Investigating Factors Influencing Student Academic Outcomes in Online Higher Education: A Cross-Sectional Observational Study

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Abstract
Evolving student demands and technological advancements have facilitated the rise of online learning in higher education, fostering greater access to online educational opportunities. The purpose of this research was to investigate the impact of self-directed learning, collaborative learning, and isolation (independent variables) on academic achievement and academic resilience (dependent variables) among online undergraduate university students, using self-determination theory as the foundation for the research. This study employed a quantitative cross-sectional observational design for population-based surveys and captured a single data collection point from the participants, based on study criteria. Multiple regression analysis revealed self-directed learning and collaborative learning positively correlated with academic achievement and academic resilience, while student isolation showed a negative relationship. Although the study provides valuable insights for online education practitioners, it acknowledges potential limitations due to context-specificity and unexplored factors. This research contributes empirical evidence to inform the design of supportive virtual educational environments in higher education.

Keywords: Academic achievement, academic resilience, collaborative learning, loneliness, self-determination theory, self-directed learning, student isolation, quantitative research

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The contemporary higher education landscape has witnessed a dramatic shift towards online learning platforms, driven by flexibility and accessibility for students (Salama & Hinton, 2023). While this trend offers undeniable advantages, it simultaneously presents distinct challenges. Research suggests that online environments can foster student isolation, potentially hindering academic achievement and resilience compared to traditional face-to-face settings (Garivaldis et al., 2022). This necessitates a move away from a singular model for online learners, prompting educators to explore alternative approaches that cater to their specific needs. While previous studies have explored the independent effects of self-directed learning, collaborative learning, and student isolation on academic achievement and academic resilience in online higher education, a critical research gap exists regarding their combined influence (Asif et al., 2022; Lenny et al., 2019; Morris, 2019; Permatasari et al., 2021; Rudd et al., 2021; Santaoja, 2024).

This study aimed to investigate the specific influence of self-directed learning, collaborative learning, and student isolation (independent variables) on academic achievement and academic resilience (dependent variables) among undergraduate online degree program university students. Utilizing a quantitative research approach, the study analyzed the relationship between the variables and contributed a more refined understanding of how to foster student success in online higher education environments. By outlining the measurable outcomes of each variable and its impact on student performance, the investigation illuminated the intricate web of factors influencing online student success. The findings hold the potential to inform the development of targeted support structures and pedagogical approaches that mitigate isolation, enhance self-directed and collaborative learning skills, and empower students to thrive in online learning environments.

Literature Review

How can educators optimize online learning to achieve the best student outcomes while minimizing challenges? Research shows that online courses have drawbacks, such as higher dropout and lower completion rates than traditional in-person classes (Charokar & Dulloo, 2022). To succeed in online courses, students must be strong independent learners and develop self-directed learning skills (Sun et al., 2023). These skills involve taking ownership of their learning process, setting goals, and independently managing their time and resources (Sun et al., 2023). Recent work in Massive Open Online Courses (MOOCs) confirms that SDL is central to motivation, learning strategies, and instructional outcomes in online contexts (Zhu et al., 2022). Charokar and Dulloo found a positive correlation between self-directed learning, academic self-efficacy, and achievement motivation in undergraduate students. The results suggest that fostering students' independence and study skills can improve their self-belief and learning motivation.

While self-directed learning is crucial, collaborative online learning (COL) also plays a significant role in student success. Blau et al. (2020) investigated student perceptions of COL activities in a Management Information System course, finding that well-structured activities with strong peer interaction led to increased perceived learning and satisfaction. Heilporn et al. (2021) examined strategies for fostering communication and interaction in online learning environments and proposed a framework to aid instructors and instructional designers in creating well-structured, interactive online courses for higher education, promoting collaboration among educators, and improving student learning outcomes.

However, the solitary nature of online learning can make it difficult for students to develop these skills independently (Sarkar, 2020). Olugbara et al. (2023) examined factors influencing student support in open and distance learning (ODL) environments, aiming to guide institutions in developing effective support services. Their review suggested that student support is crucial for ODL success, particularly in addressing isolation and dropout rates.

While online programs offer flexibility and accessibility, they may lead to student isolation (ISO) and a lack of engagement (Garivaldis et al., 2022). Research during remote online classes further shows that loneliness and belonging are central concerns for online learners (Hansen-Brown et al., 2022). Studies suggest that ISO in online learning environments can negatively impact academic achievement (AA) and hinder the development of academic resilience (AR), especially when compared to traditional face-to-face learning. This highlights the need for educators to consider alternative approaches beyond a one-size-fits-all model for online learners (Lamon et al., 2020; Sarkar, 2020).

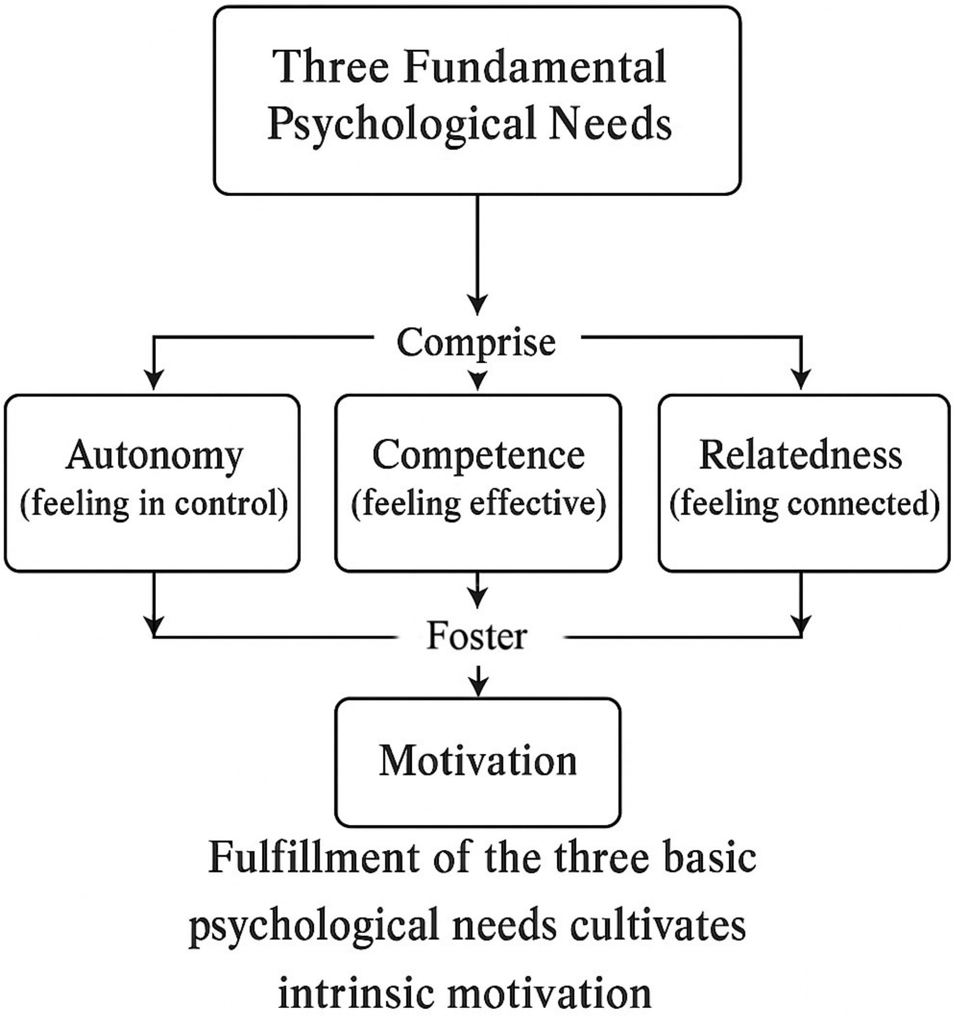
Academic achievement is a student's performance outcome, indicating their met educational goals within an instructional environment (Kassaw & Demareva, 2023). These goals can be cognitive (i.e., critical thinking) or domain-specific (i.e., knowledge acquisition, science, history). Torun (2020) investigated the link between e-learning readiness and AA in an online higher education course and found that motivation emerged as a significant predictor of academic achievement. These findings suggest that fostering students' autonomy and motivation is crucial for success in online environments.

Online learning success also depends on students' academic resilience (AR), which is their ability to bounce back from challenges (Polat, 2024). AR refers to a student's capacity to overcome acute or chronic adversities seen as major assaults on educational processes (Zarrinabadi et al., 2022). Online learning challenges require strong resilience in students as universities work to equip them with coping skills unique to the stressors of the online learning format (Nuryana et al., 2023). The notion of resilience explains why some people respond adaptively to extreme stress while others do not (Avci, 2022; IJntema et al., 2023).

Theoretical Framework

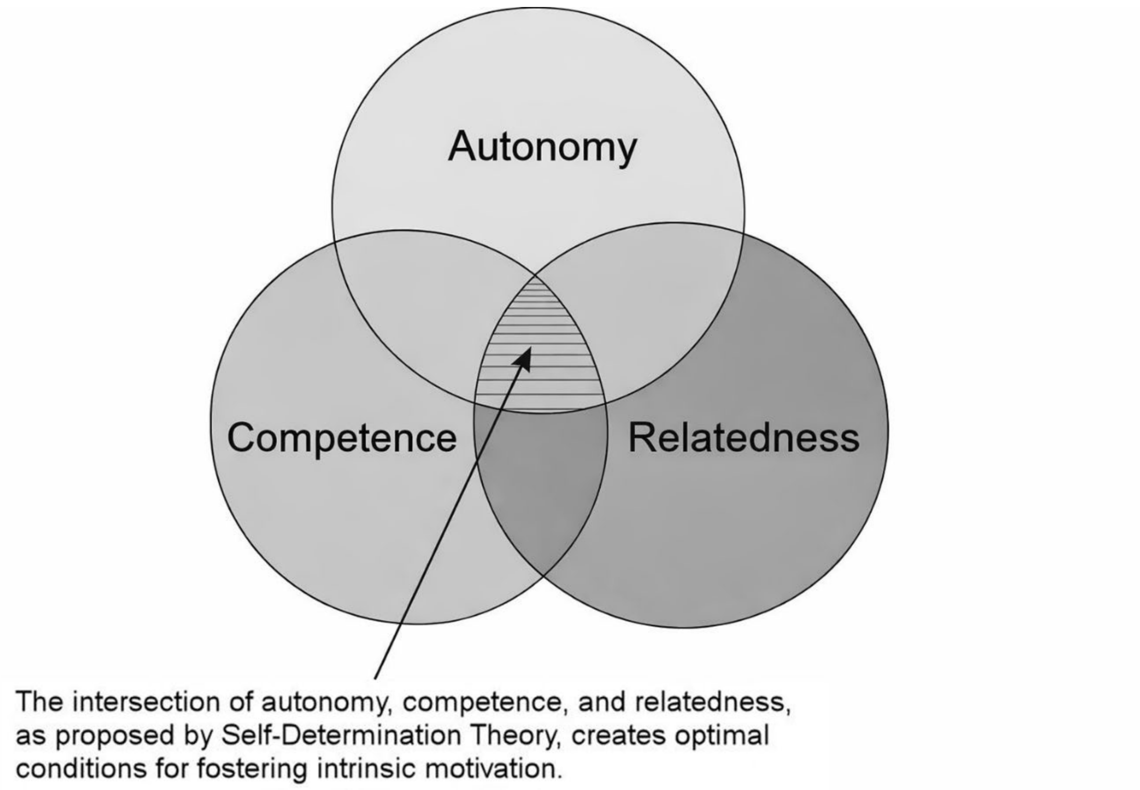
The self-determination theory (SDT), with its focus on the three basic psychological needs of autonomy, competence, and relatedness, provides a valuable theoretical framework for understanding the dynamics of SDL, COL, and ISO in online learning environments (Ryan & Deci, 2020). SDL aligns closely with the need for autonomy, COL supports the need for relatedness, while ISO may hinder the fulfillment of these needs, potentially affecting both AA and AR (Liu & Huang, 2021). These three basic psychological needs are defined as: (1) autonomy, the need to feel a sense of volition and choice in one's actions, (2) competence, the need to feel effective and capable in one's interactions with the environment, (3) relatedness, the need to feel connected and have meaningful relationships with others (Ryan & Deci, 2000).

Figure 1 *Self-Determination Theory (SDT), Fundamental Psychological Needs, Intrinsic Motivation (created by the authors based on Vansteenkiste et al., 2020).*



Note. Figure 1 illustrates the foundational role of the three fundamental psychological needs—autonomy, competence, and relatedness—in fostering intrinsic motivation. Autonomy highlights the sense of self-direction; competence represents perceived effectiveness in interaction with one's environment; and relatedness underscores the importance of meaningful social connection.

Figure 2 *Intersection of Self-Determination Theory and Basic Psychological Needs (created by the authors based on Vansteenkiste et al., 2020).*



Note. Figure 2 illustrates the intersection of autonomy, competence, and relatedness as conceptualized in Self-Determination Theory. The overlap of autonomy and competence reflects a sense of self-directed mastery and confidence. The overlap of autonomy and relatedness reflects support and connection while maintaining individuality, whereas the intersection of competence and relatedness promotes belonging accompanied by effectiveness. The central intersection of all three needs represents the optimal psychological state in which individuals experience empowerment, intrinsic motivation, engagement, and overall well-being.

In the application to educational contextual settings, SDT provides a valuable framework for understanding how structured learning environments promote student motivation and academic success. The theory suggests that how students experience a sense of autonomy, feel competent in their abilities, and have positive relationships with peers and teachers, are likely to exhibit higher levels of intrinsic motivation (Lopez-Garrido & McLeod, 2023). Environments supportive of the three basic psychological needs enhance performance, engagement, and well-being.

Study Variables

This study operationalized key constructs within the framework of self-determination theory (SDT) to investigate the influence of learning contexts and social connection on academic outcomes. The following variables have been identified as central to this inquiry. Each variable is defined and contextualized within the SDT framework, providing a theoretically grounded basis for the subsequent analyses and interpretations. The following outlines each variable and its relationship with SDT.

<u>Independent Variables.</u>

(1) Self-directed learning (SDL) refers to the process by which individuals take initiative in diagnosing their learning needs, formulating learning goals, identifying resources for learning, choosing and implementing appropriate learning strategies, and evaluating learning outcomes (Knowles, 1975). Within the SDT framework, SDL aligns with the need for autonomy, as it empowers learners to take control of their learning process.

(2) Collaborative learning (COL) involves the joint intellectual effort of students, or of students and teachers together, typically in groups of two or more, mutually searching for understanding, solutions, or meanings, or creating a product (Smith & MacGregor, 1992). In the context of SDT, COL primarily addresses the need for relatedness by fostering social connections and a sense of belonging. Additionally, it may contribute to competence as students learn from and with their peers.

(3) Student isolation (ISO) refers to the perceived lack of meaningful interactions with peers, instructors, or the broader academic community in educational settings (Erichsen & Bolliger, 2011). Within the SDT framework, ISO is hypothesized to primarily hinder the fulfillment of the relatedness need but may also impact autonomy and competence by limiting social support and learning resources. Consequently, ISO is expected to negatively influence intrinsic motivation and academic outcomes.

Dependent Variables.

Academic achievement (AA) encompasses the extent to which a student has achieved their short or long-term educational goals (York et al., 2015). In the context of SDT, AA is hypothesized to be enhanced when the three basic psychological needs are met. SDL and COL are expected to positively influence AA by supporting these needs, while ISO is anticipated to have a negative impact.

Academic resilience (AR) refers to students' capacity to overcome acute or chronic adversities that threaten their educational development (Martin & Marsh, 2009). Through the lens of SDT, AR is expected to bolster students' basic psychological needs, equipping them with the motivation and resources to persevere through academic challenges. SDL and COL are hypothesized to enhance AR by supporting these needs, whereas ISO is expected to diminish AR by impeding need fulfillment.

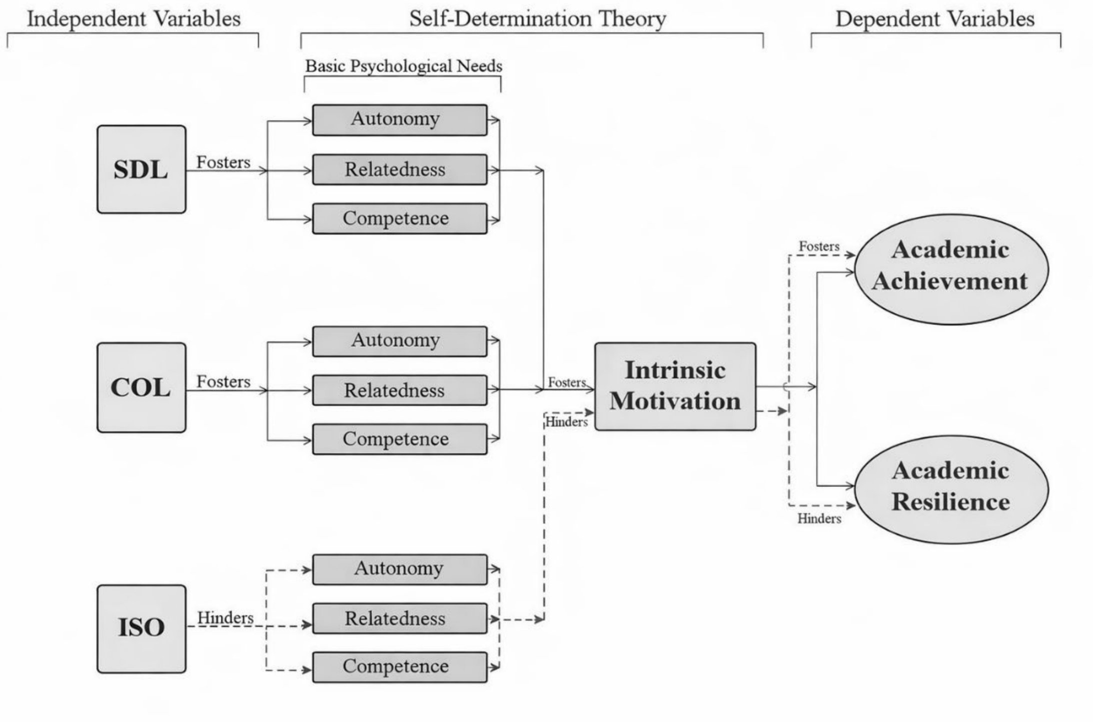
Problem

The literature review highlights the importance of self-directed learning, collaborative learning, and student isolation in higher education online learning environments as they affect student academic achievement and academic resilience. This study investigated the following gaps: (1) Multivariable Analysis (core gap): Extant research within the domain of online higher education learning has primarily focused on the influence of a limited number of independent variables, measured by dependent variables (Fernández-Batanero et al., 2022; Uilah et al., 2023). This study addressed the gap by separately investigating the effect of the independent variables on each dependent variable, utilizing a multivariable multiple regression analysis. (2) Context-Specific Analysis (secondary gap): Current research examined online learners in general and as a broad population, potentially overlooking the influence of specific institutional contexts.

Purpose

This study investigated the relationships between three independent and two dependent variables, providing insights into how educational practices aligned with SDT principles.

Figure 3 *Conceptual Framework of Hypothesized Relationships (created by the authors)*



Note. Figure 3 illustrates the hypothesized relationships between the study variables and SDT psychological components.

Addressing this methodological gap is critical because inadequate handling of heterogeneous scales and psychosocial variables risk obscuring valid predictors of student success in online higher education.

Research Questions and Hypotheses

This study aimed to determine the independent variables' influence on each dependent variable. The primary objective of this research was to analyze the variables and test formulated hypotheses.

Research Question 1: Do self-directed learning, collaborative learning, and student isolation influence academic achievement of undergraduate online degree program university students?

Research Question 1: Hypothesis

H_{01}: Self-directed learning, collaborative learning, and student isolation do not influence academic achievement of undergraduate online degree program university students.

H_{A1}: Self-directed learning, collaborative learning, and student isolation influence academic achievement of undergraduate online degree program university students.

Research Question 2: Do self-directed learning, collaborative learning, and student isolation influence academic resilience of undergraduate online degree program university students?

Research Question 2: Hypothesis

H_{02}: Self-directed learning, collaborative learning, and student isolation do not influence academic resilience of undergraduate online degree program university students.

H_{A2}: Self-directed learning, collaborative learning, and student isolation influence academic resilience of undergraduate online degree program university students.

Methods

Research Design

This study employed a quantitative cross-sectional observational design. The cross-sectional approach captured a single data collection point from the participants, based on inclusion or exclusion criteria (Cuschieri, 2019; Setia, 2016; STROBE, 2025). Cross-sectional designs are used for population-based surveys in conjunction with the study's objectives to investigate the influence of various factors on academic achievement and academic resilience. The study was grounded in self-determination theory (Deci & Ryan, 1985; Ryan & Deci, 2000), which proposes that three basic psychological needs—autonomy, competence, and relatedness are essential for fostering intrinsic motivation and optimal functioning. This theoretical framework provided the lens to examine the factors influencing academic achievement and academic resilience, particularly in the context of higher education.

Operational Definitions and Measuring Instruments or Study Variables

This section described the operational definitions and corresponding measurement instruments for the principal variables in this study. The selected instruments have demonstrated good psychometric properties in previous research, supporting their validity and reliability for use in this study.

Self-Directed Learning

SDL is the extent to which students demonstrate initiative in their learning process, including goal setting, progress monitoring, and independent knowledge acquisition (Knowles, 1975; Lounsbury et al., 2009).

Measurement Instrument. Self-directed learning scale (SDLS), developed by Lounsbury et al. is a 10-item unidimensional scale that evaluated an individual's capacity to independently seek and acquire knowledge, establish personal learning objectives, and actively engage in the learning process without exclusive reliance on external guidance or instruction. Responses were recorded on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The SDLS demonstrated good internal consistency with a Cronbach's α of 0.87 in previous studies. Participant data was collected using the "Self-Directed Learning Scale" developed by Lounsbury et al. with prior authorization to use the instrument.

Collaborative Learning

COL is defined as the frequency and quality of peer and instructor interactions within online learning environments (Ng et al., 2022). This construct encompassed various aspects of collaborative engagement, including group discussions, peer feedback mechanisms, and collaborative project work.

Measurement Instrument. The Online collaborative learning scale (OCLS), a multidimensional instrument developed by Ng et al. (2022) was employed to assess collaborative learning. The scale utilized a seven-point Likert scale, ranging from "1 = strongly disagree" to "7 = strongly agree" for all items in the survey. Seven dimensions were evaluated: (1) online collaborative tools; (2) collaboration with peers; (3) student engagement; (4) idea generation; (5) idea organization; (6) intellectual convergence; and (7) student learning outcomes. The OCLS demonstrated high reliability with Cronbach's α values ranging from 0.87 to 0.96. Participant data was collected using the "Online Collaborative Learning Scale" developed by Ng et al. with prior authorization to use the instrument.

Student Isolation

ISO is the degree to which students experience a perceived disconnect from peers and instructors, specifically within the context of online learning environments (Hays & DiMatteo, 1987). This construct encompassed social disconnection, loneliness, and the perceived absence of close relationships within the academic setting.

Measurement Instrument. The UCLA Loneliness Scale, ULS-8 (alternative short-form version of the UCLA Loneliness Scale ULS-20) by Hays and DiMatteo (1987) consisted of an 8-item instrument that measured subjective feelings of loneliness and social isolation, including perceived social disconnection, lack of companionship, and feelings of being left out or isolated. Participants respond on a 4-point Likert scale from 1 (never) to 4 (often). ULS-8 demonstrated good internal consistency with a Cronbach's α of 0.84 in previous studies. Participant data was collected using the "ULS-8" developed by Hays and DiMatteo with prior authorization to use the instrument.

Academic Achievement.

AA is a student's self-perceived academic success, such as personal goal attainment, effort expenditure, and relative performance compared to peers. This construct goes beyond traditional objective measures to capture a more holistic view of academic accomplishment (Stadler et al., 2021).

Measurement Instrument. The subjective academic achievement scale (SAAS), developed by Stadler et al. (2021) is a 5-item unidimensional instrument that assessed various aspects of perceived academic success, including grade satisfaction, overall study success, perceived grade-effort appropriateness, study progress, and comparative peer performance. Responses were recorded on a 5-point Likert scale from 1 (low satisfaction) to 5 (high satisfaction). The SAAS has shown good internal consistency with a Cronbach's α of 0.82 in pilot studies (Stadler et al., 2021). Participant data was collected using the "Subjective Academic Achievement Scale" developed by Stadler et al. with prior authorization to use the instrument.

Academic Resilience

AR is defined as the capacity to recover from academic setbacks and challenges while maintaining motivation and perseverance (Cassidy, 2016). This construct encompassed various dimensions of resilience specific to academic contexts, including adaptive coping strategies and positive responses to educational adversities.

Measurement Instrument. The academic resilience scale (ARS-30), developed by Cassidy (2016) is a 30-item instrument. Responses were recorded on a 5-point Likert scale from 1 (strongly agree) to 5 (strongly disagree). The ARS-30 demonstrated high internal consistency with a Cronbach's α of 0.90. Participant data was collected using the "Academic Resilience Scale" developed by Cassidy with prior authorization to use the instrument.

A consolidated summary of reliability and validity statistics, including Cronbach's α, McDonald's ω, factor structures, and fit indices for all study instruments, is provided in Supplemental Materials A1 (Psychometric Properties of Instruments). Team assignment participation data were collected through self-report measures. These reports were not independently verified against course records, which should be considered when interpreting collaborative learning findings.

Power Analysis

A priori power analysis was conducted using G*Power (version 3.1.9.7) to determine the required sample size for the regression models. Based on Cohen et al. (2017), and Kang (2021), guidelines, a medium effect size ($f^2 = 0.15$) was chosen, as it represented a moderate relationship between predictors and outcomes, which is common in educational research. The analysis assumed $\alpha = 0.05$, power ($1 - \beta$) = 0.85, and three predictors. A power of 0.85 was selected, which represented a midpoint between the conventional standard of 0.80 in educational research and a more stringent 0.90 level (Cohen et al., 2017; Faul et al., 2007; Faul et al., 2009; Kang 2021). This choice struck a balance between enhancing the probability of detecting true effects and minimizing the risk of Type II errors (false negatives) while accounting for practical resource limitations. At this power level, the study had an 85% chance of identifying a genuine effect (if one existed) in the population, thereby increasing the robustness of the findings (compared to a standard 0.80 power) without incurring the substantial increase in required sample size associated with a power of 0.90. The resulting minimum required sample size was 87 participants. The study target population of 268 exceeded this requirement, ensuring adequate statistical power to detect medium-sized effects. This sample size also allowed for the detection of smaller effects and provided more precise parameter estimates, enhancing the robustness of the findings.

Sensitivity Analyses

Using G*Power revealed the sample size of 268, $\alpha = 0.05$, and power = 0.85, effect sizes as small as $f^2 = 0.0466$ could be detected. The regression analyses yielded effect sizes of $f^2 = 0.212$ for academic achievement ($R^2 = 0.175$) and $f^2 = 0.198$ for academic resilience ($R^2 = 0.165$), both falling within the medium effect size range guidelines (Cohen et al., 2017; Faul et al., 2007; Faul et al., 2009; Kang, 2021). These results indicated that the sample size of 268 participants provided robust statistical power.

Study Participants and Sample Criteria

Study participants were recruited through eligibility criteria. This method aligns with the cross-sectional observational study design (Cuschieri, 2019; STROBE, 2025). The inclusion criteria was a target population of online college students ≥18 years old, enrolled in online bachelor's degree programs from five colleges incorporated within a university campus in Southwestern United States within 60 days preceding the receipt of the survey, and had participated in class team assignments. Exclusion criteria were students < 18 years old and not currently enrolled in online bachelor's degree programs at the university. This carefully structured inclusion-exclusion framework ensured that the study sample accurately represented the target population, thereby enhancing the validity and generalizability of the research findings within the context of online higher education (Cuschieri, 2019; STROBE, 2025).

Recruitment Process

Recruitment was conducted through the university's marketing department. A total of 25,450 survey invitations were emailed to students meeting the inclusion criteria. Invitations were sent in five batches on consecutive Mondays over a 30-day data collection period from July 22, 2024, to August 20, 2024. To prevent duplicate responses, subsequent batches excluded recipients who had already accessed the survey link.

Data Collection

Data collection, through Google Forms, a secure online survey platform, ensured participant anonymity, and efficiency in data gathering (Creswell & Creswell, 2022). The survey captured essential participant demographic information and allowed for a more detailed understanding of the sample population (Hakimi et al., 2024; Kayyali, 2024). No incentives were offered to participants to ensure unbiased responses.

Survey Response

The survey yielded 561 responses during the 30-day data collection period, resulting in a gross response rate of 2.2% (561/25,450). On average, online survey response rates are 11% below mail and phone surveys, and rates as low as 2% have been reported (Monroe & Adams, 2012; Petchenik & Watermolen, 2011). Several contributing factors to the low response rate were: (1) Monday distributions; (2) 94-item questionnaire and personal time investment; (3) demographics of the target population (age) may have influenced response rates; (4) survey fatigue and (5) a lack of personal interest or perceived relevance in the research topic. Despite the low overall response rate, the study achieved a more than sufficient sample size for robust statistical analysis.

Data Cleaning

A systematic approach was initiated to ensure the quality and relevance of the collected responses:

Removal of responses lacking informed consent	(*n* = 3)
Exclusion of participants with associate degrees	(*n* = 7)
Exclusion of participants with certifications	(*n* = 1)
Elimination of incomplete responses	(*n* = 180)
Exclusion of responses from the College of Business & IT	(*n* = 19)
Removal of suspicious responses exhibiting repetitive, conflicting and extreme answer patterns	(*n* = 83)

The last criterion involved a meticulous examination of response patterns to identify suspicious or potentially non-genuine participation. This included responses with identical answers across multiple constructs, uniform selection of extreme values, or consistent selection of the same response option throughout the survey. Additionally, responses were deemed conflicting if they indicated no engagement in teamwork assignments while providing answers to collaborative learning experience questions. This rigorous data cleaning process aimed to enhance the overall quality and reliability of the study's dataset by excluding responses (293) that did not meet predefined criteria for completeness, relevance, and authenticity. The resulting sample of 268 responses was utilized for subsequent analyses, ensuring a more robust and valid dataset for the study.

Sample Distribution

Table 1

Demographic Characteristics of Participants (n = 268) Compared with Raw Data (N = 561)

College	Analyzed (*n* = 268)	%	Raw Data (*N* = 561)	%
Social-Behavioral Sciences	115	43	220	39
Health Professions	65	24	118	21
Education	54	20	125	22
General Studies	30	11	64	11
Nursing	4	1	12	2

Note. The demographic distribution of the analyzed sample closely mirrors that of the original sample, with the percentages from each college remaining consistent. This indicates that the data cleaning process did not introduce significant bias.

Data Transformation

The presence of heterogeneous Likert scales, coupled with non-normal data distributions and the identification of outliers, necessitated a rigorous data preprocessing approach prior to subsequent analyses. Accordingly, all variables were standardized using a rank-based inverse normal z-score transformation (Chien, 2020; Solomon & Sawilowsky, 2009), which ensured comparability across instruments and improved residual properties. Full transformation steps are detailed in Supplemental Materials A2.1, with sensitivity analyses reported in A2.2.

Data Analysis

Data analyses were accomplished using JASP (Version 19.1), a statistical analysis open-source software package suitable for this study's analytical requirements. Data were categorized in Microsoft Excel prior to JASP analyses and data standardization.

Ethical Considerations

Informed consent was obtained from participants, clearly describing the study's purpose, potential risks and benefits, and the voluntary nature of participation. Participants were assured of their right to withdraw without consequence and skip any uncomfortable questions, respecting their autonomy. Anonymity was maintained by not collecting any personal identifying information (PII) from the participants. To minimize potential biases, the study employed strategies such as rigorous participant selection based on established eligibility criteria, standardized data collection procedures, and systematic analysis methods. All raw data and digital files were slated for permanent deletion upon completion of the study, and no physical copies were generated or retained throughout the research process. This collective approach ensured the protection of participants' rights, enhanced research validity, and supported scientific integrity while balancing research objectives with ethical considerations (Ravitch & Riggan, 2016).

Results

This section represents the empirical findings of the effects of self-directed learning, collaborative learning, and student isolation on academic achievement and academic resilience among undergraduate online degree program university students. Statistical analyses revealed significant relationships between SDL, COL, and ISO and academic outcomes, providing a deeper understanding of the factors that contribute to student success in the online learning environment.

Demographic Descriptive Statistics

Table 2

Demographic Characteristics of Participants (n = 268)

Characteristic	***n* = 268 responses**	**%**
Gender		
Female	236	88.06
Male	29	10.82
Other	3	1.12
Age		
18-24	8	2.99
25-34	60	22.39
35-44	90	33.58
45-54	77	28.73
55-64	29	10.82
65 and over	4	1.49
College		
Social and Behavioral Sciences	115	42.91
Health Professions	65	24.26
Education	54	20.15
General Studies	30	11.19
Nursing	4	1.49
1st Generation College Student?		
Yes	170	63.43
No	98	36.57
Employment Status		
Full-time employed (35+ hours/week)	158	58.96
Part-time employed (less than 35 hours/week)	38	14.18
Not currently employed	65	24.25
Prefer not to answer	7	2.61

The majority of participants identified as female (88.06%, $n = 236$), with a small proportion identifying as male (10.82%, $n = 29$) and other gender identities (1.12%, $n = 3$). Age distribution was between 25-54 years, with 33.58% ($n = 90$) in the 35-44 age range, followed by 28.73% ($n = 77$) in the 45-54 range, and 22.39% ($n = 60$) in the 25-34 range. Regarding college affiliation, 42.91% ($n = 115$) were from the college of social and behavioral sciences, with the remaining distributed across other colleges. Notably, 63.43% ($n = 170$) of participants identified as first-generation college students. Employment status varied among participants, with 58.96% (n = 158) reporting as full-time employed, 24.25% (n = 65) not currently employed, and 14.18% (n = 38) employed part-time.

Statistical Analysis

To explore potential associations between demographic factors, several statistical analyses were conducted. A χ^2 test of independence revealed no significant relationship between gender and age ($\chi^2(20) = 27.691$, $p = 0.117$), first-generation status ($\chi^2(4) = 3.323$, $p = 0.505$), college affiliation ($\chi^2(16) = 21.900$, $p = 0.146$), or employment status ($\chi^2(12) = 8.806$, $p = 0.719$). However, using Kendall's τb test, a weak positive correlation was found between gender and age (Kendall's $\tau b = 0.167$, $p = 0.003$). The contradictory results between gender and age highlight the importance of using multiple statistical approaches to fully understand the relationships between variables in complex datasets.

<u>Demographics Effects on the Academic Achievement Linear Regression Model</u>

Analysis of demographic variables' effects on academic achievement (AA) revealed that gender significantly influenced AA, with male students showing a notable positive effect ($\beta = 0.180$, $p = 0.044$). Other demographic factors, including age, college affiliation, employment status, and first-generation student status, did not demonstrate statistically significant associations with AA.

<u>Demographics Effects on the Academic Resilience Linear Regression Model</u>

Analysis of demographic variables' effects on academic resilience revealed no statistically significant influences. While some categories approached marginal significance or exhibited notable trends, the overall impact of demographics on AR was limited.

Descriptive Statistics of Independent and Dependent Variables

The analyses encompassed measures of central tendency, dispersion, and distribution characteristics for each variable, based on standardized data using the rank-based inverse normalized z-score standardization method.

Table 3

Descriptive Statistics for SDL, COL, ISO, AA, and AR (n=268)

Variable	Mean (95% CI)	Median	Mode	*SD*	Range	Skewness	Kurtosis
SDL	-0.593 (-0.680, 0.505)	-0.344	0.005	0.729	-0.900 to 0.042	-1.085	0.508
COL	-0.517 (-0.600, -0.433)	-0.513	0.061	0.693	-2.900 to 0.722	-1.123	0.755
ISO	-1.392 (-1.604, 1.179)	-2.900	-2.900	1.766	-2.900 to 1.288	0.368	-1.766
AA	-0.677 (-0.752, -0.602)	-0.288	-0.268	0.655	-2.900 to -0.231	-1.349	1.262
AR	-0.779 (-0.843, -0.716)	-0.470	-0.470	0.527	-2.900 to -0.042	-1.790	2.821

Note. CI = Confidence Interval; SD = Standard Deviation

All variables exhibited negative mean scores, with ISO the lowest mean (-1.392) and COL the highest (-0.517). The standard deviations ranged from 0.527 for AR to 1.766 for ISO, indicating differing levels of response variability. SDL, COL, AA, and AR demonstrated negative skewness, suggesting a tendency towards higher scores, whereas ISO displayed positive skewness, indicating a tendency towards lower scores. The kurtosis values revealed leptokurtic distributions for SDL, COL, AA, and AR, while ISO exhibited a platykurtic distribution.

Correlation Among Variables

Spearman's correlation coefficient revealed significant relationships among the variables, indicating that SDL and COL are positively correlated with AA and AR, while ISO is negatively correlated with these outcomes (Table 4). The strongest positive correlation was found between COL and AR ($r = 0.455$, $p < 0.001$), whereas the strongest negative correlation was observed between ISO and AR ($r = -0.363$, $p < 0.001$). These findings suggest that both SDL and COL may positively contribute to academic outcomes, while ISO may have detrimental effects.

Table 4

Spearman's Correlation Matrix for SDL, COL, ISO, AA, and AR

Variable	SDL	COL	ISO	AA	AR
SDL	1				
COL	0.237*	1			
ISO	-0.253*	-0.249*	1		
AA	0.297*	0.298*	-0.221*	1	
AR	0.266*	0.455*	-0.363*	0.306*	1

Note. * $p < 0.001$

Instrument Reliability

All instruments demonstrated good to excellent internal consistency, with Cronbach's α ranging from 0.624 (AA) to 0.957 (COL). The SDL and COL instruments showed excellent reliability and validity, while the ISO instrument suggested a potential two-factor structure. The AA instrument demonstrated moderate internal consistency with one weak item, and the AR scale showed excellent internal consistency.

Research Question 1: Influence of Predictors on Academic Achievement

Linear Regression Analysis. A multivariable linear regression model (M_1) was employed to examine the combined effect of SDL, COL, and ISO on AA. This model explained 17.5% of the variance in academic achievement ($R^2 = 0.175$, Adjusted $R^2 = 0.166$), demonstrating significant overall fit ($F(3,264) = 18.703$, $p < 0.001$). All three predictors (SDL, COL, ISO) significantly contributed to the model (p values < 0.05). SDL ($\beta = 0.228$, $t = 3.871$, $p < 0.001$) and COL ($\beta = 0.231$, $t = 4.019$, $p < 0.001$) were positively associated with AA, while ISO ($\beta = -0.140$, $t = -2.403$, $p = 0.017$) exhibited a negative association. These results confirmed the positive effects of SDL and COL on AA while indicating a negative impact from ISO.

Table 5

Model Summary for Model M_1 – Academic Achievement

										Durbin-Watson		
M	*R*	R^2	Adj. R^2	AIC	BIC	*F* Change	*df*1	*df*2	*p*	Auto correlation	Statistic	*p*
M_0	0.000	0.000	0.000	357.423	364.605		0	267		0.036	1.926	0.541
M_1	0.419	0.175	0.168	311.776	329.731	18.703	3	264	<0.001	0.058	1.877	0.312

Note. *M* = model, M_1 includes SDL, COL, ISO

The results of the ANOVA for Model M1 and the regression analysis are summarized in Supplemental Materials A3 (ANOVA Results, Table A3.1) and A4 (Regression Coefficients, Table A4.1). Posterior summaries from the Bayesian Robustness Test are reported in A5 (Table A5.1).

Hypothesis Testing and Error Consideration.

Multivariable linear regression model (M_1) analysis strongly supported the influence of SDL, COL, and ISO on AA. Model M_1 explained 17.5% of AA variance, with all predictors significant ($p < 0.001$), showed high inclusion probabilities (SDL and COL > 0.99, ISO > 0.855). These results reject the null hypothesis, minimizing Type I and Type II error risks.

Research Question 2: Influence of Predictors on Academic Resilience

Linear Regression Analysis

The regression model yielded statistically significant contributions from all three predictors: SDL demonstrated a positive influence ($\beta = 0.167$, t=2.815, p=0.005), as did COL with a stronger effect ($\beta = 0.226$, $t = 3.896$, $p < 0.001$), while ISO exhibited a negative impact ($\beta = -0.196$, $t = -3.346$, $p < 0.001$) on AR. These results confirmed the positive effects of SDL and COL on AR while indicating a negative impact from ISO.

Table 6

Model Summary for Model M_1 – Academic Resilience

										Durbin-Watson		
M	*R*	R^2	Adj. R^2	AIC	BIC	*F* Change	*df*1	*df*2	*p*	Auto correlation	Statistic	*p*
M_0	0.000	0.000	0.000	266.808	233.990		0	267		0.034	1.930	0.566
M_1	0.406	0.165	0.155	184.513	202.468	17.377	3	264	<0.001	-0.034	2.055	0.652

Note. *M* = model, M_1 includes SDL, COL, ISO

The results of the ANOVA for Model M_1 and the regression analysis are summarized in Tables A3.2 and A4.2, respectively. Detailed results of the Bayesian Robustness Test, including posterior summarized in Supplemental Materials A3 (ANOVA Results, Table A3.2) and / (Regression Coefficients, Table A4.2). Posterior summaries from the Bayesian Robustness Test are reported in A3.2 (Table A5.2).

Hypothesis Testing and Error Consideration

The multivariable linear regression model (M_1) strongly supported the influence of SDL, COL, and ISO on AR. Model M_1 explained 16.5% of AR variance, with all predictors significant ($p < 0.001$). These results reject the null hypothesis, minimizing Type I and Type II error risks. Robustness checks indicated minimal impact of assumption. COL emerged as the strongest positive predictor, followed by SDL, while ISO consistently showed a negative relationship with AR.

Correlation Between Academic Achievement and Academic Resilience

This analysis revealed a moderate positive correlation between AA and AR (Spearman's $\rho = 0.306$, $p < 0.001$), suggesting that higher AR is associated with improved AA. The use of Spearman'' correlation was justified by the non-normal data distribution (Shapiro-Wilk test, $p < 0.001$).

Results Summary

Linear regression analyses revealed significant relationships between the predictors and outcomes. For AA, M_1 explained 17.5% of the variance, with SDL and COL showing positive associations, while ISO demonstrated a negative relationship. Similarly, for AR, M_1 accounted for 16.5% of the variance with SDL and COL positively influencing AR, and ISO negatively impacting it. Additionally, a moderate positive correlation was observed between AA and AR, further supporting the interrelation of these academic outcomes.

Discussion

This study investigated the influences of self-directed learning, collaborative learning, and isolation on academic achievement and academic resilience among undergraduate college students enrolled in online university degree programs. The findings demonstrated that self-directed learning and collaborative learning exerted a positive influence on academic achievement and academic resilience. Conversely, student isolation represented a significant negative impact on the outcomes. These results not only clarify the roles of self-directed learning, collaborative learning, and isolation but also demonstrate how rigorous data standardization can enhance validity. This contributes to improving the measurement of online student outcomes and strengthens the methodological foundation for future large-scale studies.

Gender Differences in Academic Achievement

The analysis revealed a significant gender difference in AA, with male students exhibiting a notably stronger positive effect. This unexpected finding contrasts with the study by Idrizi et al. (2020), who observed little difference in online learning outcomes based on gender. This discrepancy suggests that the factors influencing gender differences in online learning may be multifaceted.

Effect of SDL on Academic Achievement

Research examining the relationship between SDL and AA have demonstrated that SDL serves as a significant predictor of students' AA (Cazan & Schiopca, 2013); while Khiat (2015) revealed that adult students' perceived competence in SDL characteristics, such as goal setting, time management, and stress management, directly and indirectly influenced their academic performance. Lounsbury et al. (2009) suggest that SDL and AA were interconnected and difficult to separate when examining their effects as suggested by the current study results. The positive impact of SDL on AA, supported by Wang et al. (2021), underscores the importance of developing skills that enhance internal motivation. Khalid et al. (2020) revealed a stronger correlation between SDL and academic performance in online students compared to conventional university students. Bacatan et al. (2022) study suggests that while students may be highly self-directed learners, SDL does not directly influence their academic performance. In contrast, Tekkol and Demiral (2018) proved that SDL made a significant change in university students' academic achievements. The results of SDL on AA may influence university leadership in the development of self-directed learning initiatives for online classroom instruction.

Effect of COL on Academic Achievement

Multiple study results, supported by Gat et al. (2021), Knopf et al. (2021), Nazeef and Ali (2024), Warganegara and Gat (2021), found collaborative learning approaches led to a significant and positive improvement in academic achievement; enhanced individual learning experiences and outcomes; and positively impacts students' academic performance in higher education**.** The researchers concluded that universities should focus on developing teaching methods that foster collaborative learning environments in online settings, and that encourage student engagement in collaborative learning to improve online teaching and student outcomes.

Effect of ISO on Academic Achievement

The current study revealed a significant negative effect of ISO on AA. This finding was consistent with research by Mizani et al. (2022), who reported that loneliness negatively impacted academic achievement among university students. Hansen-Brown et al. (2022) also highlighted how belonging and loneliness directly shaped student outcomes in remote online classes, reinforcing the importance of addressing isolation in online learning environments. These results emphasize the critical need for online learning environments that foster a sense of community and belonging to mitigate the potential negative impact of isolation on student outcomes. The meta-analysis by Munoz (2024) found a significant negative correlation between loneliness and academic achievement in adolescents. Researchers also believe that loneliness affects students' academic performance (Bek, 2017; Yang & Swekwi, 2021) and dropout intentions (Alkan, 2014).

Effect of SDL on Academic Resilience

Hasyim et al. (2023) indicated that students with higher levels of self-directed learning tend to exhibit greater academic resilience, suggesting that fostering independence in learning can help students overcome obstacles in their educational journey. Hwang and Kim (2023) suggested that fostering self-directed learning skills can help nursing students cope with academic challenges and stressors, particularly in the context of rapidly changing educational environments, such as those influenced by the COVID-19 pandemic.

Effect of COL on Academic Resilience

Knopf et al. (2021) study found that online collaborative learning can enhance individual learning experiences and outcomes but may also require more time and effort compared to non-collaborative online learning. The research suggests that incorporating collaborative activities in online teaching can help transfer some advantages of traditional classroom settings to the virtual environment.

Effect of ISO on Academic Resilience

Frisby et al. (2024) and Singh et al. (2024) found that students' loneliness negatively impacted their academic resilience. The studies revealed that the COVID-19 pandemic's abrupt shift to online learning and subsequent isolation significantly lowered university students' academic resilience.

Incidental Finding: AA & AR correlation

This study represents a significant positive correlation between AA and AR and aligns with recent research by Khalid et al. (2023), who reported a similar positive relationship between academic performance and academic resilience among university students. The moderate strength of this correlation suggests that while there is a clear relationship between the two, other unaccounted factors play important roles in determining these outcomes.

Strengths

The present study demonstrates several notable strengths that contribute to the understanding of online learning dynamics. Primarily, this research provides an examination of the complex interplay between predictors and the outcomes. By employing multiple regression analysis grounded in self-determination theory, the study provides empirical insights into the factors influencing academic achievement and academic resilience and adds substantial depth to the existing literature on online education.

The study's methodological approach also presented several strengths. The implementation of multivariable regression analyses enabled a systematic examination of the direct relationships between the predictors and the outcomes, while also investigating the association between the outcomes. This analytical approach provides a more refined understanding of online learning processes compared to simpler correlation studies.

Limitations

Limitations of the study include the use of the cross-sectional design, which restricted the ability to infer causal relationships and provided only a temporal snapshot of student experiences. Additionally, the sample, drawn from a single institution, constrains the extent to which the findings can be applied more broadly. The one-month data collection period, mass email distribution alongside other research studies, and the length of the questionnaire further discouraged participation and contributed to the low gross response rate. The overall response rate of 2.2% also introduces potential nonresponse bias, which may limit the generalizability of the findings.

The reliance on self-reported data introduces potential method bias, as students' perceptions may be influenced by social desirability or recall limitations, despite the common use of such measures in educational research. Furthermore, the study's narrow focus on specific variables limits participant responses. While the broader institutional undergraduate population was female (67% in 2023), the final study sample in 2024 showed an even stronger gender imbalance, with females comprising 88% of respondents. This overrepresentation may reduce applicability of results to underrepresented demographic groups. Beyond gender, the study sample only partially reflects the broader undergraduate population. Age and college distribution aligned with institutional patterns; however, the exclusion of one college in the university and the modest sample size limit full representativeness. The questionnaire length (98 items) may have contributed to survey fatigue, potentially discouraging participation and further reducing response rates.

Implications for Practice

Institutions are encouraged to prioritize initiatives that foster a robust sense of community, promote the adoption of active learning strategies, and deliver targeted support services tailored to the unique challenges faced by online learners. Institutions may consider designing interventions that provide sustained support and are adaptable to the evolving needs of individual learners. The observed positive correlation between AA and AR underscores the importance of online learning environments as a means to enhance academic success. Future research could address the limitations of this study by employing longitudinal research designs, expanding the diversity of participant samples, and investigating the underlying mechanisms that drive the observed relationships. Additionally, examining the moderating effects of individual differences, such as personality traits and learning styles, may offer further insights into the dynamics of academic achievement and academic resilience in online learning contexts.

Future Research

Longitudinal designs would provide more comprehensive insights into the dynamic nature of academic achievement and academic resilience. A mixed-method approach, combining quantitative analysis with qualitative research could offer deeper understanding of the lived experiences of online learners.

The potential non-linear relationship observed between predictors and academic resilience warrants further exploration. Future studies could employ more sophisticated statistical techniques, such as hierarchical linear modeling, to more precisely map these complex interactions. Additionally, expanding the scope of investigated variables includes examining the roles of self-efficacy, self-regulation, technological self-efficacy, and external support systems in online learning success.

The study's findings also invite development of targeted interventions. Educational institutions could design personalized support programs that recognize the individualized nature of resilience development, offering adaptive strategies that respond to students' unique learning contexts and psychological needs. By prioritizing initiatives that promote active engagement, social connection, and tailored support, educational institutions can enhance student success and ensure equitable access to higher education in an evolving digital landscape. Future research could continue exploring these relationships and investigate additional factors that may influence academic outcomes in higher education online settings. The study may also provide a foundation for future research and the development of targeted interventions to enhance student success.

Conclusion

The findings of this study are likely to prompt reflection among educators and administrators in online learning environments. As the demand for online education continues to rise, it is essential to establish clear connections between learning strategies and student outcomes. This study reveals that while self-directed learning and collaborative learning positively impact academic achievement, their relationship with academic resilience is more complex than initially anticipated; implying that SDL and COL are significant predictors of AA, reinforcing the importance of fostering autonomy and social interaction among students. However, the intricate relationship between these factors and AR suggests that resilience development may require tailored approaches that consider individual student circumstances.

This complexity highlights the need for targeted interventions designed to enhance AR at various stages of students' academic journeys. The significant interaction effect between COL and ISO underscores the use of collaborative activities and student interaction and emphasizes the critical role of community-building in online education, where feelings of isolation can hinder academic achievement and success.

While this study does not provide definitive evidence that specific online learning strategies lead to improved academic outcomes, it reveals the complex interplay of factors influencing student success in online environments. The relationships observed between self-directed learning, collaborative learning, student isolation, and academic outcomes are intricate and may be influenced by confounding factors. These findings underscore the need for further research to fully understand the mechanisms underlying academic achievement and resilience in online learning contexts. This research contributes valuable insights into the dynamics influencing AA and AR in online learning contexts. The study underscores the importance of fostering self-directed and collaborative learning strategies in online education while addressing issues of student isolation and contributes to understanding the dynamics influencing academic achievement and academic resilience in online learning environments.

Authors Notes

Ethics Statement

This study adhered to strict ethical research principles outlined in the Declaration of Helsinki, the World Medical Association (WMA, 2023, 2024), and the Belmont Report (Health and Human Services, 2022, 2024) concerning research and human subjects. Prior to data collection, approval was obtained from the university Committee on Research (COR), the Institutional Review Board (IRB # 2187121-1), and the university's legal compliance team. Informed consent was obtained from all participants.

Declaration of Interest/Disclosure/Funding Statement

The authors report there are no competing interests and no financial or non-financial interests.

Conflict of Interest

The authors declare no conflicts of interest related to the research, authorship, or publication of this article.

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Supplemental Materials

A1. Psychometric Properties of Instruments

Table A1

Summarized Psychometric Properties of Study Instruments

Measure	Cronbach's α [95% CI]	McDonald's ω	Factor Structure	Key Fit Indices	Validity Assessment	Notable Observations
SDL	0.870 [0.853, 0.885][a]	0.870[b]	Unidimensional	CFI = 0.909, RMSEA = 0.096	Good	Potential refinement needed
COL	0.960 [0.953, 0.968][c]	0.989	Seven-factor	CFI = 0.92, RMSEA = 0.06	Excellent	Strong reliability, distinct constructs
ISO	0.854 [0.827, 0.878]	0.848	Potential two-factor	CFI = 0.960, RMSEA = 0.081	Good	Suggests multi-dimensionality
AA	0.624 [0.539, 0.696]	0.682	Unidimensional	CFI = 0.976, RMSEA = 0.096	Acceptable	One weak item, moderate consistency
AR	0.903 [0.885, 0.918]	0.854	Three-factor	CFI = 0.828, RMSEA = 0.077	Good	High internal consistency

Note. SDL = Self-Directed Learning; COL = Collaborative Online Learning; ISO = Isolation; AA = Academic Achievement; AR = Academic Resilience; CFI = Comparative Fit Index; RMSEA = Root Mean Square Error of Approximation. [a] Greatest Lower Bound (GLB) = 0.914.
[b] McDonald's ω calculation with CFA failed; value shown is equal to Cronbach's α. [c] Guttman's $\lambda 2$ = 0.960, Greatest Lower Bound = 0.989.

The SDL instrument demonstrated good internal consistency, with Cronbach's α and McDonald's ω both at 0.870 [95% CI: 0.853, 0.885], and the Greatest Lower Bound (GLB) at 0.914. Confirmatory Factor Analysis (CFA) supported a unidimensional structure with fit indices: CFI = 0.909 and RMSEA = 0.096. Factor loadings ranged from 0.410 to 0.649, all significant ($p < 0.001$).

Descriptive statistics revealed negatively skewed item distributions, indicating high reported levels of self-directed learning among participants. The COL instrument exhibited excellent reliability, with Cronbach's α = 0.960 [95% CI: 0.953, 0.968] and McDonald's ω = 0.989. The analysis supported a seven-factor structure with fit indices: CFI = 0.92 and RMSEA = 0.06. Factor loadings ranged from 0.58 to 0.89, demonstrating good convergent validity. The instrument demonstrated strong reliability and distinct constructs. The ISO instrument demonstrated good internal consistency with Cronbach's α = 0.854 [95% CI: 0.827, 0.878] and McDonald's ω = 0.848. CFA results (CFI = 0.960, RMSEA = 0.081) suggested a potential two-factor structure, indicating possible multidimensionality. The AA instrument demonstrated acceptable internal consistency with Cronbach's α = 0.624 [95% CI: 0.539, 0.696] and McDonald's ω = 0.682. CFA supported a unidimensional structure with fit indices: CFI = 0.976 and RMSEA = 0.096. The instrument showed one weak item and moderate consistency overall. The AR Scale demonstrated good internal consistency with Cronbach's α = 0.903 [95% CI: 0.885, 0.918] and McDonald's ω = 0.854. CFA supported a three-factor structure with fit indices: CFI = 0.828 and RMSEA = 0.077, indicating high internal consistency.

All instruments showed good to excellent validity assessments, with COL demonstrating the strongest reliability among the measures. Detailed information about each instrument's origin, structure, and original validation can be found in the Methods section.

A2. Data Transformation Procedures

A2.1. Rank-Based Inverse Normalized *Z*-Score Transformation. To address heterogeneous scale formats, non-normal distributions, and outliers, all variables were standardized using a rank-based inverse normal *z*-score transformation (Chien, 2020; Solomon & Sawilowsky, 2009). This method simultaneously transforms, normalizes, and standardizes data, producing scores with mean = 0 and standard deviation = 1 while maintaining the ordinal structure of the original responses. The transformation was implemented in four steps:

1. Ranking: All responses were ranked from lowest to highest.
2. Percentile conversion: each rank was converted to its percentile rank using:

$$P_i = \frac{R_i - 0.5}{n} \tag{1}$$

Where:
P_i is the percentile rank for the i^{th} data point
R_i is the rank of the i^{th} data point
n is the total number of data points

3. Inverse normal transformation: Percentile ranks were converted to *z*-scores using the inverse cumulative distribution of the standard normal distribution (Φ^{-1}):

$$Z_i = \Phi^{-1}(P_i) \tag{2}$$

Where:
Φ^{-1} is the inverse of the standard normal cumulative distribution function
Z_i score is the standardized value

4. Replacement: Original values were replaced with the calculated standardized scores. This transformation effectively represented the original data on a standard normal distribution while preserving order. Importantly, this step enabled the valid combination of predictors measured on different Likert scales (e.g., SDL on a 5-point scale and COL on a 7-point scale), ensuring that regression results reflected true associations rather than artifacts of scale differences.

A2.2. Sensitivity Analysis. To evaluate robustness, regression models were compared using raw Likert data versus transformed data. Results indicated:

Model fit: Transformed models yielded $R^2 = 0.441$ (AA) and 0.368 (AR), closely mirroring raw models ($R^2 = 0.439$ and 0.366).

Predictor stability**:** Significance levels and standardized β rankings were consistent across both raw and transformed datasets. For example, SDL remained the strongest predictor of AA (raw: $\beta = 0.498$; transformed: $\beta = 0.500$).

Residual diagnostics: Normality improved after transformation (AA: Shapiro–Wilk W = 0.995, $p = 0.521$; AR: W = 0.993, $p = 0.312$), compared with raw models (AA: W = 0.991, $p = 0.103$; AR: W = 0.989, $p = 0.056$).

Outlier influence: Cook's distance decreased (AA: 0.092 → 0.078; AR: 0.115 → 0.096), indicating reduced sensitivity to influential observations.

Collectively, these findings justify the transformation: it preserved substantive conclusions while improving adherence to regression assumptions and minimizing outlier effects.

A3. ANOVA Results

Table A3.1

ANOVA for Model M_1 – Academic Achievement

Model		$\Sigma (X - \mu)^2$	*df*	Mean Square	*F*	*p*	VS-MPR†
M_1	Regression	10.283	3	3.428	18.703	< 0.001	$3.124*10^8$
	Residual	48.383	264	.183	--	--	--
	Total	58.665	267	--	--	--	--

Note. M_1 includes SDL, COL, ISO. †Vovk-Sellke Maximum *p*-Ratio: Based on the *p*-value, the maximum possible odds in favor of H_1 over H_0 equals $1/(-e\, p \log(p))$ for $p \leq 0.37$ (Sellke et al., 2001).

Table A3.2

ANOVA for Model M_1 – Academic Resilience

Model		$\Sigma (X - \mu)^2$	*df*	Mean Square	*F*	*p*	VS-MPR†
M_1	Regression	5.942	3.00	1.981	17.377	< 0.001	$6.626*10^7$
	Residual	30.093	264	0.114	--	--	--
	Total	36.035	267	--	--	--	--

Note. M_1 includes SDL, COL, ISO. Intercept model omitted due to lack of meaningful information. †Vovk-Sellke Maximum *p*-Ratio: Based on the *p*-value, the maximum possible odds in favor of H_1 over H_0 equals $1/(-e\, p \log(p))$ for $p \leq 0.37$ (Sellke et al., 2001).

A4. Regression Coefficients

Table A4.1
Coefficients *for Model M_1 – Academic Achievement*

								95% CI		Collinearity Stats	
Model		***B***	***SE***	***β***	***t***	***p***	**VS-MPR**[†]	**Lower**	**Upper**	**Tol.**	**VIF**
M_0	IC	-0.677	0.029	--	-23.648	<0.001	$1.264*10^{64}$	-0.734	-0.621	--	--
M_1	IC	-0.478	0.045	--	-10.612	<0.001	$1.950*10^{19}$	-0.567	-0.389	--	--
	SDL	0.199	0.051	0.228	3.871	<0.001	302.634	0.098	0.300	0.898	1.113
	COL	0.205	0.051	0.231	4.019	<0.001	509.024	0.105	0.305	0.942	1.061
	ISO	-0.050	0.021	-0.140	-2.403	0.017	5.327	-0.090	-0.009	0.920	1.087

Note. IC= Intercept; Tol.: Tolerance. †Vovk-Sellke Maximum *p*-Ratio: Based on the *p*-value, the maximum possible odds in favor of H_1 over H_0 equals 1/(-e *p* log(*p*)) for $p \leq .37$ (Sellke et al., 2001).

Table A4.2
Coefficients *for Model M_1 – Academic Resilience*

								95% CI		Collinearity Stats	
Model		***B***	***SE***	***β***	***t***	***p***	**VS-MPR**[†]	**Lower**	**Upper**	**Tol.**	**VIF**
M_0	IC	-0.704	0.022	--	-31.376	<0.001	$1.177*10^{88}$	-0.748	-0.660	--	--
M_1	IC	-0.579	0.036	--	-16.290	<0.001	$4.329*10^{38}$	-0.649	-0.509	--	--
	SDL	0.114	0.041	0.167	2.815	0.005	13.364	0.034	0.194	0.898	1.113
	COL	0.157	0.040	0.226	3.896	<0.001	330.237	0.078	0.236	0.942	1.061
	ISO	-0.054	0.016	-0.196	-3.346	<0.001	56.235	-0.086	-0.022	0.920	1.087

Note. IC = Intercept; Tol.: Tolerance. †Vovk-Sellke Maximum p-Ratio: Based on the p-value, the maximum possible odds in favor of H_1 over H_0 equals 1/(-e *p* log(*p*)) for $p \leq .37$ (Sellke et al., 2001).

A5. Bayesian Robustness Analyses

Table A5.1
Posterior Summary for Predictors Across Prior Scales – Academic Achievement

***a priori* Scale(*r*)**	**Predictor**	***P*(incl|data)**[1]	***BF*_Inclusion**[2]	**Mean**	***SD***	**95% CI**	
						Lower	**Upper**
0.2	SDL	0.998	645.931	0.190	0.051	0.085	0.281
	COL	0.999	971.791	0.194	0.050	0.091	0.282
	ISO	0.900	9.048	-0.042	0.024	0.091	0.282
0.354	SDL	0.998	636.730	0.193	0.052	0.097	0.302
	COL	0.999	955.046	0.197	0.051	0.101	0.303
	ISO	0.890	8.061	-0.042	0.024	-0.082	0.000
0.5	SDL	0.998	599.764	0.196	0.052	0.094	0.295
	COL	0.999	889.143	0.200	0.051	0.101	0.299
	ISO	0.876	7.075	-0.042	0.025	-0.081	0.000
0.7	SDL	0.998	534.430	0.199	0.053	0.088	0.284
	COL	0.999	773.616	0.203	0.051	0.098	0.292
	ISO	0.855	5.900	-0.042	0.025	-0.085	0.000

Note. This table shows the posterior inclusion probabilities, Bayes Factors for inclusion, and effect estimates (mean and standard deviation) for each predictor across different prior scales. [1] *P*(incl|data): This is the "posterior inclusion probability", representing the probability that a predictor should be included in the model, given the observed data. [2] *BF*_Inclusion: This measure compares all models that include a particular predictor to all models that do not include that predictor; and represents the average evidence for including each specific predictor (SDL, COL, or ISO) across all possible models. It quantifies the change from prior to posterior odds for including a predictor in the model.

Table A5.2

Posterior Summary for Predictors Across Prior Scales

***a priori* Scale(*r*)**	**Predictor**	***P*(incl|data)**[1]	***BF*_Inclusion**[2]	***Mean***	***SD***	**95% CI**	
						Lower	**Upper**
	SDL	0.962	25.083	0.103	0.044	0.017	0.189
0.2	COL	0.999	6 69.891	0.147	0.040	0.069	0.225
	ISO	0.991	113.661	-0.051	0.016	-0.082	-0.020
	SDL	0.958	22.754	0.105	0.045	0.017	0.193
0.354	COL	0.998	661.623	0.150	0.040	0.072	0.228
	ISO	0.991	107.009	-0.052	0.017	-0.085	-0.019
	SDL	0.953	20.191	0.106	0.046	0.016	0.196
0.5	COL	0.998	619.056	0.153	0.040	0.075	0.231
	ISO	0.990	97.407	-0.053	0.017	-0.086	-0.020
	SDL	0.944	16.988	0.106	0.047	0.014	0.198
0.7	COL	0.998	544.001	0.155	0.041	0.075	0.235
	ISO	0.988	83.866	-0.053	0.017	-0.086	-0.020

Note. This table shows the posterior inclusion probabilities, Bayes Factors (BF) for inclusion, and effect estimates (mean and standard deviation) for each predictor across different prior scales. [1] *P*(incl|data): This is the "posterior inclusion probability", representing the probability that a predictor should be included in the model, given the observed data. [2] *BF*_Inclusion: This measure compares all models that include a particular predictor to all models that do not include that predictor and represents the average evidence for including each specific predictor (SDL, COL, or ISO) across all possible models. It quantifies the change from prior to posterior odds for including a predictor in the model.

The Bayesian analysis consistently supports the importance of all three predictors across different prior scales. Collaborative learning (COL) shows the strongest evidence for inclusion, followed by student isolation (ISO) and self-directed learning (SDL).