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Harnessing Artificial Intelligence to Predict Timely Degree Progression through Self-Efficacy Profiling

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Dr. Rukiya Deetjen Ruiz[1]* and Lodz Deetjen[2]

[1]*Zayed University, Abu Dhabi, UAE*

[2]*The Learning Nest Academy, USA*

***Corresponding Author:** Dr. Rukiya Deetjen-Ruiz, Zayed University, Abu Dhabi, UAE.

Abstract

This study investigates the predictive relationship between academic self-efficacy and timely degree progression among Arab university students in the UAE. Using binary logistic regression on data from 1,420 students, results show modest predictive value and highlight cultural variables influencing academic timelines. The findings underscore the need for AI-enhanced, context-sensitive student support systems. This research contributes to educational policy and practice by aligning predictive analytics with equity-focused retention strategies.

Introduction

Self-efficacy, as defined by Bandura (1977), is a person's belief in their capability to organize and execute actions required to manage prospective situations. Within educational contexts, academic self-efficacy directly correlates with persistence, resilience, and ultimately academic achievement (Bandura, 1986). In the UAE, where higher education institutions are rapidly expanding to accommodate a growing, diverse student population, understanding how psychosocial variables like self-efficacy influence student outcomes has become a policy and practice priority (Deetjen-Ruiz, 2023). Despite the deployment of robust student support systems, dropout rates and delayed graduation continue to challenge institutional performance across the Middle East Arab Gulf (MEAG) region (Mansouri & Moumine, 2017; Aljohani, 2016).

This study sought to quantitatively examine the relationship between academic self-efficacy and timely degree progression (TDP) among Arab university students in the UAE. Additionally, the study explored how artificial intelligence (AI) could support student retention efforts through early detection and tailored interventions. Specifically, it posed whether AI-driven predictive modeling or learning analytics could identify students at academic risk by analyzing self-efficacy profiles. As the UAE continues its national push toward digital transformation, especially under its AI Strategy 2031, educational institutions must align their internal data infrastructures to facilitate student success (Deetjen-Ruiz et al., 2024; UAE Ministry of AI, 2022). This study therefore carries theoretical and applied significance in informing UAE institutions on how AI tools can be human-centered, equity-focused, and empirically grounded.

Research Question and Methods

The research was guided by two primary questions: (1) What relationship exists between self-efficacy and timely degree progression among Arab university students in the United Arab Emirates? and (2) What relationship exists between self-efficacy and dropout intentions in the same population? For the purposes of this article, only the first question—concerning timely degree progression—is explored in depth. The study hypothesized that students with higher levels of self-efficacy would demonstrate a statistically significant likelihood of graduating on time, as defined by a four-year or four-and-a-half-year trajectory (Juszkiewicz, 2017).

To answer this question, a quantitative, non-experimental, correlational research design was employed. A purposive sample of 1,420 undergraduate students, all of whom identified as Arab, were recruited from three public UAE universities. Participants were selected based on enrollment status (minimum of three years at the institution) and academic risk indicators. Data were collected through a 30-item, Likert-type digital survey developed using Google Forms. The survey adapted the General Self-Efficacy Scale (GSE) and academic commitment subscales aligned with the theoretical frameworks of Bandura (1997), Spady (1970), Tinto (1975), and Bean (1980). Data analysis was conducted using SPSS Version 29.0, and Binary Logistic Regression was performed to determine the relationship between self-efficacy (independent variable) and timely degree progression (dependent variable) (Deetjen-Ruiz, 2023).

Interpretation of Results

The Binary Logistic Regression analysis produced statistically significant model results, with the Omnibus test revealing a chi-square of 24.979 and a p-value of .002. Despite the statistical significance of the overall model, none of the individual self-efficacy indicators independently predicted timely degree progression at the $p < .05$ level. The Nagelkerke R^2 was .127, indicating that the model explained approximately 12.7% of the variance in the outcome variable, a modest effect size that calls for further investigation into latent variables. The Hosmer and Lemeshow test confirmed the model's fit ($p = .267$), and classification accuracy stood at 58.8%, providing moderate support for the model's predictive utility. These results partially challenge long-standing theories asserting a strong and direct relationship between self-efficacy and academic success (Bandura, 1977; Tinto, 1993). One plausible explanation may lie in cultural moderating variables not captured in the quantitative instrument, such as familial influence, institutional culture, or gender-specific role expectations.

This study contributes to a growing body of literature that suggests academic self-efficacy, while important, operates within a broader network of psychological, institutional, and cultural factors (Yokoyama, 2019). It also underscores the limitations of Western-centric theoretical frameworks when applied to non-Western educational settings (Ka Zenzile, 2017). Notably, gender-specific trends emerged, with female students more likely to complete their degrees within five years, compared to five and a half years for male students, suggesting sociocultural dynamics may mediate academic outcomes beyond self-efficacy levels alone. These findings suggest the potential for more comprehensive, multidimensional predictive models—particularly those utilizing AI—that integrate behavioral, demographic, and psychosocial data (Hilty et al., 2025). AI-driven systems could refine self-efficacy constructs using real-time data from learning management systems, digital attendance records, and assignment submissions to generate dynamic risk profiles (Latif, 2022). By synthesizing these multiple data streams, future analytics platforms could provide early alerts and customize intervention strategies, surpassing the limitations of standalone psychosocial scales (Singh et al. 2024).

Educational Practice Implications in the UAE

The implications of this research for educational practice in the UAE are particularly urgent and impactful. First and foremost, it suggests that interventions focused solely on improving students' general self-efficacy may not be sufficient unless they are embedded within a broader institutional strategy that considers the sociocultural and structural context in which students operate. In example, Zayed University, a federally funded public institution, has developed integrated an integrated student success ecosystems where academic support, career readiness, and psychosocial mentoring are informed by data analytics and student profiling (Benkwitz, 2019). AI-enabled dashboards could be designed to analyze behavioral patterns such as LMS usage, participation in group activities, and response times to course tasks, creating predictive flags for low-efficacy indicators (Darvishi, 2022). These analytics could inform faculty and academic advisors to deploy just-in-time interventions personalized to each student's learning trajectory (Deetjen-Ruiz et al., 2024).

Furthermore, embedding self-efficacy development into foundational coursework and first-year seminars could normalize conversations around academic confidence, goal-setting, and resilience. Co-curricular activities such as peer mentoring, student leadership opportunities, and experiential learning should be intentionally aligned with efficacy-building outcomes and monitored through analytics platforms that capture engagement quality, not just quantity. For example, at Zayed University, the Uniquely ZU platform exemplifies this approach by enabling students to log, reflect on, and analyze their personal development across academic and co-curricular dimensions—turning participation into purposeful growth (UniquelyZU, n.d.). The UAE's higher education system, with its substantial government investment and innovation agenda, is uniquely positioned to pioneer such AI-integrated self-efficacy models. As national goals in education increasingly prioritize student-centered learning and outcome-based education, this study affirms the necessity of aligning technological tools with humanistic principles of student development. In doing so, the UAE can serve as a global exemplar of AI-augmented, equity-driven student support that goes beyond predictive algorithms to empower student agency.

Policy Implications

From a policy standpoint, the study's findings prompt a reexamination of how higher education governance in the UAE defines, measures, and responds to academic risk. Ministries and accrediting bodies should consider mandating that institutions use AI-enhanced predictive analytics systems that include psychosocial metrics, not merely academic performance indicators. Policies could require institutions to develop early warning systems that integrate behavioral analytics and self-efficacy scores to provide a real-time picture of students' academic and psychological engagement. Furthermore, data privacy and ethical use policies must accompany these initiatives to ensure transparency, consent, and the avoidance of algorithmic bias (Deetjen-Ruiz, 2023).

To operationalize these recommendations, policymakers might fund institutional research labs that specialize in the development of ethical AI tools for higher education. These labs could be tasked with creating culturally responsive frameworks that account for gender, language, and social stratification unique to the UAE. Policies could also incentivize faculty development programs that train instructors to interpret AI-generated student insights and translate them into actionable teaching and mentoring strategies. By aligning institutional performance funding with the adoption of AI-informed, student-centered success models, UAE higher education policy can shift from reactive troubleshooting to proactive empowerment. In a rapidly digitizing world, embedding AI within educational policy not only ensures institutional resilience but also amplifies student success and system-wide equity.

Future Research Directions

The findings of this study point to several promising avenues for future research. First, longitudinal studies are needed to explore how academic self-efficacy evolves throughout a student's university journey. This approach would allow researchers to examine not only if self-efficacy predicts timely degree progression but how fluctuations in efficacy correlate with pivotal academic events such as course failures, major changes, or institutional transfers. Future studies should also incorporate additional psychological variables, including academic resilience, locus of control, and institutional fit, to create more robust predictive models. Employing mixed-methods research that combines quantitative metrics with qualitative interviews would provide nuanced insights into the mechanisms behind the statistical relationships uncovered in this study.

Importantly, future research should explore the integration of AI-based interventions in real-time academic advising and learning support systems. For instance, deploying AI-powered virtual assistants to monitor and respond to student behavior could offer real-time scaffolding for at-risk students, particularly those exhibiting patterns of disengagement or declining self-confidence (David, 2024). Pilot programs that assess the efficacy of such interventions—comparing cohorts with and without AI support—could validate the potential for large-scale implementation. Additionally, gender-based efficacy patterns identified in this study merit more focused research into culturally situated gender dynamics in educational performance and motivation. By continuing to investigate how self-efficacy operates within dynamic, technologically mediated learning ecosystems, researchers can contribute to a reimagining of student success in the AI era.

Conclusion

This study reaffirms self-efficacy as a critical, though not solitary, factor influencing timely degree progression among Arab university students in the UAE. While the logistic regression model revealed only a modest relationship between self-efficacy indicators and degree completion timelines, it also illuminated the broader complexity of academic persistence in the region. These findings affirm the partial validity of Western retention models but stress the necessity of contextualized, data-rich frameworks that address the cultural, institutional, and psychological ecosystems within which students learn. Self-efficacy must be seen not just as an individual trait but as a construct shaped by peer networks, institutional responsiveness, and educational technology systems.

The study's most compelling contribution lies in its integration of self-efficacy theory with AI-forward thinking. By proposing AI-supported predictive models grounded in student self-efficacy profiles, it lays the groundwork for a new generation of retention strategies that are both data-informed and human-centered. These systems, if designed and implemented ethically, have the potential to detect disengagement before it manifests in dropout and to prescribe personalized, adaptive interventions that bolster academic confidence and motivation. In so doing, institutions in the UAE and beyond can achieve more than improved graduation rates—they can cultivate empowered, resilient learners equipped for the 21st century.

As global higher education enters an era of intelligent systems and big data, the insights generated from this study serve as a call to action. The fusion of psychological theory and AI analytics must be leveraged not as a surveillance tool but as an equity instrument. In a region as forward-looking as the UAE, this synthesis offers a blueprint for educational transformation—one that begins with belief and ends with achievement.

References

1. Bandura A. "Self-efficacy: Toward a unifying theory of behavioral change". Psychological Review 84.2 (1977): 191-215.
2. Bandura A. "Social foundations of thought and action: A social cognitive theory". Prentice-Hall (1986).
3. Bean JP. "Dropouts and turnover: The synthesis and test of a causal model of student attrition". Research in Higher Education 12.2 (1980): 155-187.
4. Benkwitz A., et al. "Using student data: Student-staff collaborative development of compassionate pedagogic interventions based on learning analytics and mentoring". Journal of Hospitality, Leisure, Sport & Tourism Education 25 (2019): 100202.
5. Darvishi A., et al. "Incorporating AI and learning analytics to build trustworthy peer assessment systems". British Journal of Educational Technology 53.4 (2022): 844-875.
6. David N. AI-powered virtual assistant solution for supporting international students (2024).
7. Deetjen-Ruiz R. Self-efficacy's relationship with untimely university graduation and student retention: A quantitative regression study [Doctoral dissertation, American College of Education] (2023).
8. Deetjen-Ruiz R, Toman T and England D. "Rethinking higher education in the AI era: Some thoughts from the United Arab Emirates". Policy Briefing (2024).
9. Hilty DM, Cheng Y and Luxton DD. "Artificial Intelligence and Predictive Modeling in Mental Health". In Digital Mental Health: The Future is Now. Cham: Springer Nature Switzerland (2025): 323-350.
10. Juszkiewicz J. "Trends in community college enrollment and completion data". American Association of Community Colleges (2017).
11. Ka Zenzile M. Decolonizing visualities: changing cultural paradigms, freeing ourselves from Western-centric epistemes (2017).
12. Latif G., et al. "Identifying "at-risk" students: An AI-based prediction approach". International Journal of Computing and Digital Systems 11.1 (2022).

13. Ministry of Artificial Intelligence. UAE National Strategy for Artificial Intelligence. In National Program for Artificial Intelligence (2018).
14. Singh H., et al. “Framework for suggesting corrective actions to help students intended at risk of low performance based on experimental study of college students using explainable machine learning model”. Education and Information Technologies 29.7 (2024): 7997-8034.
15. Singh H., et al. “Framework for suggesting corrective actions to help students intended at risk of low performance based on experimental study of college students using explainable machine learning model”. Education and Information Technologies 29.7 (2024): 7997-8034.
16. Spady WG. “Dropouts from higher education: An interdisciplinary review and synthesis”. Interchange 1.1 (1970): 64-85.
17. Tinto V. “Leaving college: Rethinking the causes and cures of student attrition (2nd ed.)”. University of Chicago Press (1993).
18. UniquelyZU. (n.d.). zu.ac.ae. (2025).
19. Yokoyama S. “Academic self-efficacy and academic performance in online learning: A mini review”. Frontiers in psychology 9 (2019): 2794.
20. Zander L, Höglund P and Rantatalo O. “Self-efficacy and academic resilience: Predicting academic performance and persistence”. Journal of Educational Psychology 110.7 (2018): 970-985.