across the entire class contribute more to the novelty score. The novelty score for student i is calculated as:

$$\text{Novelty}_i = \frac{1}{n_i}\sum_{j=1}^{n_i} \text{TF-IDF}_{ij} \quad (4)$$

where n_i is the number of words in student i's comments, and TF-IDF_{ij} represents the TF-IDF value of word j.

Expert-based parameter calibration:

To transform TTR and novelty into a single creativity score, we apply a weighted formula:

$$\text{Creativity}_i = \alpha \cdot \text{TTR}_i + \beta \cdot \text{Novelty}_i \quad (5)$$

The weights α and β are empirically determined using an expert-rating method. A representative sample of 20 comments was anonymized and rated by 12 instructors on a 0-100 scale. The average of these expert ratings served as the dependent variable in a linear regression model, with TTR and novelty as independent variables:

$$\text{Expert Score}_i = \alpha \cdot \text{TTR}_i + \beta \cdot \text{Novelty}_i + \varepsilon_i \quad (6)$$

The fitted regression coefficients for α and β were then used to compute creativity scores for the full student dataset. This approach ensures alignment between quantitative indicators and human expert judgments, providing a valid measurement of student creativity from their textual behaviors.

Generalized Estimating Equations (GEE)

To examine how online learning duration, gender, and ethnicity influence students' performance in knowledge mastery, knowledge expression, and creative thinking, we used GEE as the main analysis method. GEE is suitable in this context because it accounts for potential correlations among students within the same class.

Separate GEE models were developed for each learning outcome. Each model included online learning duration (one-year vs. two-year groups), gender, and ethnicity as independent variables, along with their two-way and three-way interaction terms. The general structure of the model is as follows:

$$Y_{ij} = \beta_0 + \beta_1 X_{1ij} + \beta_2 X_{2ij} + \cdots + \epsilon_{ij} \qquad (7)$$

Where Y_{ij} represents the outcome variable (knowledge mastery, knowledge expression, or creative thinking) for student i in group j, and ϵ_{ij} is the error term.

To reflect the clustered nature of the data, we first specified an exchangeable correlation structure. Robust standard errors (sandwich estimators) were used to ensure reliable estimates even if standard assumptions were violated. We also ran sensitivity checks using alternative correlation structures, such as unstructured. This approach allowed us to assess not only the direct effects of each factor but also how gender and ethnicity may change the relationship between online learning duration and student performance. In particular, to explore potential intersectional effects, we included three-way interaction terms (Online Learning Duration × Gender × Ethnicity) in all GEE models. This enabled us to investigate whether students with intersecting marginalized identities (e.g., female minority students) experience differentiated outcomes across cognitive, expressive, and creative learning dimensions.

Quantile regression analysis

While GEE models offer insights into the average effects of online learning duration, gender, and ethnicity on student outcomes, they do not show how these effects differ across performance levels. To better understand these differences, we apply quantile regression, which estimates relationships at different outcome distribution points. This method reveals how predictors affect below-average, median, or above-average students. We ran quantile regressions at the 10th, 25th, 50th (median), 75th, and 90th percentiles for each outcome (knowledge mastery, expression, creative thinking), enabling assessment of marginal and extreme effects across the performance spectrum. The general form of the quantile regression model is:

$$Q_Y(\tau|X) = X^{\top}\beta(\tau) \qquad (8)$$

$Q_Y(\tau|X)$ denotes the τ-th conditional quantile of the outcome variable Y (knowledge mastery, creative thinking, or knowledge expression) given the predictor matrix X . $X^{\top}$ represents the transpose of X, which includes online learning duration, gender, ethnicity, and their interaction terms. $\beta(\tau)$ is the vector of quantile-specific regression coefficients, capturing the heterogeneous effects of predictors on Y across different performance levels (10th, 25th, 50th, 75th, 90th percentiles in this study). By using this method, we can identify patterns that may be hidden in average-based models. For example, online learning duration might have a stronger effect on high-performing students than on low-performing ones, or vice versa. This analysis provides a deeper view into equity-related issues and the varied effects of online learning across different student groups.

Data source

This study used data from Rain Classroom (YuKetang), an online learning platform widely adopted by Chinese universities. The dataset includes detailed learning behavior records from third-year undergraduate students across three academic cohorts:

2022 cohort: These students experienced nearly two full years of online learning during their first and second years (2020 and 2021), largely due to the COVID-19 pandemic.

2023 cohort: These students received approximately one year of online instruction in 2021, followed by a return to in-person classes.

2024 cohort: These students had minimal exposure to online learning, as traditional teaching had resumed fully by the time of their enrolment.

All data were collected from the same third-year course across cohorts. Notably, the instructor, teaching materials (e.g., slides), and textbooks remained consistent, controlling for content delivery/teaching style differences to clarify the impact of online learning duration.

The dataset records a variety of student activities, including attendance, assignment and exercise results, bullet comment activity, access to courseware, and exam scores. All data collection procedures adhered to strict ethical guidelines to protect anonymity and data confidentiality.

Results

Descriptive Statistics

Figure 2, Figure 3 and Table 1 show how key learning indicators - novelty score, knowledge mastery, and knowledge expression - vary among students with different durations of online learning (0, 1, or 2 years). The bar plots illustrate group-level averages stratified by gender and ethnicity, while the table offers statistical comparisons using ANOVA or Kruskal-Wallis tests, depending on the distribution of variables.

Overall, students with more online experience showed higher levels of knowledge expression and novelty, but significantly lower scores in knowledge mastery ($p<0.001$ for both). For example, students in the 2-year group generated more bullet comments and used more unique vocabulary, yet their exercise accuracy was notably lower than that of students with less exposure.

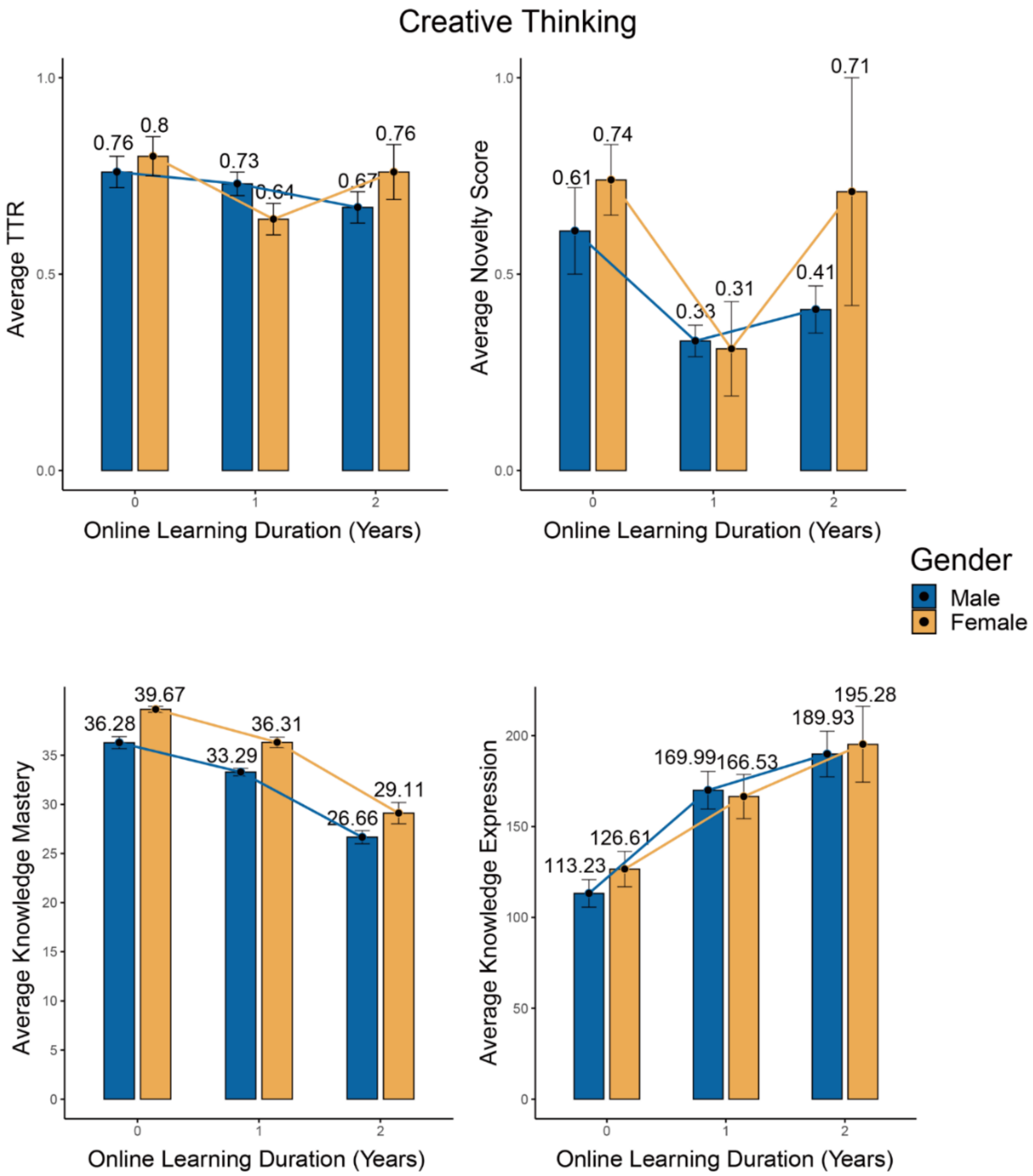

Figure 2. Distribution of learning outcomes by year (gender).

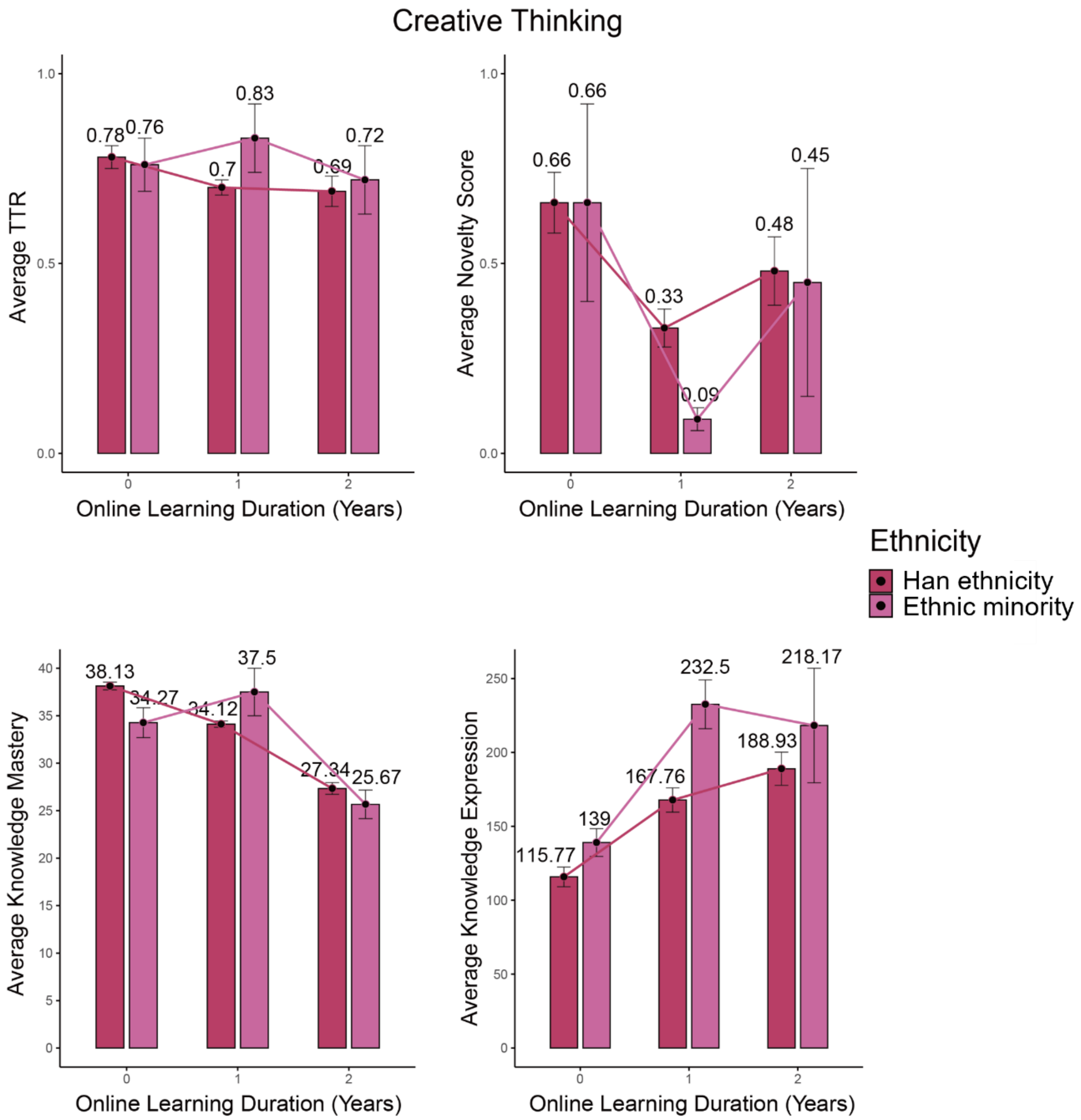

Figure 3. Distribution of learning outcomes by year (ethnicity).

Gender and ethnicity distributions also showed variation. Female students had higher mean scores across most dimensions but also displayed greater variability. However, gender differences across the three groups were not statistically significant (p=0.043). With increased online exposure, ethnic minority students showed improvements in knowledge expression, and the performance gap in knowledge mastery between them and Han students narrowed. In contrast, differences in creative thinking metrics between ethnic groups remained largely stable.

Additionally, neither gender nor ethnicity varied significantly across the three duration groups, indicating that the observed learning differences are less likely to be influenced by demographic disparities. This reinforces the internal validity of our group comparisons and increases confidence in the effects attributed to online learning duration.

Table 1. Descriptive statistics by online learning duration.

Variable	0 (N=89)	1 (N=108)	2 (N=79)	p-value
Gender	/	/	/	/
Male	53 (59.6%)	76 (70.4%)	61 (77.2%)	0.043

Variable	0 (N=89)	1 (N=108)	2 (N=79)	p-value
Female	36 (40.4%)	32 (29.6%)	18 (22.8%)	/
Ethnicity	/	/	/	/
Majority	78 (87.6%)	104 (96.3%)	76 (96.2%)	0.025
Minority	11 (12.4%)	4 (3.7%)	3 (3.8%)	/
Knowledge mastery (Mean ± SD)	37.7±4.0	34.2±3.5	27.2±5.2	<0.001
Knowledge expression (Mean ± SD)	118.6±56.5	169.0±84.2	191.2±95.3	<0.001
Creative thinking (Mean ± SD)	103.4±58.8	79.9±38.5	90.3±58.8	0.007

Generalized Estimating Equations (GEE) analysis

To examine the combined effects of online learning duration, gender, and ethnicity on students' learning performance, GEE models were estimated for each of the three outcome variables. The results reveal distinct patterns across cohorts and demographic groups as shown in Table 2.

The GEE analysis revealed distinct patterns across learning outcomes. In creative thinking, one year of online learning resulted in a 21.68-point reduction in scores (p<0.05), with minority female students experiencing a pronounced decline after two years (β=99.46, p<0.05) - a disparity that potentially reflects compounded socio-technical barriers.

For knowledge mastery, extended online exposure correlated with poorer performance (2-year β= − 10.24, p<0.001), though female students maintained an advantage (β=2.98, p<0.001). Minority students generally scored lower (β=–3.87, p<0.05), yet short-term online learning appeared beneficial for this group (Duration1 × Minority: β=4.60, p<0.05), hinting at initial engagement gains. Knowledge expression showed the strongest gains (1-year β=61.43, 2-year β=77.25; both p<0.001), particularly among minority students (β=33.01, p<0.05).

However, the three-way interaction revealed a critical nuance: minority female students' initial surge (1-year β=84.58, p<0.05) reversed with sustained exposure (2-year β= − 94.91, p=0.09), suggesting that structural supports may erode over time in virtual settings.

Table 2. GEE results for learning outcomes with three-way interaction terms.

Predictor	Creative thinking (β, SE)	Knowledge mastery (β, SE)	Knowledge expression (β, SE)
Intercept	104.55 (9.12)	36.87 (0.59)	108.24 (8.37)
Online learning duration = 1 year	21.68 (9.63)*	−3.60 (0.70)***	61.43 (13.45)***
Online learning duration = 2 years	−16.09 (10.21)	−10.24 (0.92)***	77.25 (15.26)***
Female	6.43 (11.20)	2.98 (0.65)***	17.79 (13.37)
Minority	−7.05 (24.93)	−3.87 (1.90)*	33.01 (14.38)*
Duration1 × Female	−5.41 (14.93)	−0.02 (0.93)	−25.33 (21.02)
Duration2 × Female	22.54 (26.04)	0.26 (1.37)	−2.09 (28.96)
Duration1 × Minority	−8.87 (25.15)	4.60 (2.06)*	−21.18 (35.55)
Duration2 × Minority	23.94 (37.97)	4.24 (2.23)†	34.75 (47.05)
Female × Minority	30.04 (31.28)	1.68 (2.35)	−26.04 (20.13)†
Duration1 × Female × Minority	−35.21 (32.83)	−1.15 (3.10)	84.58 (41.84)*

Predictor	Creative thinking (β, SE)	Knowledge mastery (β, SE)	Knowledge expression (β, SE)
Duration2 × Female × Minority	−99.46 (48.40)*	−8.93 (3.98)*	−94.91 (55.58)†

(1) Robustness checks

To test the robustness of the main findings, particularly the three-way interaction effect of online learning duration, gender, and ethnicity, we re-estimated the GEE models using two alternative working correlation structures: the exchangeable and unstructured structures.

As shown in Table 3, the three-way interaction term (Duration = 2 × Female × Minority) remained statistically significant in both alternative models for the outcomes of creative thinking ($\beta=-99.46$, $SE=48.40$, $p<0.05$) and knowledge mastery ($\beta=-8.93$, $SE=3.98$, $p<0.05$). For knowledge expression, the interaction term was marginally significant ($\beta=-94.91$, $SE=55.58$, $p<0.10$).

These results indicate that the intersectional moderation effects observed in the main analysis are robust to different assumptions about the within-cluster correlation structure.

Table 3. Robustness check: Key three-way interaction term under alternative GEE correlation structures.

Model structure	Outcome	Duration = 2 × Female × Minority (β, SE)	p-value	Significant
Independence	Creative thinking	–99.46 (48.40)	0.041	Yes
	Knowledge mastery	–8.93 (3.98)	0.025	Yes
	Knowledge expression	–94.91 (55.58)	0.088	†Marginal
Exchangeable	Creative thinking	–99.46 (48.40)	0.041	Yes
	Knowledge mastery	–8.93 (3.98)	0.025	Yes
	Knowledge expression	–94.91 (55.58)	0.088	†Marginal
Unstructured	Creative thinking	–99.46 (48.40)	0.041	Yes
	Knowledge mastery	–8.93 (3.98)	0.025	Yes
	Knowledge expression	–94.91 (55.58)	0.088	†Marginal

Notes: Values based on robust standard errors. †Marginally significant at $p<0.10$.

Quantile Regression results

To further explore the heterogeneous effects of online learning duration, gender, and ethnicity across different levels of student performance, we employed quantile regression models focusing on three learning outcomes: knowledge mastery, knowledge expression, and creative thinking. The analysis was conducted at five quantiles (τ=0.10, 0.25, 0.50, 0.75, and 0.90), covering both main effects and interaction effects.

(1) Main effects across quantiles

To further examine the variability in the effects of online learning, gender, and ethnicity across different performance levels, we performed quantile regression analyses for the three outcome domains: creative thinking, knowledge mastery, and knowledge expression. Figure 4 shows the main effects of key predictors across five quantiles (τ=0.10, 0.25, 0.50, 0.75, 0.90).

Longer online learning periods negatively affected creative thinking, especially for high-performing students (top 10%: $\beta=-41.2$), compared to average students ($\beta=-1.1$). Female students generally scored higher than males, with the largest gap among top performers (β=12.1). Interestingly, minority students only showed a significant advantage at the highest level (β=82.4), possibly due to unique cultural perspectives in creative tasks. Online learning duration consistently lowered knowledge mastery scores ($\beta \approx -11.0$ across all performance levels). Female students maintained a steady advantage ($\beta \approx$+2.0 to +5.0), while minority students scored slightly lower, except at the highest level where the gap disappeared.

Online learning strongly improved knowledge expression, particularly for high-achieving students (β=+138.0 at the top 10% vs. +36.0 for lower performers). However, the benefits for female and minority students decreased at the highest level (β=−14.0), suggesting diminishing returns for these groups among the great performers.

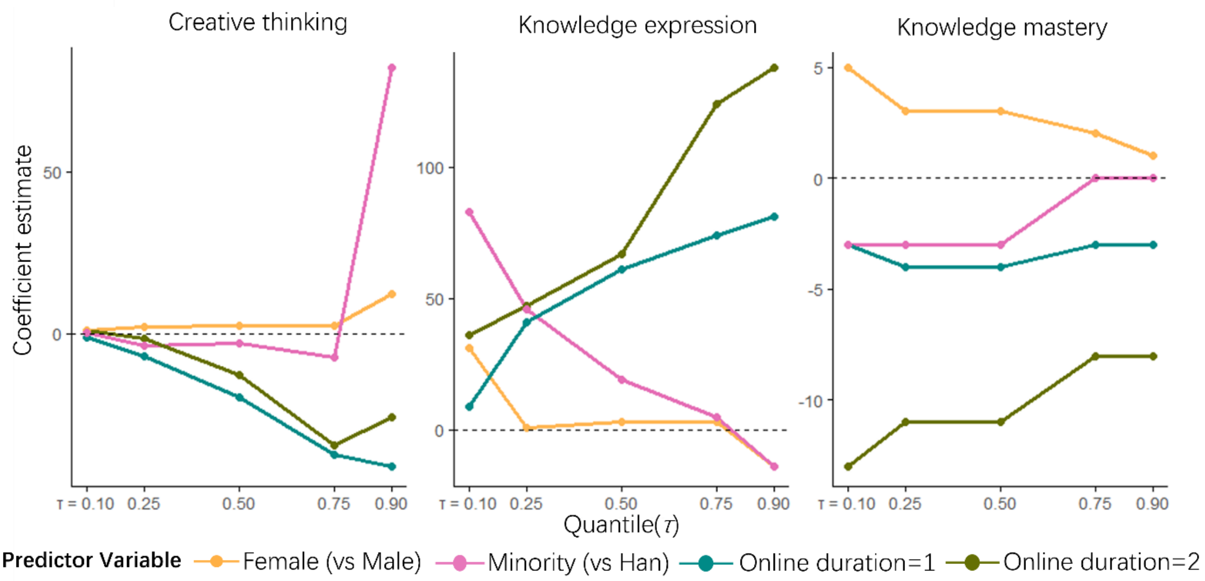

Figure 4. Main effects of key predictors across five quantiles.

(2) Interaction effects

Table 4 shows the results of quantile regression analyses exploring the diverse effects of online learning duration, gender, ethnicity, and their interactions on students' learning outcomes across five performance quantiles (τ = 0.10, 0.25, 0.50, 0.75, 0.90). All models include two-way and three-way interaction terms to capture identity-based and exposure-related disparities.

In creative thinking, the two-way interaction between online duration and gender became increasingly negative at higher quantiles (e.g., β=−43.6 at τ=0.75), suggesting that female students with longer online exposure may experience sharper declines at the top end of the distribution. The interaction between online duration and minority groups was positive at low and median quantiles. However, it turned strongly negative at τ = 0.90 (β=−174.8, p<0.05), indicating potential cumulative disadvantages for high-performing minority students. A notable three-way interaction was observed at the lower and middle quantiles (β=124.6 at τ=0.10 and β=131.0 at τ=0.25), suggesting short-term benefits for multiply marginalized students. However, this effect attenuated at higher quantiles.

For knowledge mastery, the interaction effects were generally small across different quantiles. The Duration × Minority interaction was consistently positive but became weaker at higher performance levels. Duration × Female turned slightly positive at τ=0.75 and τ = 0.90 (β=3.0, p<0.01), indicating that prolonged online exposure might benefit high-performing female students in foundational knowledge. Three-way interactions were negligible across all quantiles.

In knowledge expression, a reversal trend was observed in the Duration × Female interaction: It was positive at lower quantiles (β=37.0 at τ=0.10). However, it became significantly negative at the upper end (β= − 65.0 at τ=0.90, p<0.05). This suggests a shift in expressive engagement patterns among female students. The Duration × Minority interaction also declined from strongly positive at τ=0.10 (β=99.0, p<0.05) to negative at τ=0.90 (β= − 88.0). A significant three-way interaction emerged only at the highest quantile (β=130.0 at τ=0.90), indicating a unique uplift in expression scores for high-performing minority females with 1-year exposure.

Table 4. Quantile regression results.

Predictor	(β, SE)				
	τ=0.10	τ=0.25	τ=0.50	τ=0.75	τ=0.90
Performance: creative thinking					
Intercept	61.4** (23.40)	69.0*** (2.50)	85.5*** (5.60)	103.4*** (10.70)	153.8*** (55.73)
Online duration (1Y)	−1.1 (24.41)	−5.1* (2.89)	−13.3** (6.17)	−10.9 (13.50)	−24.0 (58.96)
Online duration (2Y)	0.8 (32.45)	0.0 (3.67)	−6.6 (5.69)	−13.3 (11.92)	−26.0 (67.34)
Female	7.6 (33.42)	12.2* (6.40)	18.5* (10.14)	31.3* (18.40)	12.1 (56.40)
Minority	−1.5 (23.60)	−5.1 (6.36)	−13.3 (12.57)	−14.0 (61.78)	113.5 (101.92)
Duration × Female	−6.6 (36.21)	−11.3* (6.61)	−21.5* (11.28)	−43.6** (20.91)	-53.9 (88.70)
Duration × Minority	7.6 (30.99)	7.6 (19.92)	9.6 (29.81)	-10.0 (60.77)	-174.8* (102.24)
Female × Minority	23.2 (42.30)	14.6 (38.09)	61.4 (38.16)	38.4 (69.85)	−120.3 (104.09)
Three-way interaction (1Y)	−28.9 (43.14)	−20.2 (39.64)	−65.2 (41.61)	−30.7 (64.32)	157.5 (107.39)
Three-way interaction (2Y)	124.6** (63.41)	131.0** (53.01)	89.6 (54.17)	114.3 (95.60)	50.0 (128.73)
Performance: knowledge mastery					
Intercept	31.0*** (1.15)	35.0*** (1.20)	38.0*** (0.90)	41.0*** (0.86)	41.0*** (0.10)
Online duration (1Y)	−2.0 (1.49)	−4.0** (1.32)	−5.0*** (1.02)	−5.0*** (1.02)	−4.0*** (0.56)
Online duration (2Y)	−13.0*** (2.02)	−11.0*** (1.90)	−10.0*** (1.33)	−10.0*** (1.06)	−9.0*** (0.57)
Female	7.0*** (1.39)	4.0** (1.45)	3.0** (1.04)	0.0 (0.86)	0.0 (0.10)
Minority	−5.0* (2.12)	−6.0** (2.42)	−6.0 (3.20)	−4.0 (3.33)	0.0 (2.63)
Duration × Female	−4.0* (1.89)	−1.0 (1.85)	1.0 (1.37)	3.0* (1.32)	3.0*** (0.78)

Predictor	(β, SE)				
	τ=0.10	τ=0.25	τ=0.50	τ=0.75	τ=0.90
Duration × Minority	11.0*** (3.01)	10.0*** (2.97)	8.0* (3.66)	5.0 (3.75)	0.0 (2.90)
Female × Minority	3.0 (2.66)	3.0 (3.09)	1.0 (3.68)	4.0 (4.08)	0.0 (3.43)
Three-way interaction (1Y)	−6.0 (3.93)	−6.0 (3.86)	0.0 (4.32)	-4.0 (4.46)	0.0 (3.52)
Three-way interaction (2Y)	−3.0 (3.41)	−1.0 (3.09)	0.0 (3.44)	− 5.0 (3.34)	−1.0 (2.92)
Performance: knowledge expression					
Intercept	5.0 (23.79)	86.0*** (16.42)	113.0*** (8.33)	144.0*** (7.84)	159.0*** (13.85)
Online duration (1Y)	−1.0 (38.20)	30.0 (25.48)	72.0*** (17.32)	87.0*** (15.27)	125.0*** (20.44)
Online duration (2Y)	33.0 (34.24)	40.0 (24.98)	74.0*** (19.33)	133.0*** (23.02)	179.0*** (19.91)
Female	56.0 (41.08)	−4.0 (20.09)	25.0 (16.05)	28.0** (13.56)	32.0 (21.47)
Minority	83.0*** (29.12)	19.0 (25.19)	26.0 (21.78)	14.0 (20.36)	29.0 (19.89)
Duration × Female	37.0 (64.47)	14.0 (32.80)	−51.0** (24.58)	−40.0* (23.82)	−65.0** (31.27)
Duration × Minority	99.0** (43.79)	51.0 (35.13)	14.0 (38.54)	−20.0 (36.25)	−88.0 (52.31)
Female × Minority	−34.0 (50.11)	9.0 (33.75)	−22.0 (31.46)	−39.0 (35.73)	−73.0** (36.23)
Three-way interaction (1Y)	−29.0 (60.34)	11.0 (35.95)	39.0 (44.42)	75.0 (58.78)	130.0* (70.47)
Three-way interaction (2Y)	1.0 (76.55)	−11.0 (71.23)	20.0 (60.77)	−91.0 (55.52)	−23.0 (57.10)

Notes: significance levels: *p<0.1, **p<0.05, ***p<0.0; "online duration (1Y)" = 1-year online learning cohort; "(2Y)" = 2-year cohort.

Discussion

Main findings

This study examined how the length of online learning affects student performance in three key areas: knowledge mastery, creative thinking, and knowledge expression. The findings show different patterns across these learning outcomes.

First, longer exposure to online learning consistently correlates with lower levels of knowledge mastery. In contrast, knowledge expression improves as online learning experience increases, indicating possible gains in students' ability to communicate in digital environment.

However, creative thinking follows a nonlinear pattern, with no consistent improvement and often declining with extended exposure. This phenomenon highlights the potential limitations of long-term virtual instruction in developing higher-order thinking skills.

Second, gender and ethnicity interact in complex ways with online learning duration. While female and minority students display certain advantages in creativity and expression, these effects are not uniformly positive or persistent. Notably, minority female students exhibit early gains in creative thinking and expressive ability, but these benefits diminish or reverse over time. For knowledge mastery, identity-related differences are generally small and statistically insignificant.

Third, the effects of online learning vary significantly across different student performance levels. For knowledge expression, the most significant improvements are seen among high-performing students. In contrast, for creative thinking, even top-performing students often experience stagnation or decline. Regarding knowledge mastery, the negative impact of extended online learning is clear across all quantiles, affecting both low- and high-achieving students. Notably, minority female students show unique distributional patterns: They experience significant benefits at the lower quantiles of creativity and expression, but these benefits diminish or even reverse at the higher quantiles. This indicates that subgroup disparities and educational inequalities might be hidden in average-effect models and become apparent only when looking at the distribution.

Together, these findings highlight the diverse and unequal effects of extended online learning, which are influenced by individual traits and initial performance levels. They underscore the importance of inclusive, tailored teaching approaches that cater to different learning paths and promote equitable outcomes in digital education.

Comparison with existing literature

Our findings reveal a clear divergence across different learning areas. While students' ability to express knowledge improved with increased exposure to online learning, both creative thinking and knowledge mastery declined significantly. One possible explanation is that online platforms, by integrating more flexible and interactive digital tools, reduce the psychological barriers to participation, thereby encouraging expression. In contrast, the decline in mastery and creativity may result from reduced cognitive engagement and diminished classroom discipline, features often associated with online environments [38]. This is also consistent with studies showing that creativity tends to decline in virtual settings that lack feedback, real-time interaction, or cultural responsiveness [39]. A promising idea is adopting more active, communication-driven designs like the Communication, Inquiring, Networking, Teaching, Applying (CINTA) model, which has been shown to boost students' critical and creative thinking [40].

The interactive effects of gender and ethnicity also warrant attention. While many studies report that female students perform more consistently and successfully in online learning environments than their male counterparts, our results indicate that this advantage is not evident when gender and minority status intersect [41,42]. Specifically, minority female students experienced the most pronounced declines in creative thinking after long-term online instruction, even more than their male counterparts. This challenges the presumed neutrality of online education and points to underlying structural inequities. Several mechanisms may contribute to this difference.

Firstly, online learning often requires a high degree of self-regulated engagement. If minority female students participate less actively - whether due to a lack of confidence, limited access, or inadequate support - this may compound their disadvantage over time. Supporting this view, Reinholz found that gender gaps widen in active learning environments when female participation is low [43]. Secondly, teachers in online settings may be less able to recognize students' cultural backgrounds, leading to interactions that unintentionally favor the dominant culture. As noted by Ebabuye, such dynamics can marginalize minority students whose identities and experiences are different [44]. Finally, the psychological strain caused by the COVID-19 pandemic when most online learning occurred, it may have affected students already facing structural and social vulnerabilities, including minority girls [45].

Beyond average trends, our quantile regression results revealed additional disparities across student performance levels. For example, while female students showed an average advantage in expression, those at the highest quantile (τ=0.90) exhibited weaker outcomes than expected. Similar patterns were found for creative thinking among top-performing minority female students. These findings suggest that online learning may not have a uniform impact on all learners. Some high-performing students may encounter a "ceiling effect", where limited opportunities for challenge or growth lead to disengagement [46]. Others may lose motivation over time as online instruction becomes repetitive and lacks novelty or personalized feedback [47]. Such patterns cannot be captured by mean-based analyses alone. While average outcomes may appear neutral or even positive, they risk masking important distributional disparities. Our findings emphasize the importance of using methods like quantile regression to uncover hidden inequalities and better inform inclusive, differentiated educational practices [48].

Limitations and future directions

Several limitations of our research still exist. First, although the data captured student performance after a return to in-person instruction, we relied on retrospective online learning exposure rather than concurrent measurement, which limited our ability to track within-student change fully. Second, although the study included gender and ethnicity as identity markers, other potentially influential factors were not considered, such as digital access, family background, or regional policy differences. Additionally, in terms of methodology, using Generalized Estimating Equations and quantile regression improves the robustness and depth of the analysis. However, the cross-sectional nature of the data still limits causal inference. Longitudinal data and experimental designs are necessary to better distinguish between time effects and cohort or context effects.

Future research can expand upon these findings by incorporating qualitative data (e.g., interviews or classroom observations) to gain a deeper understanding of the behavioral and emotional dynamics underlying observed performance patterns. Further, comparative studies across institutions or regions could help identify structural conditions that either amplify or mitigate digital learning disparities. Exploring how curriculum design, peer dynamics, and teacher support shape the long-term impact of online learning for marginalized student groups will be a valuable direction for building more equitable post-pandemic education systems.

Conclusion

This study explores how online learning duration impacts knowledge mastery, creative thinking, and knowledge expression, and their variations by gender and ethnicity via GEE and quantile regression. Findings show extended online learning reduces knowledge mastery, enhances knowledge expression, and causes non-linear changes in creative thinking. Demographic factors moderate these effects: Minority female students gain initial advantages in creativity and expression that fade with prolonged exposure. Quantile regression reveals heterogeneous impacts across performance levels, with high-achievers facing creative stagnation and ceiling effects in expression.

These results enrich sustainable digital education literature by highlighting the interplay of online learning duration, social identities, and outcomes. They emphasize inclusive pedagogical designs for marginalized groups to align with Sustainable Development Goal 4. Limitations include cross-sectional design and retrospective data. Future research should use longitudinal/experimental approaches and integrate qualitative insights. This study provides empirical evidence to optimize post-pandemic higher education for equitable, high-quality learning.

Funding

This work was not supported by any funds.

Acknowledgements

The authors would like to show sincere thanks to those techniques who have contributed to this research.

Conflicts of Interest

The authors declare no conflict of interest.

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