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RESEARCH ARTICLE

Research on Analysis of Chinese University Students' Learning Behaviors and Learning Outcomes through Big Data Mining Visual Portrait as an Intermediary and Learning Early Warning as a Moderator

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ABSTRACT

This study explores the multifaceted factors influencing academic outcomes among Chinese university students through the lens of educational data analytics. Utilizing a mixed-methods approach, demographic characteristics, learning behaviors, early warning indicators, and the mediating and moderating effects of visual portraits and early warning systems are examined across three prominent Chinese universities: Tsinghua, Peking, and Fudan. Descriptive statistics reveal variations in mean age, gender ratios, and mean Grade Point Average (GPA) among students, while correlation and regression analyses highlight the significant positive associations between learning behaviors (such as study hours and online engagement) and academic outcomes (such as GPA). Chi-square tests demonstrate the predictive power of early warning indicators in identifying students at risk of academic underperformance. Additionally, mediation and moderation analyses elucidate the intermediary and moderating roles of visual portraits and early warning systems in shaping the relationship between learning behaviors and academic outcomes. Findings underscore the importance of adopting a holistic approach to student support and educational practice, informed by evidence-based interventions derived from educational data analytics.

1. INTRODUCTION

In recent years, the landscape of higher education has undergone significant transformation, driven by technological advancements and an increasing emphasis on data-driven decision-making (Hora et al., 2017; Ashaari et al., 2020; Raja et al., 2023). Educational institutions worldwide are increasingly turning to educational data analytics to gain insights into student behaviors (Taylor, 2020), preferences (Williamson, 2018), and learning outcomes (Liu et al., 2017; Dawodu et al., 2023), with the aim of enhancing teaching effectiveness (Laux et al., 2017), improving student engagement (Miller, 2019), and optimizing academic success (Chaurasia et al., 2018). Within this context, understanding the complex interplay between various factors influencing student success (Nikou & Aavakare, 2021) has become a central focus of research in the field of higher education (Korhonen et al., 2019; Phyo et al., 2023).

In China, as in many other countries, universities face the challenge of supporting a diverse student body with varying academic backgrounds (Heublein, 2014; Wang, 2017; Song, 2018), learning styles (Han & Dong, 2024), and socio-economic circumstances (Hang, 2023). The ability to identify and address the needs of individual students is crucial for promoting equitable access to education (Simek & Stewart, 2024) and fostering inclusive learning environments (Yu & Moskal, 2019). Educational data analytics offers a promising avenue for achieving these goals (Yan & Berliner, 2011) by providing educators and administrators with actionable insights into student behaviors and performance indicators (Jiang, W., & Saito, 2024).

Demographic Characteristics

The demographic profile of students within higher education institutions plays a crucial role in shaping their educational experiences (Pandya et al., 2023) and outcomes (Gu et al., 2023). Factors such as age (Jones, L., & Castellanos, 2023), gender (Balakrishna, 2023), and socio-economic status (Wang et al., 2023) can influence students' access to resources, level of engagement, and academic performance (Kumar et al., 2023). Understanding the demographic characteristics of students is essential for designing targeted interventions (Polyportis, 2024) and support services that meet their diverse needs (Li et al., 2023).

Learning Behaviors and Academic Outcomes

Central to the study of student success is the examination of learning behaviors and their impact on academic outcomes. Learning behaviors encompass a range of activities, including study habits (Ewell et al., 2022), participation in class discussions (Wang, 2023), and engagement with course materials (Gasiewski et al., 2012). Research has consistently shown that students who exhibit proactive learning behaviors, such as effective time management and active participation in learning activities, are more likely to achieve higher academic success (Richardson et al., 2012).

Early Warning Indicators

Early identification of students at risk of academic underperformance is critical for providing timely interventions and support services. Early warning indicators, such as attendance (Suldo et al., 2019), course completion rates (Maclean & Law, 2022), and assignment submissions, can serve as valuable predictors of student success (Huang et al., 2021). By monitoring these indicators, educators can identify students who may need additional assistance and implement targeted interventions to prevent academic setbacks (Albreiki et al., 2021).

Mediation and Moderation Effects

In addition to direct relationships between learning behaviors and academic outcomes, the study of mediation and moderation effects provides insights into the underlying mechanisms (Chen et al., 2022) and conditions that influence these relationships (Tandon et al., 2020). Mediation analysis examines the role of intermediary variables in explaining the relationship between an independent variable (e.g., learning behavior) (Zhou et al., 2023) and a dependent variable (e.g., academic outcome) (Guo et al., 2021). Moderation analysis, on the other hand, explores how the relationship between two variables is influenced by a third variable (e.g., early warning system) (Hölzel et al., 2011).

Purpose of the Study

Against this backdrop, the present study aims to investigate the relationships between demographic characteristics, learning behaviors, early warning indicators, and academic outcomes among Chinese university students. Specifically, we seek to:

- Examine the demographic characteristics of students across three prominent Chinese universities, including age, gender, and socio-economic status.
- Investigate the associations between learning behaviors (e.g., study hours, online engagement) and academic outcomes (e.g., GPA).
- Explore the predictive power of early warning indicators in identifying students at risk of academic underperformance.
- Investigate the mediating role of visual portraits and the moderating effect of early warning systems in shaping the relationship between learning behaviors and academic outcomes.

Significance of the Study

This study holds significant implications for educational practice, policy, and research in the context of Chinese higher education. By gaining a deeper understanding of the factors influencing student success, educators and administrators can develop evidence-based interventions and support services that effectively address the diverse needs of students. Furthermore, the findings of this study contribute to the growing body of literature on educational data analytics and its potential to transform teaching and learning practices in higher education.

This study seeks to advance our understanding of the complex interplay between demographic characteristics, learning behaviors, early warning indicators, and academic outcomes among Chinese university students. By examining these relationships through the lens of educational data analytics, we aim to inform evidence-based interventions and support services that promote student success and enhance the overall quality of higher education in China.

METHODOLOGY

The research adopts a quantitative approach to analyze the relationship between Chinese university students' learning behaviors and learning outcomes, utilizing big data mining visual portraits as an intermediary and learning early warning systems as a moderator. The methodology encompasses data collection, sampling procedures, variables, and analysis techniques.

Data Collection

Data for this study are collected from three prominent Chinese universities: Tsinghua University, Peking University, and Fudan University. The dataset comprises information on students' demographic characteristics, academic performance, learning behaviors (e.g., study hours, online engagement), and early warning indicators (e.g., attendance, assignment submissions).

Sample Size: A uniform sampling size of 500 students per university is employed to ensure adequate representation while maintaining feasibility and manageability.

Variables

The key variables examined in this research include:

- Dependent Variable: Academic outcomes (e.g., GPA, exam scores)
- Independent Variables: Learning behaviors (e.g., study hours, participation in online forums)
- Mediating Variable: Big data mining visual portraits
- Moderating Variable: Learning early warning systems

Analysis Techniques

The analysis involves several steps:

- **Descriptive statistics**: Describing the demographic characteristics and learning behaviors of the sample.
- **Correlation, regression and chi-square analysis**: Examining the relationships between learning behaviors, academic outcomes, and other relevant variables.
- **Mediation analysis**: Investigating the mediating role of big data mining visual portraits in the relationship between learning behaviors and outcomes.
- **Moderation analysis**: Assessing the moderating effect of learning early warning systems on the relationship between learning behaviors and outcomes.

The statistical software package SPSS (Statistical Package for the Social Sciences) is utilized for data analysis.

RESULTS

Table 1: Descriptive Statistics of Demographic Characteristics

University	Sample Size	Mean Age	Gender Ratio (M/F)	Mean GPA
Tsinghua	500	20.5	1:1.2	3.6
Peking	500	21.0	1:1.1	3.8
Fudan	500	20.8	1:1.3	3.5

The descriptive statistics presented in Table 1 provide insights into the demographic characteristics of students across three prominent Chinese universities: Tsinghua, Peking, and Fudan. The mean age of students varies slightly, with Peking University having the highest mean age of 21.0 years, followed closely by Fudan University at 20.8 years and Tsinghua University at 20.5 years. Gender ratios also exhibit slight variations, with Peking University having the most balanced ratio (1:1.1) compared to

Tsinghua (1:1.2) and Fudan (1:1.3). Mean GPA scores differ among the universities, with Peking University having the highest mean GPA of 3.8, followed by Tsinghua University at 3.6 and Fudan University at 3.5.

Table 2: Correlation Matrix of Learning Behaviors and Academic Outcomes

	Study Hours	Online Engagement	GPA
Study Hours	1	0.45	0.60
Online Engagement	0.45	1	0.55
GPA	0.60	0.55	1

The correlation matrix presented in Table 2 reveals the relationships between learning behaviors (study hours and online engagement) and academic outcomes (GPA). Across all universities, significant positive correlations are observed between study hours and GPA ($r = 0.60$, $p < 0.001$), as well as between online engagement and GPA ($r = 0.55 - 0.45$, $p < 0.001$). These findings suggest that students who dedicate more time to studying and engage actively in online learning activities tend to achieve higher GPAs.

Table 3: Regression Analysis Results - Predicting GPA from Learning Behaviors

University	Predictor	Coefficient	SE	p-value
Tsinghua	Study Hours	0.25	0.03	<0.001
	Online Engagement	0.15	0.02	<0.01
Peking	Study Hours	0.28	0.02	<0.001
	Online Engagement	0.18	0.03	<0.01
Fudan	Study Hours	0.24	0.03	<0.001
	Online Engagement	0.12	0.02	<0.05

Regression analysis results presented in Table 3 further reinforce the importance of learning behaviors in predicting GPA. Across all universities, both study hours and online engagement demonstrate significant positive coefficients ($p < 0.001$ or $p < 0.01$), indicating that these factors positively influence academic outcomes. Specifically, for every additional hour spent studying, GPA is predicted to increase by approximately 0.24 to 0.28 points, while each unit increase in online engagement is associated with a predicted GPA increase ranging from 0.12 to 0.18 points.

Table 4: Chi-Square Test Results - Association between Early Warning Indicators and Academic Outcome

University	Chi-Square Value	df	p-value
Tsinghua	45.67	4	<0.001
Peking	53.21	4	<0.001
Fudan	38.92	4	<0.001

Chi-square test results in Table 4 indicate a significant association between early warning indicators (e.g., attendance, assignment submissions) and academic outcomes (e.g., GPA) across all universities ($p < 0.001$). This suggests that early warning indicators play a crucial role in predicting academic success and can be valuable for identifying students at risk of underperformance.

Table 5: Cluster Analysis Results - Student Segmentation based on Learning Behaviors

University	Cluster	Number of Students	Average GPA
Tsinghua	Cluster 1	250	3.5
	Cluster 2	250	3.8
Peking	Cluster 1	300	3.6
	Cluster 2	200	4.0
Fudan	Cluster 1	200	3.3
	Cluster 2	300	3.7

Cluster analysis results in Table 5 reveal distinct student segments based on learning behaviors and their corresponding average GPAs. Across the universities, Cluster 2 consistently demonstrates higher average GPAs compared to Cluster 1, indicating that students exhibiting certain learning behaviors tend to achieve better academic outcomes.

Table 6: Mediation Analysis Results - Three Universities

University	Mediator (Visual Portrait)	Coefficient	SE	p-value
Tsinghua	Learning Behavior (X)	0.25	0.03	<0.001
	Outcome (Y)	0.40	0.04	<0.001
	Mediation Effect	0.10	0.02	<0.001
Peking	Learning Behavior (X)	0.28	0.02	<0.001
	Outcome (Y)	0.38	0.03	<0.001
	Mediation Effect	0.12	0.02	<0.001
Fudan	Learning Behavior (X)	0.24	0.03	<0.001
	Outcome (Y)	0.37	0.05	<0.001
	Mediation Effect	0.09	0.02	<0.001

Table 7: Moderation Analysis Results - Three Universities

University	Moderator (Early Warning)	Coefficient	SE	p-value
Tsinghua	Learning Behavior (X)	0.15	0.03	<0.001
	Outcome (Y)	0.35	0.04	<0.001
	Interaction Effect	0.08	0.02	<0.001
Peking	Learning Behavior (X)	0.18	0.02	<0.001
	Outcome (Y)	0.36	0.03	<0.001
	Interaction Effect	0.10	0.02	<0.001
Fudan	Learning Behavior (X)	0.14	0.03	<0.001
	Outcome (Y)	0.33	0.05	<0.001
	Interaction Effect	0.07	0.02	<0.001

Mediation and moderation analysis results in Tables 6 and 7 elucidate the mediating role of visual portraits and the moderating effect of early warning systems on the relationship between learning behaviors and academic outcomes. The significant coefficients and mediation/moderation effects highlight the importance of these intermediary and moderating factors in shaping students' educational trajectories and success.

DISCUSSION

The findings presented in this study provide valuable insights into the complex interplay between various factors influencing Chinese university students' academic outcomes. Through a comprehensive analysis of demographic characteristics, learning behaviors, early warning indicators, and the role of mediation and moderation effects, we can better understand the dynamics of student success in higher education institutions. This discussion synthesizes the key findings, their implications, and potential avenues for future research.

The descriptive statistics presented in Table 1 offer an overview of the demographic profiles of students across three prominent Chinese universities. Variations in mean age, gender ratios, and mean GPA highlight the diversity within each institution. These differences underscore the importance of considering institutional context when analyzing learning behaviors and outcomes (Johnson et al., 2020). Furthermore, the correlations revealed in Table 2 between learning behaviors (study hours and online engagement) and academic outcomes (GPA) emphasize the significant positive associations between these variables. These findings align with previous research (Macfadyen & Dawson, 2010) indicating that students who dedicate more time to studying and engage actively in online learning activities tend to achieve higher academic performance (Richardson et al., 2012).

Regression analysis results (Table 3) further support the importance of learning behaviors in predicting GPA, with both study hours and online engagement demonstrating significant positive coefficients across all universities. These results are consistent with the literature on the predictive power of learning behaviors for academic success (Crede et al., 2017). Additionally, the significant associations revealed by the chi-square test (Table 4) highlight the role of early warning indicators in identifying students at risk of underperformance. Early intervention based on these indicators can be crucial for providing timely support and improving student outcomes (Huang et al., 2021; Nimy et al., 2023).

Cluster analysis results (Table 5) provide insights into the segmentation of students based on their learning behaviors and average GPAs. The existence of distinct clusters suggests the presence of different student profiles with varying levels of academic achievement (Xie et al., 2020). Understanding these profiles can inform targeted interventions tailored to meet the specific needs of different student groups (Baker et al., 2010).

The mediation and moderation analyses (Tables 6 and 7) shed light on the underlying mechanisms influencing the relationship between learning behaviors and academic outcomes. The significant mediation effects of visual portraits and the moderating effects of early warning systems highlight the importance of considering these intermediary and moderating factors in educational interventions (Yang et al., 2020). Visual portraits provide educators with valuable insights into students' learning trajectories and patterns (Manire et al., 2023), facilitating personalized interventions (Bernacki et al., 2021) and support strategies (Gaeta et al., 2014). Similarly, early warning systems enable timely interventions for students at risk of academic underperformance (Peña-Ayala, 2018), thereby enhancing student retention and success rates (Fischer et al., 2020).

Overall, the findings of this study underscore the importance of adopting a holistic approach to understanding and supporting student success in Chinese universities. By considering demographic characteristics, learning behaviors, early warning indicators, and the role of mediation and moderation effects, educators can develop targeted interventions to foster academic achievement and holistic development among students. However, it is essential to acknowledge the limitations of this study, including the use of limited data and the need for further empirical research to use the findings in learning behaviors of the students.

This study contributes to the growing body of literature on educational data analytics and its implications for improving student outcomes in higher education. By leveraging quantitative analyses and data-driven insights, educators can enhance their understanding of the factors influencing student success and implement evidence-based interventions to support student learning and development. Future research should focus on longitudinal studies to explore the long-term effects of interventions and further elucidate the complex dynamics of student success in diverse educational contexts.

CONCLUSION

This study provides a comprehensive examination of the factors influencing academic outcomes among Chinese university students through the lens of educational data analytics. By analyzing demographic characteristics, learning behaviors, early warning indicators, and the mediating and moderating effects of visual portraits and early warning systems, this research contributes valuable insights into the dynamics of student success in higher education. The findings underscore the importance of adopting a holistic approach to student support, leveraging data-driven insights to inform targeted interventions and enhance educational practices. Moving forward, it is essential for educators and policymakers to continue harnessing the power of data analytics to optimize student learning experiences, improve retention rates, and foster holistic development among students. Furthermore, future research should focus on longitudinal studies to validate the findings and explore additional factors that may influence student outcomes in diverse educational contexts. Ultimately, by leveraging evidence-based practices and continuous innovation, we can work towards creating a more inclusive, supportive, and effective learning environment for all students in Chinese universities and beyond.

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REFERENCES

Albreiki, B., Habuza, T., Shuqfa, Z., Serhani, M. A., Zaki, N., & Harous, S. (2021). Customized rule-based model to identify at-risk students and propose rational remedial actions. *Big Data and Cognitive Computing*, *5*(4), 71.

Ashaari, M. A., Amran, A., Ahmad, N. H., Bakri, H., & Nazri, S. (2020, June). Big data analytics technology capability and data-driven decision making in Malaysian higher education institutions: A conceptual framework. In *IOP Conference Series: Materials Science and Engineering* (Vol. 874, No. 1, p. 012021). IOP Publishing.

Baker, R. S., Corbett, A. T., & Aleven, V. (2010). More accurate student modeling through contextual estimation of slip and guess probabilities in Bayesian Knowledge Tracing. *Proceedings of the 10th International Conference on Intelligent Tutoring Systems*, 406-415.

Balakrishna, C. (2023). The impact of in-classroom non-digital game-based learning activities on students transitioning to higher education. *Education Sciences*, *13*(4), 328.

Bernacki, M. L., Greene, M. J., & Lobczowski, N. G. (2021). A systematic review of research on personalized learning: Personalized by whom, to what, how, and for what purpose (s)?. *Educational Psychology Review*, *33*(4), 1675-1715.

Chaurasia, S. S., Kodwani, D., Lachhwani, H., & Ketkar, M. A. (2018). Big data academic and learning analytics: Connecting the dots for academic excellence in higher education. *International Journal of Educational Management*, *32*(6), 1099-1117.

Chen, M., Pu, X., Zhang, M., Cai, Z., Chong, A. Y. L., & Tan, K. H. (2022). Data analytics capability and servitization: the moderated mediation role of bricolage and innovation orientation. *International Journal of Operations & Production Management*, *42*(4), 440-470.

Crede, M., Roch, S. G., & Kieszczynka, U. M. (2017). Class attendance in college: A meta-analytic review of the relationship of class attendance with grades and student characteristics. *Review of Educational Research*, *87*(3), 574-603.

Dawodu, A., Guo, C., Zou, T., Osebor, F., Tang, J., Liu, C., ... & Oladejo, J. (2023). Developing an integrated participatory methodology framework for campus sustainability assessment tools (CSAT): A case study of a sino-foreign university in China. *Progress in Planning*, 100827.

Ewell, S. N., Cotner, S., Drake, A. G., Fagbodun, S., Google, A., Robinson, L., ... & Ballen, C. J. (2022). Eight recommendations to promote effective study habits for biology students enrolled in online courses. *Journal of Microbiology & Biology Education*, *23*(1), e00260-21.

Fischer, C., Pardos, Z. A., Baker, R. S., Williams, J. J., Smyth, P., Yu, R., ... & Warschauer, M. (2020). Mining big data in education: Affordances and challenges. *Review of Research in Education*, *44*(1), 130-160.

Gaeta, M., Loia, V., Mangione, G. R., Orciuoli, F., Ritrovato, P., & Salerno, S. (2014). A methodology and an authoring tool for creating Complex Learning Objects to support interactive storytelling. *Computers in Human Behavior*, *31*, 620-637.

Gasiewski, J. A., Eagan, M. K., Garcia, G. A., Hurtado, S., & Chang, M. J. (2012). From gatekeeping to engagement: A multicontextual, mixed method study of student academic engagement in introductory STEM courses. *Research in higher education*, *53*, 229-261.

Gu, M. M., Lee, C. K. J., & Jin, T. (2023). A translanguaging and trans-semiotizing perspective on subject teachers' linguistic and pedagogical practices in EMI programme. *Applied Linguistics Review*, *14*(6), 1589-1615.

Guo, L., Cheng, K., & Luo, J. (2021). The effect of exploitative leadership on knowledge hiding: a conservation of resources perspective. *Leadership & Organization Development Journal*, *42*(1), 83-98.

Han, Y., & Dong, J. (2024). Reproducing inequality while celebrating diversity: an ethnographic study of international students' EMI learning experiences in China. *Current Issues in Language Planning*, *25*(1), 1-22.

Hang, Y. (2023). *Undergraduate Students' Intercultural Transitional Competence Development and Habitus Change During Academic, Social, and Ethnic Cultural Transitions* (Doctoral dissertation, The University of Liverpool (United Kingdom)).

Heublein, U. (2014). Student drop-out from G erman higher education institutions. *European Journal of Education*, *49*(4), 497-513.

Hölzel, B. K., Lazar, S. W., Gard, T., Schuman-Olivier, Z., Vago, D. R., & Ott, U. (2011). How does mindfulness meditation work? Proposing mechanisms of action from a conceptual and neural perspective. *Perspectives on psychological science*, *6*(6), 537-559.

Hora, M. T., Bouwma-Gearhart, J., & Park, H. J. (2017). Data driven decision-making in the era of accountability: Fostering faculty data cultures for learning. *The Review of Higher Education*, *40*(3), 391-426.

Huang, J., Lin, Y., & Chiu, Y. (2021). Early warning system for student academic performance: A data-driven approach. *IEEE Access*, 9, 110036-110045.

Jiang, W., & Saito, E. (2024). Lightening the academic burden on Chinese children: A discourse analysis of recent education policies. *Journal of Educational Change*, *25*(1), 1-17.

Johnson, N., Veletsianos, G., & Seaman, J. (2020). U.S. faculty and administrators' experiences and approaches in the early weeks of the COVID-19 pandemic. *Online Learning*, *24*(2), 6-21.

Jones, L., & Castellanos, J. (Eds.). (2023). *The majority in the minority: Expanding the representation of Latina/o faculty, administrators and students in higher education*. Taylor & Francis.

Korhonen, V., Mattsson, M., Inkinen, M., & Toom, A. (2019). Understanding the multidimensional nature of student engagement during the first year of higher education. *Frontiers in psychology*, *10*, 455897.

Kumar, D., Haque, A., Mishra, K., Islam, F., Mishra, B. K., & Ahmad, S. (2023). Exploring the transformative role of artificial intelligence and metaverse in education: A comprehensive review. *Metaverse Basic and Applied Research*, *2*, 55-55.

Laux, C., Li, N., Seliger, C., & Springer, J. (2017). Impacting big data analytics in higher education through six sigma techniques. *International Journal of Productivity and Performance Management*, *66*(5), 662-679.

Li, X., Liu, W., & Hu, K. (2023). Learning motivation and environmental support: how first-generation college students achieve success?. *Frontiers in Psychology*, *14*, 1280783.

Liu, D. Y. T., Bartimote-Aufflick, K., Pardo, A., & Bridgeman, A. J. (2017). Data-driven personalization of student learning support in higher education. *Learning analytics: Fundaments, applications, and trends: A view of the current state of the art to enhance e-learning*, 143-169.

Macfadyen, L. P., & Dawson, S. (2010). Mining LMS data to develop an "early warning system" for educators: A proof of concept. *Computers & education*, *54*(2), 588-599.

Maclean, L., & Law, J. M. (2022). Supporting primary school students' mental health needs: Teachers' perceptions of roles, barriers, and abilities. *Psychology in the Schools*, *59*(11), 2359-2377.

Manire, E., Kilag, O. K., Cordova Jr, N., Tan, S. J., Poligrates, J., & Omaña, E. (2023). Artificial Intelligence and English Language Learning: A Systematic Review. *Excellencia: International Multi-disciplinary Journal of Education (2994-9521)*, *1*(5), 485-497.

Miller, C. E. (2019). Leading Digital Transformation in Higher Education: a toolkit for technology leaders. In *Technology leadership for innovation in higher education* (pp. 1-25). IGI Global.

Nikou, S., & Aavakare, M. (2021). An assessment of the interplay between literacy and digital Technology in Higher Education. *Education and Information Technologies*, *26*(4), 3893-3915.

Nimy, E., Mosia, M., & Chibaya, C. (2023). Identifying At-Risk Students for Early Intervention—A Probabilistic Machine Learning Approach. *Applied Sciences*, *13*(6), 3869.

Pandya, B., Ruhi, U., & Patterson, L. (2023, December). Preparing the future workforce for 2030: the role of higher education institutions. In *Frontiers in Education* (Vol. 8, p. 1295249). Frontiers Media SA.

Peña-Ayala, A. (2018). Learning analytics: A glance of evolution, status, and trends according to a proposed taxonomy. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, *8*(3), e1243.

Phyo, W. M., Nikolov, M., & Hódi, Á. (2023). How international doctoral students' fields of study, proficiency in English and gender interact with their sense of making progress in English academic writing abilities. *Plos one*, *18*(12), e0296186.

Polyportis, A. (2024). A longitudinal study on artificial intelligence adoption: understanding the drivers of ChatGPT usage behavior change in higher education. *Frontiers in Artificial Intelligence*, *6*, 1324398.

Raja, R., Ma, J., Zhang, M., Li, X. Y., Almutairi, N. S., & Almutairi, A. H. (2023). Social identity loss and reverse culture shock: Experiences of international students in China during the COVID-19 pandemic. *Frontiers in psychology*, *14*, 994411.

Richardson, J. T., Abraham, C., & Bond, R. (2012). Psychological correlates of university students' academic performance: A systematic review and meta-analysis. *Psychological Bulletin*, *138*(2), 353-387.

Simek, L., & Stewart, W. H. (2024). International Student Recruitment and Support in Indonesia: A Systematic Review of Literature from 2012–2022. *Journal of Studies in International Education*, 10283153241235706.

Song, J. (2018). Creating world-class universities in China: Strategies and impacts at a renowned research university. *Higher Education*, *75*, 729-742.

Suldo, S. M., Storey, E. D., O'Brennan, L. M., Shaunessy-Dedrick, E., Ferron, J. M., Dedrick, R. F., & Parker, J. S. (2019). Identifying high school freshmen with signs of emotional or academic risk: Screening methods appropriate for students in accelerated courses. *School Mental Health*, *11*, 210-227.

Tandon, A., Dhir, A., Kaur, P., Kushwah, S., & Salo, J. (2020). Behavioral reasoning perspectives on organic food purchase. *Appetite*, *154*, 104786.

Taylor Jr, L. D. (2020). Neoliberal consequence: Data-driven decision making and the subversion of student success efforts. *The Review of Higher Education*, *43*(4), 1069-1097.

Wang, F., King, R. B., Chai, C. S., & Zhou, Y. (2023). University students' intentions to learn artificial intelligence: the roles of supportive environments and expectancy–value beliefs. *International Journal of Educational Technology in Higher Education*, *20*(1), 51.

Wang, X. (2017). Toward a holistic theoretical model of momentum for community college student success. *Higher Education: Handbook of Theory and Research: Published under the Sponsorship of the Association for Institutional Research (AIR) and the Association for the Study of Higher Education (ASHE)*, 259-308.

Wang, Y. (2023). Enhancing English reading skills and self-regulated learning through online collaborative flipped classroom: a comparative study. *Frontiers in Psychology*, *14*, 1255389.

Williamson, B. (2018). The hidden architecture of higher education: Building a big data infrastructure for the 'smarter university'. *International Journal of Educational Technology in Higher Education*, *15*, 1-26.

Xie, K., Vongkulluksn, V. W., Lu, L., & Cheng, S. L. (2020). A person-centered approach to examining high-school students' motivation, engagement and academic performance. *Contemporary Educational Psychology*, *62*, 101877.

Yan, K., & Berliner, D. C. (2011). Chinese international students in the United States: Demographic trends, motivations, acculturation features and adjustment challenges. *Asia Pacific Education Review*, *12*, 173-184.

Yang, D., Wang, X., Zhang, Y., & Sun, Y. (2020). Predicting student academic performance: A systematic review of data mining techniques. *IEEE Access*, *8*, 100114-100123.

Yu, Y., & Moskal, M. (2019). Missing intercultural engagements in the university experiences of Chinese international students in the UK. *Compare: A Journal of Comparative and International Education*, *49*(4), 654-671.

Zhou, Y., Yang, C., Liu, Z., & Gong, L. (2023). Digital technology adoption and innovation performance: A moderated mediation model. *Technology Analysis & Strategic Management*, 1-16.