Int. J. Morphol.,
44(1):283-290, 2026.

Motivation as a Key Predictor of Academic Performance in Medical Histology Teaching in an E-Learning Format

La Motivación como Predictor Clave del Rendimiento Académico en la Enseñanza de Histología Médica en Formato E-learning

Alexis González-Donoso[1]; Sergio Jara-Rosales[2]; Bárbara Valencia-Contreras[3] & Carlos Godoy-Guzmán[4,5]

GONZÁLEZ-DONOSO, A.; JARA-ROSALES, S.; VALENCIA-CONTRERAS, B. & GODOY-GUZMÁN, C. Motivation as a key predictor of academic performance in medical histology teaching in an E-learning format. *Int. J. Morphol., 44(1*):283-290, 2026.

SUMMARY: The teaching of Histology involves the microscopic study of the human body and represents a fundamental discipline in the medical and health sciences curriculum. This study examines the impact of motivation, study habits, and student interaction on academic performance in an online medical histology course. Using a Structural Equation Modeling (SEM) approach, the research is based on a previously validated instrument, the Student Engagement in an Online Histology Course (SEOHC), and analyzes data from 154 students of medicine, nursing, and midwifery from a public university in Chile. The course was delivered in a hybrid format that combined synchronous classes, asynchronous content, and virtual microscopy practice activities. The results indicate that motivation significantly predicts academic performance, whereas study habits and interaction show limited direct effects. The SEM model demonstrates acceptable reliability and validity. These findings highlight the central role of motivation in online learning and suggest that future course designs of similar characteristics should incorporate strategies to enhance engagement and interaction. The study contributes to the growing body of literature on e-learning pedagogy in medical education and offers practical insights to optimize virtual histology teaching.

KEY WORDS: Motivation; E-learning; Medical education; Virtual microscopy.

INTRODUCTION

Medical histology, a discipline focused on the microscopic study of the euplastic, proplastic, and retroplastic states of the human body, is essential for understanding physiological processes and establishing the relationship between structural alterations and the onset of pathologies (Stevens & Lowe, 2005; Shaw & Friedman, 2012; Campos-Sánchez *et al*., 2014; Toledo-Ordoñez *et al*., 2022). Traditionally, its teaching has prioritized face-to-face laboratory sessions with conventional optical microscopy and in situ histological slides, considered the cornerstone for developing analytical and technical competencies in medical and health sciences students (Bloodgood & Ogilvie, 2006; Colthorpe & Ainscough, 2021); however, the COVID-19 pandemic disrupted this model, forcing the adoption of virtual environments and hybrid modalities that combined synchronous classes, asynchronous content, and virtual microscopy (VM) as pedagogical alternatives (Gonzalez-Donoso *et al*., 2024). In this context, VM has become an emerging resource that allows students to explore histological preparations in accessible and scalable virtual or e-learning environments. Nevertheless, debates persist regarding its capacity to replicate the educational experience and the depth of learning achieved through traditional microscopy (Chow & Sharmin, 2025; Magnani *et al*., 2025).

VM has proven to be an effective method not only for teaching histology but also for assessing student performance (Amer & Nemenqani, 2020), and the transition

[1] University of British Columbia, Faculty of Science, Department of Chemistry, Ph.D. Curriculum Studies, Vancouver, Canada.
[2] Facultad de Ciencias para el Cuidado de la Salud, Escuela de Obstetricia, Universidad San Sebastián, Santiago, Chile.
[3] Universidad de Santiago de Chile (USACH), Escuela de Medicina, Unidad de Embriología, Santiago, Chile
[4] Universidad de Santiago de Chile (USACH), Escuela de Medicina, Unidad de Histología, Santiago, Chile.
[5] Universidad de Santiago de Chile (USACH), Escuela de Medicina, Centro de Investigación Biomédica y Aplicada (CIBAP), Laboratorio de ingeniería de tejidos, Santiago, Chile.
FUNDING. This work was funded by the Universidad de Santiago's Research Vice-Rectory (PID, Nº 010-2025).

Received: 2025-10-14 Accepted: 2025-12-18

from traditional teaching methods to virtual modalities has been shown to increase student engagement without negatively affecting learning outcomes in histology education among medical students (Waugh *et al*., 2022). Previous studies have shown that students' positive perceptions of online histology courses are associated with their satisfaction and academic performance, highlighting factors such as the quality of instructional design and the adaptation of in-person practical activities to virtual formats (Gonzalez-Donoso *et al*., 2024). Nevertheless, it remains necessary to deepen our understanding of the elements that directly predict academic success in e-learning environments.

In particular, *student motivation* emerges as a key factor in learning in e-learning formats, as it influences active participation, self-regulation, and engagement with academic tasks, while study habits and peer interaction may play complementary roles. For instance, motivation is a critical factor in student engagement. It can shape how students approach their studies, persist through challenges, and connect course content to their personal and professional goals. When students perceive the material as relevant to their future careers, find ways to make learning personally meaningful, and are supported by interactive teaching practices, their motivation tends to increase. In this sense, Carneiro *et al*. (2023), suggest that motivation in histology courses can be strengthened by engaging students as co-agents in constructing their own medical knowledge and allowing them to express their opinions. These active approaches foster autonomy, competence, and both intrinsic and integrated extrinsic motivation.

Additionally, developing strong *study habits* is essential for academic success in higher education, where students are expected to manage their learning independently and engage deeply with complex material. Habits such as studying regularly, staying up to date with readings, reviewing class notes, staying organized, and actively engaging with course materials may all contribute to a better understanding of histology in university-level courses. However, research findings on the impact of study habits on students' academic performance remain mixed. For example, Selvig *et al*. (2014), surveyed approximately 440 students in three first-year medical school classes at a North American university and found no significant association between students' study habits and their final cumulative histology scores. According to Hora & Oleson (2017), this may be explained by the fact that many students in science, technology, engineering, and mathematics (STEM) courses rely on passive strategies, such as reviewing notes or memorizing content, that often lack depth or real-world applicability.

Another important component of online education is *student interaction* in e-learning environments. From a socioconstructivist perspective, knowledge can be co-constructed through interaction and collaboration; therefore, these practices are strongly encouraged in medical schools (Hennrikus *et al*., 2020; Cho *et al*., 2024). These processes play a central role in meaningful learning at the tertiary level. Furthermore, talking with instructors and peers helps students make sense of complex ideas, build shared understanding, and feel part of a learning community, while also engaging them in a metacognitive process of questioning what they have learned. When students actively participate in group discussions, whether with teaching assistants or classmates, they have the opportunity to express their ideas, ask questions, and support one another's learning, which reinforces their understanding of histology content. Moreover, peer interaction has been identified as a component that can enhance the overall learning experience for students using online platforms in medical education (Enyoojo *et al*., 2024).

Given the increasing reliance on digital tools in medical education, it is essential to evaluate how virtual laboratory formats impact student learning outcomes. This study builds on previous work by examining the structural relationships between students' motivation, interaction in VM environments, and study habits in an online histology course, and how these factors influence academic performance. By focusing on medical, nursing, and midwifery students, this research aims to inform the design of future histology curricula that balance educational innovation with the rigor of traditional laboratory training. The present study investigates:

RQ: To what extent do motivation for online learning, interaction among learners in an online environment, and study habits of online learners influence students' academic performance scores?

In this context, the present study aimed to analyze the impact of motivation, study habits, and interaction on the academic performance of medical, nursing, and midwifery students in an online medical histology course, using Structural Equation Modeling (SEM) and a previously validated instrument, SEOHC (Gonzalez-Donoso *et al*., 2023).

MATERIAL AND METHOD

This study employed a quantitative correlational design to examine participants' engagement and perceptions in an online histology course. Data were collected through structured surveys and analyzed using descriptive and inferential statistics to identify patterns of interaction and learning engagement. A postpositivist epistemological stance guided the study, as it allows for the systematic investigation of participants' experiences while acknowledging that all measurements are shaped by contextual and subjective factors (Young & Ryan, 2020). Although only quantitative data were collected, this perspective frames the survey results as approximations of engagement and perceptions, enabling the identification of patterns and relationships without claiming absolute truths about online learning dynamics.

To examine predictors of academic performance, Structural Equation Modeling (SEM) was applied (Tarka, 2017). This approach allowed testing a theoretically grounded model with validated constructs and assessing both direct and indirect effects. The analysis used data from a previously implemented blended learning intervention, focusing on the roles of motivation, study habits, and interaction in a virtual learning environment.

Context. This observational study applied a SEM model to analyze data from 154 first- and second-year medical, nursing, and midwifery students enrolled in an e-learning histology course at a state university in Chile. The course, delivered during the COVID-19 pandemic, was structured on the Moodle platform and combined synchronous sessions via Zoom with asynchronous recorded lectures and virtual microscopy (VM) activities. Spanning 17 weeks and 78 instructional hours, the course was designed to replicate the traditional face-to-face format by integrating theoretical content and practical components using free online virtual microscopy tools. Traditionally, the histology course consists of theoretical and laboratory sessions delivered twice a year. During the pandemic, as in-person laboratory activities were not possible, virtual microscopy was introduced as a complementary resource using open-access platforms (e.g., Zoomify, Histology Guide). Students analyzed micrographs, identified cell types, tissue organization, and extracellular matrix components, thereby linking structure and function.

Assessment consisted of two multiple-choice exams and a portfolio. The exams contained 60 questions (40 with images) and had a duration of 180 minutes. The portfolio compiled laboratory guides for the semester and was peer-graded. This tool functioned as a pedagogical strategy to structure learning, reinforce the analysis of histological preparations, and guide tissue identification, contributing to the understanding of microscopic structures of the human body. This blended approach provided a comprehensive framework for evaluating student satisfaction and academic performance in a fully online learning environment.

The study was approved by the University Ethics Committee of Universidad de Santiago de Chile. All participants provided informed consent prior to data collection and were informed that the survey was anonymous and voluntary.

Design and Sample. This study employed a quantitative correlational design to examine the structural relationships between students' study habits, motivation, and interaction in an e-learning histology course and their academic performance. The dataset used corresponds to the same sample as the confirmatory factor analysis (CFA) phase of the SEOHC instrument validation study (Gonzalez-Donoso *et al*., 2023), now used to examine structural relationships through SEM. All students completed the adapted version of the Student Engagement in an Online Histology Course (SEOHC) questionnaire.

Instrument: The SEOHC instrument was adapted from Dixson (2015) Online Student Engagement Scale (OSE) and validated for use in Spanish-speaking health science students (Gonzalez-Donoso *et al*., 2023). It includes items grouped into three latent constructs: Habits of online learners (Habits) (e.g., Q1. I made sure to study regularly.), Motivation for online learning (*Motivation*) (e.g., 9. I found ways to make the course interesting to me.), and Interaction of online learners (*Interaction*) (e.g., Q12. I actively participated in discussion groups with the assistant instructor). The instrument demonstrated acceptable psychometric properties in the original validation study, with Cronbach's alpha values of 0.83, 0.82, and 0.69 for the three respective factors.

Procedure: Participants completed the SEOHC questionnaire online. Their responses were used to estimate a SEM using the seminr package in R (R Core Team, 2013). The model tested the direct and indirect effects of the three latent constructs on students' academic performance (*Score*). Bootstrapping with 5,000 resamples was conducted to assess the significance of path coefficients and indirect effects.

RESULTS

Measurement model and factor loadings: The measurement model was assessed by examining the squared loadings of each indicator (Table I), in which higher absolute values closer to 1 mean a higher correlation between the item and the underlying factor (Pett *et al*., 2003). Initially, the construct *Habits* included items Q1 ("I made sure to study regularly," Q3 ("I kept abreast of the readings)", Q4 ("I reviewed the class notes to understand the material before connecting to the online class"), Q5 ("I was organized when studying"), Q6 ("I took notes about the classes, PowerPoints or video lectures"), and Q7 ("I listened and carefully read the course materials"). Item Q6 was removed due to its very low squared loading (0.165). The model was re-estimated, and loadings were examined again. Within the construct *Interaction*, item Q18 ("I met or interacted with students in the class") (0.005) was deleted because of its low loading, while item Q13 ("I helped my classmates understand the contents of the course") was retained despite showing a weaker loading and was kept to preserve construct integrity, as dropping it would have reduced the scale to only two indicators. These adjustments were made iteratively and with caution, and they are acknowledged as limitations of the study.

For the construct *Habits*, squared loadings ranged from 0.388 (Q4) to 0.686 (Q7). For *Motivation*, squared loadings ranged from 0.343 (Q11) to 0.717 (Q9. "I found ways to make the course interesting to me"), with four of five items above 0.50. The construct *Interaction* showed more variability, while Q12 ("I actively participated in discussion groups with the assistant instructor") exhibited a very strong loading (0.940), while Q13 (0.177) indicated weaker reliability. Given these results, item Q13 was flagged as problematic but retained despite its lower value. Overall, the measurement model demonstrated acceptable reliability, though *Interaction* should be interpreted with caution due to weaker item performance. Table I shows the factor loading for the measurement model.

Table I. Factor Loading.

Item	*Habits*	*Motivation*	*Interaction*
Q1	0.603		
Q3	0.542		
Q4	0.388		
Q5	0.649		
Q7	0.686		
Q8		0.475	
Q9		0.717	
Q10		0.577	
Q11		0.343	
Q14		0.661	
Q12			0.940
Q13			0.177
Q16			0.415

Reliability and construct validity analysis. In the measurement model, reliability was assessed using Cronbach's alpha (α), composite reliability (rC), and Dijkstra–Henseler's rho (rA). Construct validity was examined in terms of both convergent and discriminant validity. Convergent validity was evaluated based on the Average Variance Extracted (AVE), where values of 0.50 or higher indicate that a construct explains more than half of the variance in its indicators (Fornell & Larcker, 1981).

The *Habits* construct (a = 0.815, rC = 0.870, AVE = 0.574) and the *Motivation* construct (α= 0.809, rC = 0.860, AVE = 0.555) met all recommended criteria, showing strong internal consistency and adequate convergent validity. However, the *Interaction* construct showed marginal reliability, with a = 0.649, slightly below the 0.70 threshold. Nonetheless, its AVE (0.510) and rC (0.738) were acceptable, supporting convergent validity despite the lower alpha value. It is noteworthy that the rA (1.407) exceeded both a and rC. This discrepancy has been reported in the literature when constructs exhibit low internal consistency or unstable factor loadings (Cheung *et al*., 2024). In this case, the issue may be attributed to the removal of item Q18 due to its low loading and the retention of item Q13 despite its lower contribution, in order to prevent the construct from being reduced to only two indicators. This decision was made cautiously and is acknowledged as a limitation of the measurement model.

Additionally, the dependent variable *Score* was modeled as a single-item construct, resulting in perfect reliability values (α = 1.000, rC = 1.000, AVE = 1.000, rA = 1.000), which is expected in such cases. Overall, the results support the adequacy of the measurement model for subsequent structural analysis, although caution is advised when interpreting the Interaction construct.

Table II summarizes the results of the reliability analysis.

Table II. Construct Reliability (Cronbach Alpha and Composite Reliability) and Construct Convergent Validity (AVE)

Item	Alpha	ρC	AVE	ρA
Habits	0.815	0.870	0.574	0.848
Motivation	0.809	0.860	0.555	0.891
Interaction	0.649	0.738	0.510	1.407
Score	1	1	1	1

Discriminant validity. Discriminant validity was assessed using the Fornell–Larcker criterion, which compares the square root of the Average Variance Extracted (AVE) of each construct with its correlations with other constructs. According to this criterion, discriminant validity is established when the square root of a construct's AVE is greater than its correlations with all other constructs (Cheung *et al*., 2024).

Table III shows that the square root of the AVE for Habits (0.757), Motivation (0.745), and Interaction (0.714) exceeded their respective correlations with the other constructs, supporting discriminant validity among these latent variables.

Table III. Discriminant Validity (Fornell–Larcker Criterion).

	Habits	*Motivation*	*Interaction*	*Score*
Habits	**0.757**			
Motivation	0.654	**0.745**		
Interaction	0.326	0.285	**0.714**	
Score	0.202	0.307	-0.091	**1**

Cross-loadings. Cross-loadings were examined to further assess discriminant validity. An item is expected to load more strongly on its associated construct than on any other construct in the model (Li *et al*., 2020). The results (Table IV) show that, for the majority of items, loadings were higher on their intended construct compared to cross-loadings on other constructs. This supports the notion that the items measure their respective latent variables as intended. Most items demonstrated appropriate cross-loading patterns, indicating that discriminant validity is largely acceptable for the measurement model.

Table IV. Discriminant Validity- Cross Loadings

Item	*Habits*	*Motivation*	*Interaction*	*Score*
Q1	0.777	0.489	0.169	0.133
Q3	0.736	0.459	0.197	0.103
Q4	0.623	0.402	0.233	0.119
Q5	0.806	0.492	0.323	0.181
Q7	0.828	0.601	0.277	0.196
Q8	0.598	0.689	0.281	0.167
Q9	0.565	0.847	0.223	0.228
Q10	0.6	0.759	0.312	0.19
Q11	0.43	0.586	0.336	0.087
Q14	0.382	0.813	0.107	0.341
A12	0.307	0.207	0.969	-0.099
A13	0.386	0.406	0.42	-0.006
A16	0.193	0.359	0.644	-0.03
Score	0.202	0.307	-0.091	1

Heterotrait-Monotrait (HTMT) Ratio. Discriminant validity was further evaluated using the Heterotrait-Monotrait (HTMT) ratio. Table V presents the HTMT values among the latent constructs: *Habits*, *Motivation*, and *Interaction*. All values are below the conservative threshold of 0.85 (Kline, 2011), indicating satisfactory discriminant validity. Although *Score* is included in t Table V, this construct functions as the dependent variable in the structural model and is not part of the measurement model. Its correlations with other constructs are reported for descriptive purposes only and should not be interpreted as part of the discriminant validity assessment.

Table V. Correlations between constructs (Heterotrait-Monotrait, HTMT).

	Habits	*Motivation*	*Interaction*
Habits			
Motivation	0.829		
Interaction	0.519	0.649	
Score	0.214	0.299	0.073

Structural model evaluation and relationships (Fig. 1). Variance Inflation Factors (VIF) for the predictor constructs of *Score* ranged from 1.13 to 1.81, indicating that multicollinearity was not a concern (Hair Jr. *et al*., 2021). The structural model was evaluated using bootstrapping to determine the significance of path coefficients (5,000 resamples).

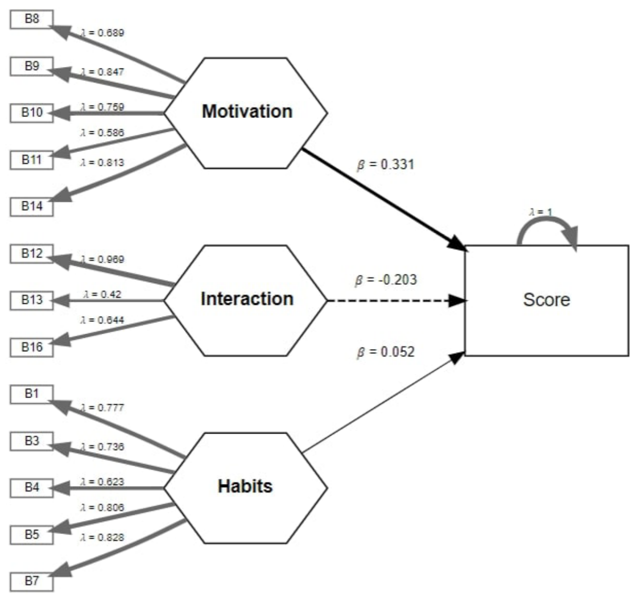

Fig. 1. Structural equation model.

The path from *Motivation* → *Score* was statistically significant (β = 0.331, t = 2.697, 95 % CI [0.093, 0.570]), supporting the hypothesis that motivation positively influences academic performance.

In contrast, the paths *Habits* → *Score* (β = 0.052, t = 0.504, 95 % CI [-0.122, 0.284]) and Interaction → Score (β = -0.203, t = -1.413, 95 % CI [-0.397, 0.135]) were not significant.

These results, based on bootstrapped estimates, provide strong evidence of *Motivation* as a key predictor of academic performance (*Score*) in the online histology course.

The structural model explained 13.1 % of the variance in student performance scores ($R^2 = 0.131$; adjusted $R^2 = 0.113$), indicating a modest level of explanatory power. Regarding effect sizes (f^2), *Motivation* showed a small but significant impact on Score ($f^2 = 0.071$) (Cohen, 1988), suggesting that higher motivation is positively associated with better academic outcomes. *Interaction* also contributed a small effect ($f^2 = 0.042$), implying that its role, although limited, adds to the overall explanatory framework. In contrast, *Habits* had a negligible effect ($f^2 = 0.002$), indicating that its direct influence on *Score* is minimal within the context of this model.

These findings underscore the central role of motivation and suggest that the influence of study habits and interaction may depend on contextual factors.

DISCUSSION

The teaching of Histology involves the microscopic study of the human body and is a fundamental discipline for medical education and other health science professions (e.g., midwifery, nursing, medical technology). Traditionally, histology has been taught in a face-to-face format, combining theoretical lectures with laboratory sessions using bright-field microscopy. The emergence of new Learning Management Systems (LMS) and technologies such as virtual microscopy (VM) has enabled the delivery of histology in an e-learning format, which students have generally evaluated positively (Gonzalez-Donoso *et al*., 2024). However, there is limited literature on the factors that directly predict academic success in online histology courses.

The findings of this study highlight motivation as a key determinant of academic performance in online medical histology education. Consistent with previous research, intrinsic motivation has been shown to significantly predict academic success (Areepattamannil *et al*., 2011). In virtual learning environments, motivation plays a central role by fostering student engagement and sustaining learning efforts (Orji & Vassileva, 2023). It is worth noting that results from the same cohort indicated that students perceived face-to-face practical histology classes as having a greater impact on their learning compared to virtual sessions (Gonzalez-Donoso *et al*., 2024). This finding aligns with international studies (e.g., Colthorpe & Ainscough, 2021) and highlights the challenges of replicating hands-on experiences in e-learning, suggesting that hybrid models (combining in-person and virtual components) may provide a more balanced approach. Furthermore, this may reflect the need for students to better understand the benefits and limitations of virtual histology environments, enabling them to use these tools more effectively. For example, digital platforms allow students to review histological images under ideal conditions, work at their own pace, and repeatedly access visual and explanatory resources from home, which can support comprehension and content retention. Another key aspect is the collaborative potential of virtual environments. Tools such as discussion forums, online group work, and joint problem-solving activities provide valuable opportunities for co-construction of knowledge, sharing perspectives, and clarifying complex concepts. This social interaction not only strengthens conceptual learning but also promotes communication, critical thinking, and teamwork skills, which are essential in medical and health science education. At the same time, students need to recognize the inherent limitations, such as the absence of direct manipulation of real samples or spontaneous interaction characteristic of physical laboratories. Xu (2013) and Pratt (2009), for example, highlight the pedagogical advantages of traditional optical microscopy over exclusive virtual microscopy. Working solely with digital slides may limit exposure to variations and abnormal morphologies, potentially complicating future practice. Conversely, handling real preparations and the questions they generate in class fosters critical learning and professional curiosity, emphasizing the importance of maintaining practical training with conventional microscopy in histology. Promoting a deeper understanding of these benefits, combined with guidance on active participation in collaborative virtual spaces and recognition of e-learning limitations, could foster a more positive and balanced attitude toward virtual environments, leading to more effective use of digital tools.

It is also important to mention that although study habits and interaction are often considered essential components of effective learning, the absence of significant direct effects in this study's model suggests that their influence may be indirect or context-dependent. Limited opportunities for peer interaction due to the online format and pandemic-related restrictions may have constrained the development of consistent study habits and collaborative learning experiences, reducing their impact on academic performance. According to Magnani *et al*. (2025), interaction with instructors and peers in virtual microscopy environments is crucial to support collaborative learning, which can contribute to improved academic outcomes.

Finally, this study contributes to the growing literature on e-learning pedagogy in medical education by providing empirical evidence on predictors of success in online human histology teaching. It complements previous findings linking student perceptions of course design to academic performance, reinforcing the importance of well-structured, interactive, and motivating e-learning environments.

Limitations. This study has several limitations that should be considered when interpreting the results. First, the sample was drawn from a single state university in Chile, which may limit the generalizability of the findings to other institutions or cultural contexts. Second, the study relied exclusively on self-reported data collected via questionnaires, which may be subject to biases such as social desirability, as students might respond in ways that project a positive image or align with what they perceive researchers expect, rather than accurately reflecting their perceptions or behaviours (Kreitchmann *et al*., 2019). To mitigate this, students were informed that participation was voluntary and would not affect their final course grades.

Third, the Structural Equation Model (SEM) was developed using the same dataset previously employed in the Confirmatory Factor Analysis (CFA) phase of the instrument validation study. While this approach ensured measurement consistency, it may introduce limitations related to overfitting or reduced generalizability. Future research should validate the model using independent samples to strengthen its robustness. Additionally, the *Interaction* construct showed marginal reliability, suggesting that further refinement of the measurement instrument may be necessary. The decision to retain certain items with low loadings to preserve construct coverage is recognized as a methodological compromise and represents an opportunity for future studies to improve the original questionnaire.

Furthermore, the absence of qualitative data limits the depth of understanding of students' experiences and perceptions regarding histology teaching in virtual environments. We also acknowledge the importance of including qualitative data in future research to explore how instructors, students, and the online platform interact and shape learning processes in histology. Such insights would enrich and triangulate our understanding, offering a more comprehensive picture of the multiple factors influencing students' learning experiences.

CONCLUSIONS

Finally, the emergence of new technologies for teaching often leads to the assumption that they automatically surpass traditional education. However, for e-learning histology courses, the existing literature on their benefits and limitations remains scarce. Therefore, decision-making in this area should be careful and balanced, leveraging the strengths of traditional histology teaching while integrating digital aspects that genuinely enhance teaching and learning. Despite these limitations, the present study provides valuable insights into the relationship between student engagement and academic performance in online histology education. By analyzing the structural relationships between motivation, study habits, and interaction, this research contributes to a deeper understanding of how to optimize virtual learning environments in medical and health science education. In particular, the emphasis on motivation as a key predictor of academic success offers practical guidance for instructors designing more effective pedagogical strategies in remote learning contexts.

ACKNOWLEDGMENTS

The authors thank Baltazar R. Espiritu, M.D. (Loyola University Chicago Stritch School of Medicine and Dartmouth Medical School) for authorizing the use of histological digital images of VIRTUAL HISTOLOGY available to them (*https:// zoomify.luc.edu/*). We are also grateful to Histology Guide.org, T. Clark Brelje and Robert L. Sorenson, University of Minnesota, Minneapolis, MN, USA.

GONZÁLEZ-DONOSO, A.; JARA-ROSALES, S.; VALENCIA-CONTRERAS, B. & GODOY-GUZMÁN, C. Motivación como predictor clave del rendimiento académico en la enseñanza de histología médica en formato e-learning. *Int. J. Morphol., 44(1)*:283-290, 2026.

RESUMEN: La enseñanza de la Histología implica el estudio microscópico del cuerpo humano y representa una disciplina fundamental en el currículo de las ciencias médicas y de la salud. Este estudio examina el impacto de la motivación, los hábitos de estudio y la interacción estudiantil sobre el rendimiento académico en un curso en línea de histología médica. Mediante un enfoque de Modelamiento de Ecuaciones Estructurales (SEM), la investigación se basa en un instrumento previamente validado, el Student Engagement in an Online Histology Course (SEOHC), y analiza datos de 154 estudiantes de medicina, enfermería y obstetricia de una universidad estatal en Chile. El curso se impartió en un formato híbrido que combinó clases sincrónicas, contenidos asincrónicos y actividades prácticas de microscopía virtual. Los resultados indican que la motivación predice significativamente el rendimiento académico, mientras que los hábitos de estudio y la interacción muestran efectos directos limitados. El modelo SEM demuestra una confiabilidad y validez aceptables. Estos hallazgos destacan el papel central de la motivación en el aprendizaje en línea y sugieren que los futuros diseños de cursos con características similares deberían incorporar estrategias para fortalecer la participación y la interacción. El estudio contribuye al creciente cuerpo de literatura sobre pedagogía en e-learning en educación médica y ofrece orientaciones prácticas para optimizar la enseñanza virtual de histología.

PALABRAS CLAVE: Motivación; E-learning; Educación médica; Microscopía virtual.

REFERENCES

Amer, M. G. & Nemenqani, D. M. Successful use of virtual microscopy in the assessment of practical histology during pandemic COVID-19: a descriptive study. *J. Microsc. Ultrastruct., 8(4)*:156-61, 2020.

Areepattamannil, S.; Freeman, J. G. & Klinger, D. A. Intrinsic motivation, extrinsic motivation, and academic achievement among Indian adolescents in Canada and India. *Soc. Psychol. Educ., 14(3)*:427-39, 2011.

Bloodgood, R. A. & Ogilvie, R. W. Trends in histology laboratory teaching in United States medical schools. *Anat. Rec. B New Anat., 289B(5)*:169-75, 2006.

Campos-Sánchez, A.; López-Núñez, J. A.; Carriel, V.; Martín-Piedra, M. Á.; Sola, T. & Alaminos, M. Motivational component profiles in university students learning histology: a comparative study between genders and different health science curricula. *BMC Med. Educ., 14*:46, 2014.

Carneiro, B. D.; Pozza, D. H. & Tavares, I. Perceptions of medical students towards the role of histology and embryology during curricular review. *BMC Med. Educ., 23(1)*:74, 2023.

Cheung, G. W.; Cooper-Thomas, H. D.; Lau, R. S. & Wang, L. C. Reporting reliability, convergent and discriminant validity with structural equation modeling: a review and best-practice recommendations. *Asia Pac. J. Manag., 41*:745-83, 2024.

Cho, H.; Jeong, H.; Yu, J.; Lee, J. & Jung, H. J. Becoming a doctor: using social constructivism and situated learning to understand the clinical clerkship experiences of undergraduate medical students. *BMC Med. Educ., 24*:236, 2024.

Cohen, J. *Statistical power Analysis for the Behavioral Sciences.* 2nd ed. Hillsdale (NJ), Lawrence Erlbaum Associates, 1988.

Colthorpe, K. & Ainscough, L. Do-it-yourself physiology labs: can hands-on laboratory classes be effectively replicated online? *Adv. Physiol. Educ., 45(1)*:95-102, 2021.

Chow, A. K. & Sharmin, N. Zoom in on learning with a virtual microscope: a convergent parallel mixed-method study. *PLoS One, 20(5)*:e0323412, 2025.

Dixson, M. D. Measuring student engagement in the online course: the online student engagement scale (OSE). *Online Learn., 19(4)*, 2015.

Enyoojo, S. F.; Ijah, C. E.; Etukudo, E. M.; Usman, I. M.; Ezeonuogu, C. S.; Adaramati, T.; Kabanyoro, A.; Fernandez, D. M. E.; Rosales, Y. D. & Aigbogun, E. Satisfaction and learning experience of students using online learning platforms for medical education. *BMC Med. Educ., 24(1)*:1398, 2024.

Fornell, C. & Larcker, D. F. Evaluating structural equation models with unobservable variables and measurement error. *J. Mark. Res., 18(1)*:39-50, 1981.

Gonzalez-Donoso, A.; Jara-Rosales, S.; Padilla-Meza, J. & Godoy-Guzmán, C. Scale to measure medical, nursing and midwifery students' engagement in an e-learning histology course. *Int. J. Morphol., 41(2)*:600-6, 2023.

Gonzalez-Donoso, A.; Jara-Rosales, S.; Rosemblatt, M.; Osses, M.; Padilla-Meza, J. & Godoy-Guzmán, C. Impact of an e-learning histology course on the satisfaction and performance of medical, nursing and midwifery students. *Int. J. Morphol., 42(4)*:1161-74, 2024.

Hair Jr., J. F.; Hult, G. T. M.; Ringle, C. M.; Sarstedt, M.; Danks, N. P. & Ray, S. *Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R. A Workbook.* Cham, Springer, 2021.

Hennrikus, E. F.; Skolka, M. P. & Hennrikus, N. Social constructivism in medical school where students become patients with dietary restrictions. *Adv. Med. Educ. Pract., 11*:505-11, 2020.

Hora, M. T. & Oleson, A. K. Examining study habits in undergraduate STEM courses from a situative perspective. *Int. J. STEM Educ., 4*:1, 2017.

Kline, R. B. *Principles and Practice of Structural Equation Modeling*. 3rd ed. New York, The Guilford Press, 2011.

Kreitchmann, R. S.; Abad, F. J.; Ponsoda, V.; Nieto, M. D. & Morillo, D. Controlling for response biases in self-report scales: forced-choice vs. psychometric modeling of Likert items. *Front. Psychol., 10*:2309, 2019.

Li, Y.; Wen, Z.; Hau, K.-T.; Yuan, K. H. & Peng, Y. Effects of cross-loadings on determining the number of factors to retain. *Struct. Equ. Modeling, 27(6)*:841-63, 2020.

Magnani, F.; Demaria, E.; Ambrosi, F.; Sala, C.; Pasquinelli, G.; Fiorentino, M. & Gri, G. The positive impact of virtual microscopy on histopathology education: a comparative, student-centered study. *Adv. Physiol. Educ., 49(1)*:136-46, 2025.

Orji, F. A. & Vassileva, J. Modeling the impact of motivation factors on students' study strategies and performance using machine learning. *J. Educ. Technol. Syst., 52(2)*:274-96, 2023.

Pett, M. A.; Lackey, N. R. & Sullivan, J. J. *Making Sense of Factor Analysis.* Thousand Oaks, SAGE Publications, 2003.

Pratt, R. L. Are we throwing histology out with the microscope? A look at histology from the physician's perspective. *Anat. Sci. Educ., 2(5)*:205-9, 2009.

Shaw, P. A. & Friedman, E. S. Clinico-histologic conferences: histology and disease. *Anat. Sci. Educ., 5(1)*:55-61, 2012.

Stevens, A. & Lowe, J. S. *Human histology*. 3rd ed. London, Elsevier Mosby, 2005.

Selvig, D.; Holaday, L. W.; Purkiss, J. & Hortsch, M. Correlating students' educational background, study habits, and resource usage with learning success in medical histology. *Anat. Sci. Educ., 8(1)*:1-11, 2014.

Tarka, P. An overview of structural equation modeling: its beginnings, historical development, usefulness and controversies in the social sciences. *Qual. Quant., 52(1)*:313-54, 2017.

Toledo-Ordoñez, I.; Onetto, N.; Concha, M.; Sanhueza, S.; Osses, M.; Padilla-Meza, J. & Godoy-Guzmán, C. Design and manufacturing of 3D printed models as a complement for medical histology practical class. *Int. J. Morphol., 40(2)*:355-9, 2022.

Xu, C. J. Is virtual microscopy really better for histology teaching? *Anat. Sci. Educ., 6(2)*:138, 2013.

Waugh, S.; Devin, J.; Lam, A. K. Y. & Gopalan, V. E-learning and the virtual transformation of histopathology teaching during COVID-19: its impact on student learning experience and outcome. *BMC Med. Educ., 22*:22, 2022.

Young, M. E. & Ryan, A. Postpositivism in health professions education scholarship. *Acad. Med., 95(5)*:695-99, 2020.

Corresponding author:
Prof. Titular, Dr. Carlos Godoy-Guzmán
Escuela de Medicina
Universidad de Santiago de Chile
Avda. Bernardo O'Higgins 3363
Correo 442
Santiago
CHILE

E-mail: carlos.godoy@usach.cl