The Mediating Effect of Academic Buoyancy on the Causal Chains of Online Learning Readiness, Academic Motivation, and Academic Performance

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Abstract
This study investigated how online learning readiness, academic motivation, and academic buoyancy influence academic performance among high school students in an online learning environment during the 2021–2022 school year. Drawing on a descriptive-correlational design and structural equation modeling, the study explored both direct and indirect relationships among these constructs. Results showed that students demonstrated high levels of readiness, motivation, and buoyancy. Notably, online learning readiness positively influenced both academic buoyancy and academic motivation, while academic buoyancy emerged as a critical mediator—channeling the effects of readiness into increased motivation and improved academic performance. In contrast, motivation alone did not significantly mediate the relationship between readiness and performance. These findings underscore the importance of buoyancy in enabling students to convert their preparedness for online learning into tangible academic success. The study highlights the need for educational interventions that not only enhance technical readiness but also build students' capacity to adapt, persist, and recover from academic challenges in an online learning environment.

Keywords: Online learning readiness, academic motivation, academic buoyancy, academic performance

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Introduction

Educational institutions worldwide, including the Philippines, have experienced a shift in learning modalities in recent years. Online learning, which complements or replaces in-person classes, offers benefits such as flexibility, convenience, and more opportunities for collaboration. However, high-aptitude Science, Technology, Engineering, and Mathematics (STEM) learners who lack the skills and resilience required for remote instruction have exhibited declining motivation, poor coping with everyday academic setbacks, and lower grades. This study, therefore, examines how students' preparedness for online learning, their academic buoyancy, and their motivation influences academic performance in an online learning environment.

Online learning—also called digital, virtual, or web-based learning—delivers instruction and content primarily via the internet, whether synchronously or asynchronously, and in hybrid or fully remote formats. This distinction matters because students' readiness and resilience needs may vary depending on whether they engage in hybrid or fully remote formats (Barbour et al., 2011; Morrison, 2003; Peña-Bandalaria, 2009; Sadiku et al., 2018; Stauffer, 2020; Tsai & Machado, 2002).

In 2020, the COVID-19 pandemic disrupted education globally. In response, schools in the Philippines adopted various learning delivery modes, such as modular, online, blended, and radio/TV-based learning (Republic of the Philippines Department of Education, 2020). The Philippine Science High School (PSHS), which serves high-aptitude STEM scholars, transitioned to blended learning, combining modular and online classes in the curriculum under remote or blended learning beginning in the 2020–2021 school year.

This sudden shift posed challenges for many students. Some experienced difficulties in submitting requirements, earning satisfactory grades, staying motivated, and managing their mental well-being. While distance learning offers flexibility and convenience, it also requires strong motivation, self-discipline, and independent study habits (Mirkholikovna, 2020; Simpson, 2013). Limited social interaction, poor internet access, and a lack of proper tools have added to the difficulties faced by learners (Barbour et al., 2011; Chung et al., 2020).

The shift to online learning has made it more important than ever for students to have the cognitive, emotional, and behavioral skills needed to succeed in less structured settings. Online learning readiness (OLR) includes computer/internet self-efficacy, learner control, motivation for online learning, online communication self-efficacy, self-directed learning, self-efficacy, and digital engagement (Chung et al., 2020; Demir Kaymak & Horzum, 2013; Doe et al., 2017; Hung et al., 2010), all crucial in online classes. However, readiness alone may be insufficient. Academic buoyancy, or the ability to deal with day-to-day academic challenges, plays a key role in keeping students engaged. Academic buoyancy predictors, as observed in various studies, include self-efficacy, certain control, academic engagement, academic anxiety, and teacher-student relationship (Einy et al., 2019; Martin & Marsh, 2008; Sadeghi & Khalili Geshnigani, 2016). Buoyant learners are more likely to maintain motivation, which can lead to better academic performance (Barnett, 2012; Colmar et al., 2019; Collie et al., 2015; Datu & Yang, 2019; Datu & Yuen, 2018; Putwain & Daly, 2013).

This study aims to examine how OLR, academic buoyancy, and academic motivation interact to influence academic performance among high-aptitude STEM students in a Philippine STEM high school by modeling the direct and indirect effects of OLR with buoyancy and motivation as mediating variables. While previous structural equation modeling (SEM) studies have linked OLR to motivation and performance (Horzum et al., 2015; Saeid & Eslaminejad, 2017), this is the first to integrate academic buoyancy as a mediator within a Philippine STEM high school context, offering a more comprehensive understanding of student success in online and blended learning environments.

Review of Related Literature

Online Learning Readiness

Online learning readiness (OLR) encompasses the cognitive, technical, and self-regulatory competencies that enable students to succeed in internet-based courses (Hung et al., 2010; Chung et al., 2020). Empirical evidence indicates that higher OLR predicts greater course satisfaction and performance: for example, computer/internet self-efficacy and motivation for online learning positively influence online discussion performance and overall satisfaction (Wei & Chou, 2020), while self-directed learning is one of the strongest predictors of achievement in online settings (Çiğdem & Öztürk, 2016). Furthermore, increased OLR has enhanced academic motivation (Horzum et al., 2015) and supports adaptive learning strategies when students have adequate technology access and guidance (Yasin et al., 2020).

Academic Motivation and Self-Determination Theory

Academic motivation refers to the processes that energize and direct students' learning behaviors. Rooted in Self-Determination Theory (SDT) (Deci & Ryan, 2004), motivation ranges from amotivation through extrinsic regulation to intrinsic regulation, with fulfillment of the basic psychological needs for competence, autonomy, and relatedness fostering more self-determined forms of motivation. In online contexts, students who feel competent (through computer/internet self-efficacy and self-directed learning), autonomous (through learner control and motivation for online learning), and connected (through online communication self-efficacy and teacher–student relationships) are more likely to develop intrinsic motivation, which in turn is linked to higher persistence and achievement (Datu, 2017; Usán et al., 2019).

While SDT posits that fulfilling competence, autonomy, and relatedness needs enhances intrinsic motivation (Deci & Ryan, 2004), few studies have tested whether motivation mediates the translation of readiness into performance.

Academic Buoyancy

Academic buoyancy is defined as students' capacity to successfully manage everyday academic setbacks—such as low grades, conflicting deadlines, and test anxiety—distinct from resilience, which addresses more severe adversities (Martin & Marsh, 2008; Martin et al., 2010). Key antecedents of buoyancy include self-efficacy, academic engagement, self-regulation, and supportive teacher–student relationships (Martin et al., 2010; Yun et al., 2018). Research shows that buoyant students maintain motivation and perform better academically under routine stressors (Colmar et al., 2019; Datu & Yuen, 2018), and that buoyancy can mediate the effects of other constructs—such as self-regulation and motivation—on performance (Datu & Yang, 2019; Putwain & Daly, 2013).

Academic buoyancy has been linked to improved performance under routine stressors (Datu & Yuen, 2018), but its role as a mediator between readiness and motivation—or between readiness and performance—has not been tested in a single integrated model.

Although OLR, academic motivation, and academic buoyancy each predict academic performance in online learning, few studies have examined their joint and mediating relationships—especially among STEM high school students in the Philippines. Past models have linked readiness to motivation (Horzum et al., 2015) and buoyancy to performance (Yun et al., 2018), but none have simultaneously tested whether academic buoyancy and motivation mediate the pathways from OLR to performance. High-aptitude STEM students may experience unique demands in blended environments, underscoring the need for an integrated model in this context.

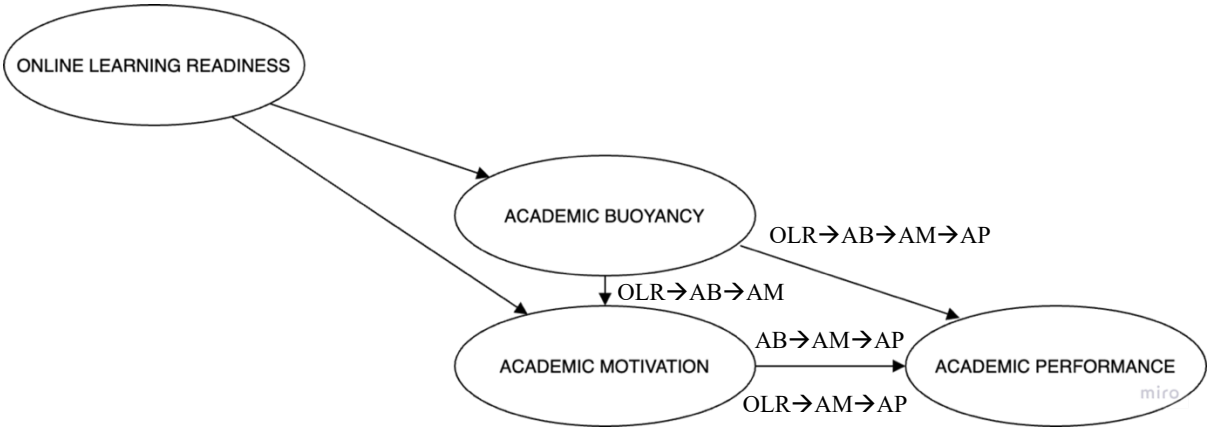
This study is grounded in SDT, which posits that fulfilling competence, autonomy, and relatedness needs enhances students' intrinsic motivation (Deci & Ryan, 2004; Martela & Riekki, 2018). This suggests that OLR provides the control beliefs and perceived competence necessary for academic buoyancy and motivation, which in turn drive academic performance.

Conceptual Framework

Figure 1 illustrates the hypothesized relationships among the study's constructs. Online learning readiness is assumed to have direct effects on academic buoyancy, academic motivation, and academic performance. Academic buoyancy is hypothesized to mediate the relationship between OLR and both motivation and performance, while academic motivation is hypothesized to mediate the relationship between buoyancy and performance, as well as between OLR and performance directly.

Figure 1

Conceptual Framework of the Mediating Roles of Academic Buoyancy and Academic Motivation in the Relationship Between Online Learning Readiness and Academic Performance



Building on these theoretical and empirical foundations, this study addresses the following questions:

1. To what extent does online learning readiness predict academic buoyancy, academic motivation, and academic performance?

2. Does academic buoyancy mediate the relationship between online learning readiness and academic motivation?
3. Does academic buoyancy mediate the relationship between online learning readiness and academic performance?
4. Does academic motivation mediate the relationship between academic buoyancy and academic performance?
5. Does academic motivation mediate the relationship between online learning readiness and academic performance?

Assumptions

1. Online learning readiness will significantly predict academic buoyancy, academic motivation, and academic performance.
2. Academic buoyancy will mediate the relationship between online learning readiness and academic motivation.
3. Academic buoyancy will mediate the relationship between online learning readiness and academic performance.
4. Academic motivation will mediate the relationship between academic buoyancy and academic performance.
5. Academic motivation will mediate the relationship between online learning readiness and academic performance.

Methods

Research Design

This study employed a quantitative research design using multivariate statistical analysis to examine the structural relationships among observed and latent variables in the context of online learning. Specifically, structural equation modeling (SEM) was used to assess both measurement validity and hypothesized relationships while accounting for measurement error. SEM is a robust analytic technique that allows for the simultaneous testing of direct and indirect effects among multiple constructs, providing deeper insights into underlying theoretical frameworks (Da Costa, 2018; Mohamad et al., 2019).

The SEM consists of two main components: confirmatory factor analysis (CFA) to validate the measurement models, and path analysis to test mediating relationships among latent variables. The approach was particularly suited for this study given its focus on testing sequential mediation and its use of validated latent constructs drawn from the Online Learning Readiness Scale (OLRS), Academic Motivation Scale (AMS), and Academic Buoyancy Scale (ABS). These instruments represent theoretically distinct domains aligned with the study's conceptual framework, and SEM's latent-variable approach minimizes measurement error across these scales (Byrne, 2013).

Participants

Participants were 489 science high school students enrolled during the 2021–2022 academic year. Given the small population size and the importance of including all relevant students, total population sampling was employed. Admission to the school is based on performance in a national competitive examination or a predicted score under special conditions, such as calamities or pandemics. The curriculum is structured into three levels: Foundation Years

(Grades 7–8), Advancement Years (Grades 9–10), and Specialization Years (Grades 11–12), with a strong emphasis on science, technology, engineering, and mathematics (STEM) education. Although the grade levels differ in age and curricular focus, data were pooled across Grades 7–12 to maximize statistical power. Table 1 presents the demographic breakdown of participants by grade level and sex.

Table 1

*Demographic Profile of Respondents (*N = *489)*

Respondents	Male	%	Female	%	Total	%
Grade 7	48	9.8%	65	13.3%	113	23.1%
Grade 8	54	11.0%	40	8.2%	94	19.2%
Grade 9	58	11.9%	41	8.4%	99	20.2%
Grade 10	37	7.6%	30	6.1%	67	13.7%
Grade 11	30	6.1%	29	5.9%	59	12.1%
Grade 12	31	6.3%	26	5.3%	57	11.7%
Total	**258**	**52.8%**	**231**	**47.2**	**489**	**100.0%**

Instruments

Three validated self-report instruments were used to measure the study's key constructs: the Online Learning Readiness Scale (OLRS) is an 18-item instrument with five subscales. Items are rated on a 5-point Likert scale. Reported reliability coefficients ranged from α = .727 to .871 (Hung et al., 2010). The Academic Motivation Scale (AMS) measures intrinsic motivation, extrinsic motivation, and amotivation on a 5-point Likert scale. Internal consistency for the full scale was α = .81, with subscale alphas ranging from .70 to .86 (Vallerand et al., 1993). The Academic Buoyancy Scale consists of four subscales, with items rated on a 5-point Likert scale. Reliability coefficients for these subscales ranged from α = .748 to .923 **(**Yun et al., 2018).

Measurement Model Validation

Given that the OLRS, AMS, and ABS instruments have well-established factor structures, exploratory factor analysis was deemed unnecessary. Following best practices for confirmatory measurement modeling (Brown, 2015), confirmatory factor analysis was conducted using the full sample ($N = 489$) to validate the factor structure of each instrument.

Model fit was assessed using multiple indices: chi-square to degrees of freedom ratio (χ^2/df), root mean square error of approximation (RMSEA), and standardized root mean square residual (SRMR), following the two-index presentation strategy (Hu & Bentler, 1999). Acceptable fit was defined as $\chi^2/df < 3.00$, RMSEA < .08, and SRMR < .08 (Awang, 2015). All factor loadings exceeded .50 ($p < .001$), confirming construct validity. Table 2 shows model fit indices for both the initial and modified models.

Table 2

Model Fit Indices for Confirmatory Factor Analysis

Model	χ^2	df	p	$\frac{\chi^2}{df} < 3$	SRMR $<.08^a$	RMSEA $<.08^a$	RMSEA 90% CI		RMSEA p
							Lower	Upper	
Initial	5785	2128	<.001	2.71	.799	.059	.057	.061	<.001
Modified	3444	1510	<.001	2.28	.062	.051	.049	.053	0.194

Note. ^{a} indicates the range of acceptable levels of fit

Although the χ^2 test remained statistically significant—an expected outcome in large samples—it is well documented that χ^2 tends to over-reject well-fitting models under such conditions (Kline, 2015). Thus, greater interpretive weight was placed on χ^2/df, RMSEA, and SRMR, all of which indicated acceptable model fit.

Reliability and Validity

To evaluate the constructs' reliability and validity, composite reliability (CR) and average variance extracted (AVE) were calculated. CR values of ≥0.70 and AVE values of ≥0.50 were considered acceptable indicators of construct reliability and convergent validity. Discriminant validity was established by confirming that the square root of each construct's AVE (shown as diagonal elements in parentheses) exceeded its inter-construct correlations (off-diagonal elements). Tables 3 to 5 present these values for the OLRS, ABS, and AMS, respectively.

Although the chi-square (χ^2) test was statistically significant—expected due to the large sample size and number of estimated parameters—this is a known limitation in SEM (Kline, 2015; Marsh et al., 1996). Therefore, model fit was primarily assessed using alternative indices: χ^2/df = 2.28**,** RMSEA = .051 (90% CI [.049–.053]), and SRMR = .062**,** all of which fall within the recommended thresholds for acceptable model fit (Awang, 2015; Hu & Bentler, 1999).

Table 3

*Reliability and Discriminant Validity for the Online Learning Readiness Scale (*N = *489)*

Sub-construct	Items	CR	AVE	CIS	SDL	OCS
CIS	3	.876	.702	(.838)		
SDL	8	.922	.529	.452	(.727)	
OCS	3	.800	.573	.423	.590	(.757)

Note. CR = composite reliability; AVE = average variance extracted. Diagonal values (in parentheses) are the square roots of the AVE; off-diagonal values are inter-construct correlations.

Table 3 summarizes the psychometric properties of the OLRS. Its CR values for its sub-constructs range from .800 to .922, while all AVEs exceed .50, indicating good construct reliability and convergent validity. The square root of the AVE for each sub-construct also exceeds its intercorrelations, supporting discriminant validity. Overall, the measurement model demonstrates acceptable reliability and validity for assessing students' OLR.

Table 4

*Reliability and Discriminant Validity for the Academic Buoyancy Scale (*N *= 489)*

Sub-construct	Items	CR	AVE	SE	CC	AE	TSR
SE	4	.868	.623	(.790)			
CC	5	.880	.596	.659	(.772)		
AE	4	.812	.520	.568	.628	(.721)	
TSR	5	.874	.585	.374	.477	.507	(.765)

Note. CR = composite reliability; AVE = average variance extracted. Diagonal values (in parentheses) are the square roots of the AVE; off-diagonal values are inter-construct correlations.

Table 4 presents the results for the ABS. Its CR values range from .812 to .880, and AVE values from .520 to .623, supporting construct reliability and convergent validity. Discriminant validity is also supported, as each sub-construct's AVE square root is higher than its correlations with other sub-constructs. These results confirm the measurement model's adequacy for assessing academic buoyancy.

Table 5

Reliability and Discriminant Validity for the Academic Motivation Scale (N = 489)

Sub-construct	Items	CR	AVE	IM	EM	AMO
IM	11	.945	.611	(.782)		
EM	9	.907	.522	.514	(.723)	
AMO	4	.922	.746	.380	.599	(.864)

Note. CR = composite reliability; AVE = average variance extracted. Diagonal values (in parentheses) are the square roots of the AVE; off-diagonal values are inter-construct correlations.

Table 5 displays findings for the AMS. Sub-constructs yield CR values between .907 and .945, with AVEs ranging from .522 to .746. The square roots of AVEs surpass inter-construct correlations, demonstrating discriminant validity. These metrics confirm the model's reliability and validity for capturing academic motivation.

Academic Performance

Academic performance was assessed using students' academic performance grades (APGs) for the corresponding academic quarter. These were obtained from official school records with the approval of the campus director. Ethical approval was granted by the school administration, and informed consent was secured from all participants. Participant anonymity and data confidentiality were strictly maintained throughout the study.

Limitations

First, although we used total-population sampling (n = 489), our study is confined to one STEM high school, limiting generalizability. Second, grades 7–12 were analyzed as a single group; future work should disaggregate by year level to explore developmental differences. Third, while SEM provided robust tests of mediation, causal inferences remain tentative in this cross-sectional design. Finally, despite our CFA steps, self-report instruments are subject to response biases.

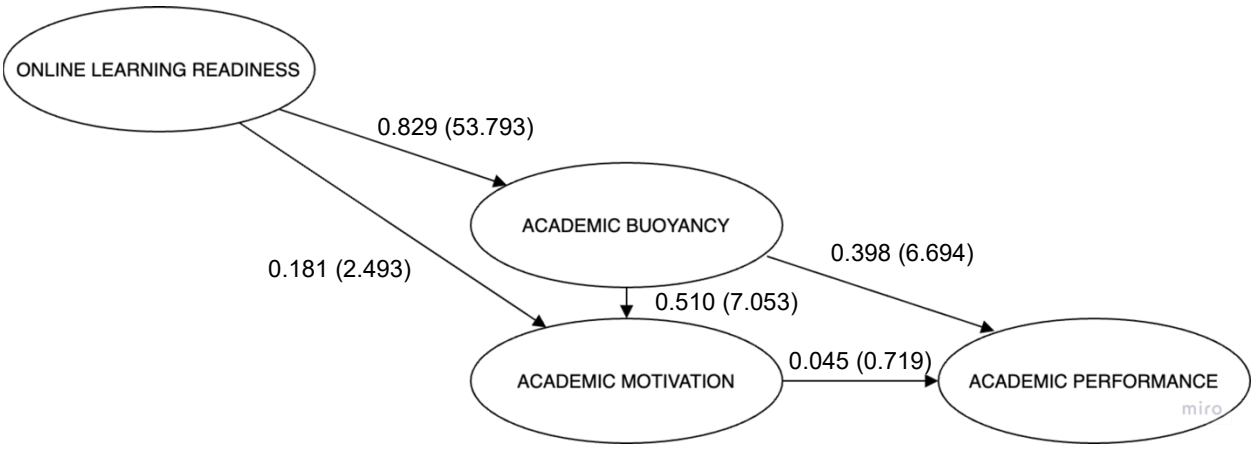
Results and Discussions

Measurement Model

Confirmatory factor analyses of the OLRS, ABS, and AMS instruments demonstrated acceptable model fit indices ($\chi^2/df \leq 2.28$, RMSEA $\leq .051$, SRMR $\leq .062$). All constructs exhibited adequate internal consistency (composite reliability $\geq .80$) and convergent validity (average variance extracted $\geq .50$), confirming the robustness of the measurement model.

Figure 2

Path Analysis Result of the Conceptual Model



Direct Effects

Online learning readiness was hypothesized to directly predict academic buoyancy and academic motivation. As shown in Figure 2, the path from OLR to academic buoyancy was strong and significant ($\beta = .829$, $t = 53.793$, $p < .001$), and the path from academic buoyancy to academic motivation was also significant ($\beta = .510$, $t = 7.053$, $p < .001$). These findings confirm that students who possess strong time-management, self-discipline, and technical self-efficacy skills report higher everyday resilience (Martela & Riekki, 2018), which in turn fosters intrinsic motivation (Deci & Ryan, 2004).

Mediated Effect

The mediation analysis as shown in Table 6 revealed several key findings. First, academic buoyancy significantly mediated the relationship between online learning readiness and academic motivation ($\beta = .423$, $p < .001$), indicating that students who are well-prepared for online learning are more likely to develop motivation through their capacity to handle everyday academic challenges. Similarly, academic buoyancy also significantly mediated the relationship between online learning readiness and academic performance ($\beta = .330$, $p < .001$), suggesting that students who can effectively rebound from setbacks are better able to convert their readiness

into higher academic achievement. In contrast, academic motivation did not significantly mediate the relationship between online learning readiness and academic performance, nor between academic buoyancy and performance, diverging from earlier findings by Horzum et al. (2015). Finally, the full chain mediation pathway—from online learning readiness through academic buoyancy and motivation to academic performance—was also not significant, indicating that while buoyancy plays a crucial role, motivation alone does not fully account for the link between readiness and achievement in this context.

Table 6

*Path Coefficients for Mediation (*N = *489)*

Assumption	Path	*β*	*t*	*p*	*LLCI*	*ULCI*	Outcome
A1	OLR →AB → AM → AP	.019	.705	.241	-0.022	0.066	Not Supported
A2	OLR → AB → AM	.423	7.212	<.001	0.319	0.521	Supported
A3	OLR → AB → AP	.330	6.195	<.001	0.242	0.413	Supported
A5	AB → AM → AP	.023	.706	.240	-0.026	0.080	Not Supported
A4	OLR → AM → AP	.008	.609	.272	-0.009	0.032	Not Supported

Note. OLR = online learning readiness; AB = academic buoyancy; AM = academic motivation; AP = academic performance; LLCI = lower-level confidence interval (95%); ULCI = upper-level confidence interval (95%).

These results indicate that in this high-aptitude STEM context, academic buoyancy, rather than motivation alone, is the more immediate driver of academic performance. Contrary to Horzum et al. (2015), motivation alone did not drive performance in this high-aptitude STEM context during pandemic-era blended learning.

Online Learning Readiness and Academic Buoyancy

The significant OLR → AB effect underscores the role of readiness in fostering adaptive academic responses. Students who are better prepared for the demands of online learning tend to exhibit greater resilience in navigating daily academic challenges. This finding is consistent with the control-value theory of achievement emotions and resilience frameworks (Martin & Marsh, 2008; Martela & Riekki, 2018).

Academic Buoyancy as a Mediator

Academic buoyancy emerged as a critical mediator, transmitting the effects of readiness to both motivation and performance. This finding extends the work of Datu and Yuen (2018) and Yun et al. (2018), showing that buoyancy not only predicts achievement but also channels online learning skills into positive outcomes.

Why Motivation Did Not Mediate Academic Performance

The non-significant mediation effects involving motivation contrast with findings in other educational settings (Ayub, 2010; Datu, 2017). In online learning and STEM environments, motivation may sustain engagement but not necessarily result in higher grades unless scaffolded by resilience and instructional support. This suggests that while academic motivation is crucial for long-term success, buoyancy may serve as the proximate mechanism enabling students to navigate immediate academic demands effectively.

Conclusions

This study highlights the pivotal role of OLR in shaping academic outcomes, primarily through academic buoyancy. Among STEM high school students engaged in online learning, OLR strongly predicted buoyancy, which in turn enhanced both motivation and academic performance. However, academic motivation did not significantly mediate the relationship between readiness and performance, suggesting that resilience is a more salient factor in achievement within this context.

The findings offer empirical support for the indirect-only mediation model: OLR enhances performance *through* buoyancy, not directly or via motivation alone. This implies that interventions targeting online readiness will be most effective when they also explicitly cultivate resilience and emotional adaptability.

Educators should emphasize stress management, recovery from setbacks, and adaptive learning strategies when teaching online readiness skills. Instructional designs must incorporate emotional support mechanisms such as feedback loops and peer discussion forums to reinforce academic buoyancy and help students navigate the challenges of blended learning. School administrators, on the other hand, are encouraged to embed academic buoyancy training within student support services. Readiness assessments can be used to identify students who are at risk of underperforming, allowing institutions to tailor interventions that combine technical skills development with resilience-building strategies. For curriculum designers, it is essential to structure online and blended learning environments in ways that foster autonomy, competence, and relatedness. By offering scaffolded opportunities for collaborative learning, designers can support the translation of students' motivation into measurable academic outcomes.

Recommendations

Basic education institutions should integrate OLR assessments as part of their standard practices to help predict academic risk and personalize instructional support for students. These screenings can inform targeted interventions that address both technical and emotional aspects of learning in digital environments. To further support student success, schools should implement buoyancy-enhancing programs that build students' capacity to manage academic stress and recover from setbacks. Interventions such as workshops on emotional regulation and peer mentoring initiatives can promote resilience and improve students' overall engagement.

Teachers also play a critical role in strengthening students' time management and communication skills. Practical exercises, including planning logs and asynchronous discussion prompts, can be incorporated into instruction to help students better manage deadlines and

express their ideas confidently in online settings. Motivation—both intrinsic and extrinsic—should be nurtured through goal-setting activities, timely and constructive feedback, and the celebration of academic progress. These strategies can sustain students' engagement and commitment throughout the learning process. Finally, ongoing monitoring and feedback are essential. Regular assessment of students' readiness, buoyancy, and motivation enables teachers to proactively adapt their strategies, ensuring continuous support for students' well-being and academic performance.

Declarations

Conflicts of Interest Statement

No conflicts of interest were reported. Ethical approval was obtained from Pampanga State University (formerly Don Honorio Ventura State University), Philippines. Informed consent from parents and assent from students were secured before data collection. Participant confidentiality and anonymity were maintained throughout the study.

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