The mediating role of students' engagement and satisfaction in the relationship between AI-based educational tools, flexible learning techniques, and the performance of students on academic probation

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The mediating role of students' engagement and satisfaction in the relationship between AI-based educational tools, flexible learning techniques, and the performance of students on academic probation

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Abstract

This study investigates the influence of Artificial Intelligence-based (AI-based) educational tools and flexible learning techniques on the academic performance of students on academic probation, emphasizing the mediating roles of students' satisfaction and engagement. Conducted at the Canadian International College (CIC) in Egypt, the study targeted 240 probationary students using a census approach. A mixed-methods design was employed, incorporating surveys, academic records, and interviews. Structural Equation Modeling (SEM) revealed that AI tools and flexible techniques significantly enhance student satisfaction and engagement, which in turn positively affect academic performance. The findings demonstrate partial mediation, with a substantial portion of the variance in academic performance explained by satisfaction and engagement. A comparative analysis across six academic terms also showed a notable improvement in success rates during the study year, reinforcing the model's effectiveness.

Keywords: AI-based educational tools, "Flexible learning techniques, Academic performance, Academic probation, "Students' satisfaction, and Students' engagement.

1. Introduction

Education in the 21st century has been significantly transformed by rapid technological advancements, particularly through the integration of Artificial Intelligence (AI) and flexible learning techniques. These innovations have reshaped traditional educational paradigms, providing opportunities for personalized learning, adaptive instruction, and enhanced student engagement. The ability of AI-driven tools to tailor educational experiences to individual students has sparked considerable interest among researchers and educators

(Zawacki-Richter et al., 2019; Holmes et al., 2021). Moreover, flexible learning approaches, such as self-paced learning and on-demand educational resources, have become essential for addressing diverse learning needs, particularly among students facing academic challenges (Graham, 2006; Bond et al., 2021).

One of the most pressing challenges in higher education worldwide is academic probation, a status assigned to students who fail to meet minimum academic performance requirements. Students on academic probation are at an increased risk of dropout and academic dismissal, often due to a combination of academic, psychological, and socio-economic factors (Tinto, 1993; Kuh et al., 2008). Traditional interventions, such as remedial courses and academic counseling, have often failed to produce sustainable improvements in student outcomes (Yorke, 2004), highlighting the need for innovative, technology-enhanced educational strategies.

AI-based educational tools offer promising solutions by providing real-time feedback, intelligent tutoring, and personalized content recommendations based on students' learning patterns. These tools can identify individual weaknesses and suggest targeted interventions, helping students overcome academic difficulties (Chen et al., 2020; Roll & Wylie, 2016). Additionally, flexible learning techniques allow students to engage with course materials at their own pace, reducing cognitive overload and promoting a deeper understanding of complex subjects (Almaiah et al., 2020; Boelens et al., 2017). By integrating these strategies, universities can create a more inclusive and supportive learning environment that fosters academic recovery.

Beyond technological interventions, students' satisfaction and engagement play a crucial role in academic success. Research has consistently demonstrated that higher levels of student engagement correlate with improved retention and achievement (Fredricks et al., 2004; Appleton et al., 2008). Moreover, satisfaction with the learning process enhances motivation and persistence, factors essential for students attempting to recover from academic probation (Kahu, 2013; Dixson, 2015). Despite the growing interest in AI and flexible learning, limited studies have explored how satisfaction and engagement mediate their effects on students at risk (Bailey et al., 2018; Selwyn, 2019).

This study aims to investigate the impact of AI-based educational tools and flexible learning techniques on the academic performance of students on academic probation, specifically through the mediating role of students' satisfaction and engagement. While previous research has explored the individual effects of AI and flexible learning on academic achievement, few studies have examined their combined impact and the mechanisms through which they influence students at risk of academic failure. By addressing this gap, the study seeks to provide a conceptual framework for integrating AI-driven and flexible learning approaches into higher education institutions, offering practical and theoretical insights into improving student outcomes.

To achieve these objectives, the study employs a mixed-methods research design, combining quantitative and qualitative data collection techniques. A judgmental sample of students on academic probation from an Egyptian higher education institution was selected, and data was gathered through questionnaires, academic records, and interviews. The findings are expected to contribute to both educational theory and practice, helping policymakers and educators develop evidence-based interventions that enhance student retention and academic performance through AI and flexible learning.

By investigating these relationships, this study aims to provide a comprehensive understanding of how AI-driven strategies and flexible learning techniques can serve as effective tools for supporting academically at-risk students. The results are expected to inform future institutional policies and teaching methodologies, ensuring a more inclusive and adaptive educational landscape that fosters student success.

2. Literature review and hypothesis development

Recent advancements in educational technology, particularly the integration of Artificial Intelligence (AI) and flexible learning methodologies, have demonstrated significant potential in enhancing student engagement, satisfaction, and overall academic performance across various educational settings [Zawacki-Richter et al., 2019; Chen et al., 2020; Veletsianos & Houlden, 2019; Graham, 2006]. The literature extensively details the capabilities of AI-based educational tools, such as intelligent tutoring systems and adaptive learning platforms, in providing personalized learning experiences, real-time feedback, and targeted support. Similarly, flexible learning techniques, encompassing adaptability in time, content, instructional approach, and logistics, are recognized for fostering student-centered pedagogies and promoting behavioral engagement. These innovations offer promising avenues for addressing diverse learning needs and improving educational outcomes.

However, despite the broad recognition of these benefits, a critical gap persists in the existing body of literature: the specific application and impact of AI-based educational tools and flexible learning techniques on students on academic probation. This particular subgroup of students faces a unique confluence of academic, psychological, and systemic challenges that often lead to delayed graduation, potential academic dismissal, and significant psychological stress. As highlighted in the literature, academic probation is a strong predictor of student attrition, and these students frequently struggle with low motivation, disconnection from their studies, and barriers that traditional, rigid educational systems fail to accommodate. Their challenges are often not rooted in course difficulty but rather in the inflexibility of conventional learning environments that do not account for their specific circumstances, such as external employment obligations or personal commitments.

Therefore, this research addresses the pressing need to investigate how a hybrid model, integrating flexible learning techniques with AI-based educational tools, can serve as a tailored intervention for students on academic probation. By leveraging the adaptive and personalized capabilities of AI, alongside the inherent flexibility of modern learning approaches, this study aims to explore their potential to enhance student satisfaction and engagement—factors empirically linked to improved academic outcomes. Ultimately, this research seeks to demonstrate how such an integrated approach can provide the necessary adaptability to support at-risk students, thereby improving their academic performance and mitigating the cycle of academic probations, contributing directly to the literature on effective interventions for student success and retention in higher education.

2-1: AI-based educational tools:

Artificial Intelligence (AI) is defined as computer-controlled systems exhibiting human-like capabilities such as learning, reasoning, and self-correction (Chen et al., 2020; Nilsson, 2014). In education, AI-based tools, including intelligent tutoring systems (e.g., AutoTutor, MetaTutor) and adaptive learning platforms (e.g., Coursera, Knewton), enhance learning outcomes by providing personalized support and real-time feedback (Zawacki-Richter et al., 2019). These tools have evolved to address diverse student needs, improving engagement and satisfaction through tailored educational experiences (Baker, 2021).

A systematic review by Zawacki-Richter et al. (2019) from 2007 to 2018 identified key AI applications in education, including adaptive systems, intelligent tutoring, and learning analytics. For instance, natural language processing tools like Grammarly offer text analysis and feedback, while virtual assistants (e.g., Google Assistant) provide on-demand study support. These tools personalize learning paths, adapting content and pace to individual student profiles (Khalil et al., 2020). Affective computing tools, such as Affectiva, analyze emotional responses to optimize learning strategies, fostering a supportive environment (Gikandi & Morrow, 2021).

For students on academic probation, who often face challenges in rigid educational systems, AI-based tools are particularly valuable. These students struggle with reading, comprehension, and retention, which can hinder academic progress (Jony & Solaiman, 2022). AI systems address these issues by offering task planning, time management, and cognitive control, enabling personalized instruction that aligns with their learning styles (Mavroudi et al., 2018; Huang & Spector, 2020). By providing adaptive feedback and interactive experiences, AI tools enhance engagement and satisfaction, critical for academic recovery in at-risk students (Allam et al., 2023).

<u>This leads to Hypothesis 1:</u>

H1: AI-based educational tools have a positive impact on both satisfaction and engagement among students on academic probation.

Which means: The personalized and adaptive nature of AI tools addresses individual learning needs, fostering greater engagement and ownership over the learning process. For probationary students, this adaptability mitigates the limitations of traditional systems, significantly improving their educational experience and involvement.

2-2: Flexible learning:

Flexible learning encompasses diverse approaches that adapt to students' needs, offering autonomy in time, content, and instructional methods (Garrick & Jakupec, 2000; Soffer et al., 2019). From a technological perspective, it leverages information and communication technologies to enable access to varied resources (Chen et al., 2003). Pedagogically, it emphasizes flexibility in learning pace, strategy selection, and assessment activities to suit individual preferences (Flannery & McGarr, 2014).

Collis et al. (1997) identified four key dimensions of flexible learning: time flexibility (e.g., adaptable schedules and deadlines, self-paced learning), content flexibility (e.g., diverse topics, balanced theoretical-practical approaches), instructional approach and resource flexibility (e.g., varied learning materials, assignment types), and course logistics flexibility (e.g., remote access, flexible event scheduling). These dimensions allow instructors to design courses that accommodate diverse student needs, particularly for those on academic probation who face rigid academic structures and external commitments (Veletsianos & Houlden, 2019).

Flexible learning promotes behavioral engagement and student-centered pedagogies by reducing cognitive overload and fostering interactive settings (Kariippanon et al., 2019). For probationary students, adjustable deadlines and accessible resources enhance satisfaction by alleviating scheduling conflicts, while autonomy in learning pace boosts engagement (Means et al., 2013; Soffer et al., 2019). This study explores these relationships to understand how perceived flexibility impacts academic outcomes for at-risk students.

This leads to Hypothesis 2:

H2: Flexible learning techniques positively influence both satisfaction and engagement among students on academic probation.

In other words: By offering adaptability in scheduling, content, and pace, flexible learning addresses the needs of probationary students, reducing friction and enhancing comfort, which drives satisfaction. Increased autonomy fosters engagement, supporting academic recovery in rigid educational systems.

2-3: Academic performance:

Academic performance refers to the extent to which students achieve educational goals, encompassing knowledge acquisition, skill development, and critical thinking enhancement (York et al., 2015). It is commonly measured through grades, grade point averages (GPAs), completion rates, and standardized test scores, with qualitative assessments like research projects and peer evaluations providing a holistic view (Tadese et al., 2022).

Several factors influence academic performance, including socioeconomic background (Gaddis, 2014), learning environments and institutional support (Lange, 2014), motivation and self-efficacy (Eisenberg et al., 2016; Zimmerman & Schunk, 2011), instructional methods (Kapur, 2018), technological integration (Olufemi et al., 2018), peer influence (Tinto, 2017), parental involvement (Dennis et al., 2005), and participation in extracurricular activities (Kuh et al., 2007). Advancements in AI-driven analytics and adaptive learning technologies have transformed how student progress is monitored and enhanced (Olufemi et al., 2018). Understanding these factors helps educators develop interventions to improve student success and retention in higher education.

2-4: Students' academic probation:

Academic probation is a critical indicator of a student’s struggle within the higher education system, signaling that the individual has failed to meet the institution’s minimum academic standards, typically a GPA below 2.0. This status marks a critical turning point that can significantly impact a student’s future academic path (Noble & Sawyer, 2004). Understanding the diverse factors leading to probation and their consequences is essential for designing effective interventions. Jony & Solaiman (2022) categorize causes into personal concerns (e.g., lack of self-motivation, family problems, health issues, financial difficulties, procrastination) and academic concerns (e.g., poor time management, inadequate study habits, weak writing and presentation skills, limited interaction with instructors, irregular class attendance).

The consequences of academic probation can be far-reaching. It is a strong predictor of student attrition, with unsupported students at higher risk of dropping out (Bean, 1985; Smith & Johnson, 2020). Probation can lower self-esteem and increase stress, creating a negative feedback loop that impairs performance (Brown & Davis, 2019; Joelle et al., 2011). Extended probation may lead to dismissal, affecting future academic and career prospects (Feldman, 1994). Effective interventions, including academic support programs and faculty-student interaction, improve outcomes, helping students overcome challenges and increasing retention and graduation rates (Lee & Thompson, 2021; Garcia & Martinez, 2022).

2-5: Students' satisfaction:

Students' satisfaction measures how content students are with specific aspects of their educational experience, including the quality of teaching, available resources, and the school's facilities and services [Malouff, J., 2010]. According to Martín et al. (2014), students' satisfaction reflects their attitudes, motivations, and overall psychological state, which can be broken down into several components:

- Academic Experience: Satisfaction with courses, curriculum, teaching methods, and instructor quality.
- Support Services: Satisfaction with academic advising, counseling services, and extracurricular activities.
- Facilities: Contentment with school facilities, such as classrooms, libraries, and recreational areas.
- Administrative Efficiency: Opinions on the effectiveness and efficiency of administrative processes.

Empirical evidence suggests that low student satisfaction often correlates with poor academic outcomes, including lower grades, higher dropout rates, and increased mental health challenges [Somo, 2013]. Conversely, high student satisfaction has been linked to improved learning outcomes, increased academic persistence, and better overall college experiences. For instance, students on academic probation often experience diminished satisfaction, characterized by discouragement, demotivation, and disconnection from their studies, which can lead to a self-reinforcing cycle of underachievement.

To address these issues, integrating AI-based educational strategies and flexible learning approaches has shown promise in positively impacting student satisfaction, particularly among those on academic probation [Allam et al., 2023; Means et al., 2013]. Personalized learning pathways, adaptive feedback, and increased autonomy can foster a greater sense of engagement and ownership over the learning process, potentially boosting satisfaction and, in turn, academic performance [Alaswad & Nadolny, 2015; Allam et al., 2023]. These strategies align with broader educational goals of enhancing student outcomes and well-being, making them relevant to the overall focus of this research and lead to Hypothesis 3:

(H3): Students' satisfaction positively influences the academic performance of students on academic probation.

That is to say: As highlighted in the literature, a direct and significant relationship exists between student satisfaction and academic outcomes. When students are content with their educational experience, they are more likely to be motivated, persistent, and engaged, leading to improved grades, higher completion rates, and better overall academic performance. This relationship is particularly critical for students on academic probation, where enhanced satisfaction can break cycles of underachievement.

2-6: Students' engagement:

Student engagement is a critical factor in academic performance and achievement. Numerous studies have shown that students who are actively engaged in their learning—both behaviorally and emotionally—tend to achieve better grades, perform well on assessments, and exhibit lower dropout rates [Fredricks et al., 2004; Kuh, 2009; Trowler, 2010].

Engagement can be defined as a student's active involvement, interest, and commitment to their studies [Christenson et al., 2012]. It encompasses three key dimensions:

- Behavioral engagement: Participation in academic and extracurricular activities.
- Emotional engagement: Positive attitudes and feelings towards learning.
- Cognitive engagement: Investment in learning and self-regulation.

Highly engaged students demonstrate behaviors such as attending classes regularly, participating in discussions, completing assignments diligently, and actively seeking out learning opportunities [Fredricks et al., 2004]. However, maintaining engagement can be particularly challenging for students on academic probation, who often struggle with low academic performance and face academic, personal, and social difficulties that negatively impact their motivation and involvement [Zepke et al., 2010]. Research indicates that these students may lack motivation, feel disconnected from their studies, or encounter barriers that prevent them from fully engaging, which leads to Hypothesis 4:

(H4): Students' engagement positively influences the academic performance of students on academic probation.

That means: The literature unequivocally establishes student engagement as a direct predictor of academic success. Actively engaged students, across behavioral, emotional, and cognitive dimensions, consistently achieve better grades, perform well on assessments, and exhibit lower dropout rates. For students on academic probation, fostering greater engagement is a direct pathway to improving their academic outcomes and overcoming their current challenges.

2-7: Mediating role of satisfaction and engagement:

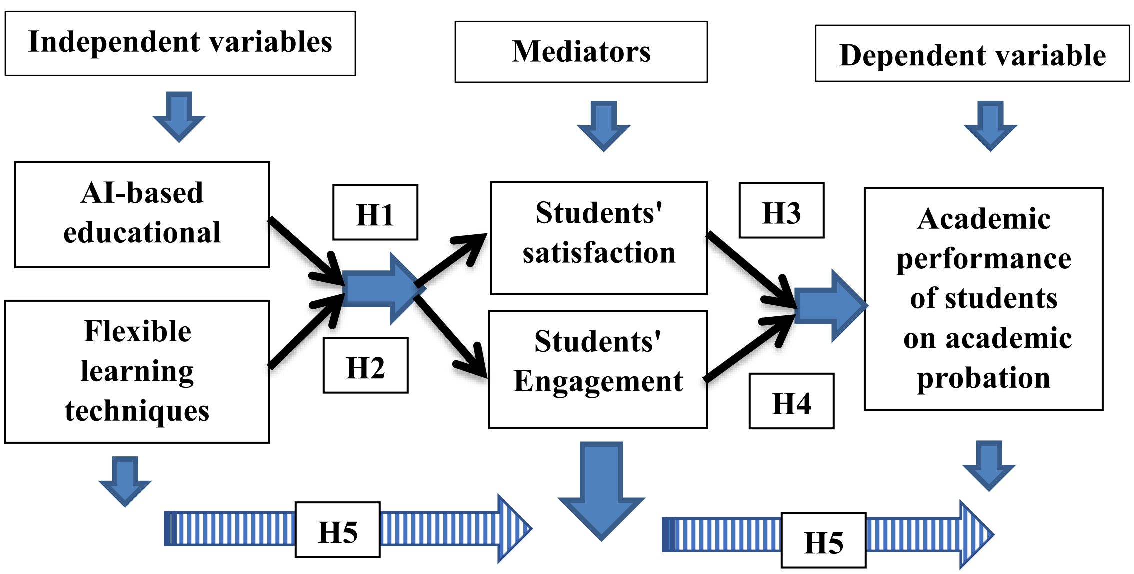
Building upon the direct relationships established above, it is posited that student satisfaction and engagement play crucial mediating roles in the impact of AI-based educational tools and flexible learning techniques on academic performance. The literature suggests that interventions, such as personalized learning and adaptive feedback (facilitated by AI) and increased autonomy (offered by flexible learning), enhance satisfaction and engagement. These enhanced states, in turn, lead to improved academic outcomes, leading to Hypothesis 5:

(H5): AI-based educational tools and flexible learning techniques have an indirect positive impact on the academic performance of students on academic probation, mediated by students' engagement and satisfaction.

This means: This comprehensive hypothesis synthesizes the preceding arguments. AI-based tools and flexible learning techniques are theorized to improve academic performance not only directly but also indirectly by first enhancing student satisfaction and engagement. The literature supports the notion that these mediating factors serve as crucial pathways through which educational interventions influence ultimate academic success. This mediation model provides a more nuanced understanding of the complex interplay between technology, pedagogy, student experience, and academic outcomes, particularly within the context of students on academic probation.

3: Conceptual frame work:

The conceptual framework expresses the relationship between AI-based educational strategies, flexible learning techniques and academic performance for students on academic probation through the mediating role of students' satisfaction and students' engagement as follows:



(Figure 1: Conceptual framework)

4. Methodology

4.1: Participants and data collection:

This study explores the impact of AI-based educational strategies and flexible learning techniques on enhancing the academic performance of students on academic probation, while also assessing their effects on student morale and engagement. The research was conducted at the Canadian International College (CIC) in Cairo, Egypt, a higher education institution.

A mixed-methods approach was adopted for this study. Quantitative data were collected through surveys and academic records, while qualitative data were gathered via interviews to gain deeper insights. The survey was designed to evaluate students' engagement, satisfaction, and academic performance, whereas the interviews provided a more comprehensive understanding of their experiences with AI-based tools and flexible learning methods.

This study employed a census approach, encompassing all 240 students on academic probation who were enrolled in the summer term during which the research was conducted. These students constitute the entire available population from a total of 660 probationary students across the college (CIC), as only 240 were registered in the summer term and subsequently included in the survey. The questionnaire was developed using Google Forms and distributed in two formats: hard copies delivered directly to students and electronic versions shared via email and social media platforms.

4.2: Research variables and measurement methods:

The survey comprised 44 items designed to evaluate the impact of the independent variables (AI-based educational tools and flexible learning techniques) on the dependent variable (academic performance), with student engagement and satisfaction as mediating variables. The measures were conceptualized based on established theoretical frameworks and prior research to ensure validity and alignment with the context of students on academic probation. Specifically:

- AI-based educational tools (8 items): Items were adapted from Zawacki-Richter et al. (2019), focusing on AI functionalities (e.g., personalized feedback, adaptive learning platforms) to address probationary students' learning needs.

- Flexible learning techniques (8 items): Items were developed based on Collis et al. (1997), capturing flexibility dimensions (e.g., time, content, instructional approaches) relevant to at-risk students' scheduling and resource needs.
- Student engagement (10 items): Measures were adapted from Heilporn et al. (2020), assessing behavioral, emotional, and cognitive engagement in blended learning environments for probationary students.
- Student satisfaction (10 items): Items were drawn from Schreiner & Juillerat's (1994) Student Satisfaction Inventory, evaluating satisfaction with teaching, resources, and learning experiences.
- Academic performance (8 items): Measures were adapted from Wu & Wang (2011), focusing on GPA, course completion, and self-reported academic progress in the probationary context.

All responses were recorded on a five-point Likert scale ranging from 5 ("Strongly agree") to 1 ("Strongly disagree").

4.3: Statistical & Analysis tools:

To ensure robust statistical analysis, the following methods and tools were used:

- Descriptive Statistics: Summarizing key study variables (mean, standard deviation, and variance).
- Reliability Analysis: Cronbach's Alpha and Composite Reliability (CR) to measure internal consistency.
- Confirmatory Factor Analysis (CFA): To validate the measurement model and assess construct validity.
- Pearson Correlation Analysis: To determine relationships among study variables.
- Structural Equation Modeling (SEM): Conducted using AMOS 23 to test the research hypotheses.
- Mediation Analysis (PROCESS by Andrew F. Hayes): To examine indirect effects through engagement and satisfaction.
- T-Test and Wilcoxon Signed Ranks Test: To compare groups and validate results.
- Additionally, the study integrated official academic records (e.g., success rates, GPAs, and probation status) obtained from the college administration to complement self-reported survey data and mitigate potential response bias.

5. Statistical analysis and study results for research hypotheses

5.1: Descriptive statistics

Descriptive statistics summarize the key study variables, providing insight into the distribution and characteristics of the dataset.

Table 1: Descriptive Statistics:

Constructs	Mean	Std. Dev
AI Tools	3.84	0.74
Flexible Learning	3.65	0.92
Satisfaction	3.72	0.95
Engagement	3.90	0.73
Academic Performance	4.65	0.28

5.2: Hypothesis Testing:

This section examines the initial relationships between the study variables to test the research hypotheses. The Pearson correlation analysis provides preliminary evidence of the associations among AI-based tools, flexible learning techniques, satisfaction, engagement, and academic performance.

Table 2: Pearson Correlation Matrix

Constructs	AI Tools	Flexible Learning	Satisfaction	Engagement	Academic Performance
AI Tools	1	0.456**	0.501**	0.472**	0.660**
Flexible Learning	0.456**	1	0.550**	0.434**	0.730**
Satisfaction	0.501**	0.550**	1	0.403**	0.550**
Engagement	0.472**	0.434**	0.403**	1	0.703**
Academic Performance	0.660**	0.730**	0.550**	0.703**	1
Note: **p < 0.001					

5.3: Structural Equation Modeling (SEM) results

Table 3: Regression weights for testing the mediating role of engagement and satisfaction

Path	Standardized Estimate	S.E.	C.R.	P-Value
AI Tools → Satisfaction	0.275	0.068	3.833	0.001***
AI Tools → Engagement	0.275	0.066	4.059	0.001***
Flexible Learning → Satisfaction	0.346	0.066	4.830	0.001***
Flexible Learning → Engagement	0.304	0.064	4.463	0.001***
Satisfaction → Academic Performance	0.501	0.036	10.668	0.006**
Engagement → Academic Performance	0.703	0.073	7.119	0.001***
[Figure 1: Structural Equation Modeling (SEM) Diagram remains unchanged]				

Interpretation of SEM results:

1. Impact of AI-Based tools and flexible Learning on Students' Satisfaction: AI-based educational tools and flexible learning techniques significantly impact students' satisfaction ($\beta = 0.275$ for AI tools, $\beta = 0.346$ for flexible learning, $p < 0.001$), **supporting the first part of H1 (related to the positive impact of AI-based tools on satisfaction) and the first part of H2 (related to the positive influence of flexible learning techniques on satisfaction)**

   <u>Regression model:</u> Y1: Students' Satisfaction = 0.275 × AI-based Tools + 0.346 × Flexible Learning

   <u>The exogenous variables explain 30.3% of the total variance in students' satisfaction.</u>

2. Impact of AI-Based Tools and Flexible Learning on Students' Engagement:
   AI-based tools and flexible learning techniques significantly impact students' engagement ($\beta = 0.275$ for AI tools, $\beta = 0.304$ for flexible

learning, $p < 0.001$), **supporting the remaining part of H1 (related to the positive impact of AI-based tools on engagement) and the remaining part of H2 (related to the positive influence of flexible learning techniques on engagement). Together, these findings fully confirm Hypotheses H1 and H2.**

Regression model: Y2: Students' Engagement = 0.275 × AI-based Tools + 0.304 × Flexible Learning

The exogenous variables explain 26.3% of the total variance in students' engagement.

3. Impact of Satisfaction and Engagement on Academic Performance: Satisfaction and engagement significantly influence academic performance ($\beta = 0.501$ for satisfaction, $\beta = 0.703$ for engagement, $p < 0.001$), **supporting H3&H4**
   Regression model: Z: Academic Performance = 0.501 × Satisfaction + 0.703 × Engagement
   The exogenous variables explain 62.2% of the total variance in academic performance.

4. Goodness of Fit: The SEM model demonstrates a good fit, with all fit indices within acceptable ranges: (GFI, AGFI, NFI, RFI, IFI, TLI, CFI > 0.90, RMSEA < 0.08). These indices indicate that the theoretical model closely matches the actual data, confirming the robustness of the structural model.

5.4: Comparative analysis of success rates over six summer terms

To further validate the effectiveness of AI-based educational tools and flexible learning techniques, a comparative analysis of student success rates in the targeted course was conducted. This analysis compares the summer term during which the study was implemented (study year) with the same term over the preceding five years, using historical academic records from the Canadian International College (CIC). Success rates, defined as the percentage of students on academic probation passing the course, were examined to assess improvements attributable to the intervention.

Table 4: Success rates in the targeted course across six summer terms:

Year	Success Rate (%)
Study Year	95
Year -1	82
Year -2	79
Year -3	75
Year -4	71
Year -5	78
The success rate in the study year reached 95%, a substantial increase compared to the previous five years, which recorded rates of 82% (Year -1), 79% (Year -2), 75% (Year -3), 71% (Year -4), and 78% (Year -5), with an average of 77% over this period. This marked improvement suggests that the integration of AI-based tools and flexible learning techniques significantly enhanced academic outcomes for students on academic probation, providing additional empirical support for the study's findings on their effectiveness.	

5.5: Mediation Analysis and Interpretation

The analysis reveals a significant indirect effect of AI-based educational tools and flexible learning techniques on academic performance, mediated by student engagement and satisfaction ($p < 0.001$). While a direct relationship between these tools and academic performance persists, partial mediation is evident through engagement and satisfaction, as indicated by the continued statistical significance of the direct effects ($p < 0.05$) from AI-based tools and flexible learning techniques to academic performance, even after accounting for the significant indirect effects mediated by satisfaction and engagement ($p < 0.001$)."

Specifically, the total indirect effect coefficients for student satisfaction (0.2195) and engagement (0.1598) indicate substantial contributions to academic performance. Standardized direct effects, with values of 0.275 and 0.703 respectively, confirm significant direct impacts ($p < 0.05$).

These findings support H5, suggesting that AI-based educational tools and flexible learning techniques enhance the academic performance of students on academic probation indirectly by improving their engagement and satisfaction. The application of the bootstrapping method reinforces the robustness and reliability of these indirect effects

Although direct effects are present, the more pronounced and significant impacts on academic performance are mediated through increased student satisfaction and engagement. This underscores the importance of integrating AI-driven personalized learning strategies and flexible academic structures to foster student-centered learning experiences.

Table 5: Standardized Direct and Indirect Effects

Constructs	Flexible Learning	Satisfaction	Engagement
Satisfaction	0.346d**	0.275d**	--
Engagement	0.304d**	0.275d**	--
Academic Performance	0.388ind*	0.332ind*	0.703d**
Note: d = Direct Effects, ind = Indirect Effects (p < 0.05, p < 0.001)** , The reported effects support partial mediation, as both direct and indirect paths remain statistically significant."			

Summary of Findings:

AI-based educational tools and flexible learning techniques significantly enhance students' satisfaction and engagement, which in turn positively impact academic performance. The comparative analysis of success rates further corroborates these findings, demonstrating a notable improvement in student outcomes following the intervention. The high explanatory power of the model (R^2 values) and the strong fit indices (GFI, CFI, RMSEA) validate the reliability and validity of the results.

6. Discussion and recommendations

6.1 Discussion of results:

The findings of this study provide robust evidence supporting the positive impact of AI-based educational tools and flexible learning techniques on the academic performance of students on academic probation, mediated by satisfaction and engagement. This section discusses these results in light of prior research from the Literature Review (Section 2), highlighting areas of agreement and divergence, and offering explanations for these patterns.

- **Impact of AI-based educational tools and flexible learning techniques on satisfaction and engagement**

The study confirmed that AI-based educational tools and flexible learning techniques significantly enhance students' satisfaction and engagement, supporting Hypotheses H1 and H2. These findings align with prior research on technology-enhanced learning and flexible pedagogies. For instance, Zawacki-Richter et al. (2019) found that AI-driven tools, such as intelligent tutoring systems and adaptive learning platforms, improve student satisfaction by offering personalized learning experiences, a pattern consistent with our results. Similarly, Means et al. (2013) reported that blended learning approaches, which often incorporate flexible techniques, enhance engagement and satisfaction, mirroring our observed effects ($\beta = 0.346$ for flexible learning on satisfaction, $\beta = 0.304$ on engagement, $p < 0.001$). The agreement with these studies can be attributed to the personalization capabilities of AI tools (e.g., Google Classroom, Coursera) and the adaptability of flexible learning methods (e.g., adjustable deadlines, diverse resources) used in our intervention, which catered to the unique needs of probationary students, such as older learners with employment commitments (Section 3).

However, our findings extend beyond these studies by focusing on a specific at-risk population—students on academic probation—rather than the general student body. While Chen et al. (2020) and Veletsianos & Houlden (2019) noted the broad benefits of AI and flexible learning, they did not specifically address probationary students, who often face heightened disengagement and stress (Jony & Solaiman, 2022). The stronger effect of flexible learning on satisfaction in our study may reflect the critical role of autonomy and reduced cognitive overload for this group, contrasting with studies on general populations where AI effects might dominate due to greater digital literacy or familiarity (Allam et al., 2023). This divergence likely stems from our context: a census-based sample in a summer term at a private Egyptian institution, where traditional rigid systems have historically underserved such students (Section 3).

- These findings have significant practical implications for educational institutions, particularly in Egypt's rigid higher education systems. Universities can leverage AI tools to provide real-time, personalized feedback, addressing probationary students' learning gaps and boosting motivation. Flexible learning strategies, such as self-paced modules and adjustable deadlines, can accommodate external commitments (e.g., part-time employment), reducing stress and enhancing satisfaction. For instance, institutions could implement platforms like Coursera or develop custom AI-driven tutoring systems to support at-risk students. These interventions could be integrated into academic recovery programs, potentially reducing dropout rates and improving institutional retention metrics, as evidenced by our study's 95% success rate compared to the 77% historical average (Section 5.4).
- The study contributes to theoretical frameworks by highlighting the unique needs of probationary students within engagement and satisfaction models. It extends Kahu's (2013) engagement framework by demonstrating how AI and flexible learning foster behavioral and emotional engagement in high-risk groups. Additionally, it refines Tinto's (1993) retention theory by integrating technology-driven interventions, suggesting that satisfaction and engagement are pivotal mediators in preventing attrition among probationary students. These insights enrich theoretical discussions on how technology can address systemic educational challenges in rigid academic environments.

Mediating Role of Satisfaction and Engagement in Academic Performance:

The study also established that satisfaction and engagement mediate the relationship between AI-based tools, flexible learning, and academic performance, supporting Hypotheses H3, H4, and H5. These results resonate with Fredricks et al. (2004), who demonstrated that engagement (behavioral and emotional) strongly predicts academic success, a finding reflected in our high engagement coefficient. Likewise, Kahu (2013) and Dixson (2015) highlighted satisfaction as a key driver of persistence and achievement, consistent with our result. The partial mediation effect (Section 5.5) aligns with Means et al. (2009), who found that technology-enhanced learning indirectly boosts performance through engagement, though their focus was on online learning rather than AI specifically.

Our study's emphasis on partial mediation diverges from some prior work suggesting full mediation in technology-driven contexts (e.g., Pardo et al., 2016), where direct effects might diminish entirely. This difference may be due to our probationary sample retaining significant direct benefits from AI tools and flexible learning (e.g., real-time feedback, adaptive scheduling), which remain critical for immediate academic recovery in a short summer term. Additionally, the comparative success rate analysis (95% in the study year vs. 77% average over prior years, Section 5.4) provides practical evidence of effectiveness, surpassing success rates reported in traditional interventions for probationary students (e.g., Lee & Thompson, 2021), likely due to the combined AI-flexible learning approach tailored to our unique institutional and cultural setting.

- The mediation findings suggest that universities should prioritize interventions that enhance satisfaction and engagement to maximize academic outcomes. For example, academic advisors could use AI-driven analytics to monitor engagement levels and tailor support plans, while flexible course designs could foster a sense of autonomy, critical for probationary students' persistence. These strategies could be scaled across faculties to create a supportive ecosystem, potentially reducing the psychological stress associated with probation (Brown & Davis, 2019).
- The partial mediation model advances the literature by clarifying the dual pathways (direct and indirect) through which AI and flexible learning impact academic performance. It builds on Means et al. (2009) by specifying the role of AI-driven personalization and flexible scheduling in high-stakes contexts, enriching mediation theories in educational technology research. This nuanced model offers a framework for future studies to explore how technology-mediated interventions can support diverse student populations.

In summary, our findings align with the broader literature on the benefits of AI and flexible learning for engagement and satisfaction, while offering novel insights into their application for students on academic probation. The agreements stem from shared mechanisms like personalization and adaptability, whereas divergences reflect our specific focus on an at-risk group in a distinct educational context. These results underscore the potential of integrating AI-driven and flexible strategies to support academic recovery, extending theoretical and practical implications for higher education.

6.2 Recommendations:

Based on the study findings, the following recommendations are proposed to enhance the academic performance of students on academic probation through AI-based educational tools and flexible learning techniques. These recommendations are presented in a table format, detailing the recommendation, implementation mechanisms, and responsible entities.

Table 6: Recommendations, implementation mechanisms, and responsible entities

Recommendation	Implementation Mechanisms	Responsible Entity
1. Adopt AI-driven adaptive learning systems	Implement platforms like Coursera or Knewton that personalize content based on student performance data; provide real-time feedback and tailored resources to address learning gaps.	University administration, IT department
2. Promote self-paced learning environments	Design courses with adjustable deadlines and modular content; offer online access to materials for asynchronous learning.	Academic departments, course instructors
3. Integrate interactive AI-based tools	Deploy intelligent tutoring systems (e.g., AutoTutor), virtual assistants (e.g., Google Assistant), and gamified platforms; train students on their use.	IT department, faculty members

4. Conduct longitudinal studies to assess long-term impact	Initiate multi-year research projects tracking student outcomes post-intervention; use statistical tools like SEM to analyze sustainability.	Research office, academic researchers
5. Develop a strategic framework for integrating AI and flexible learning	Form a task force to align AI and flexible learning with institutional goals; create a phased rollout plan for adoption across curricula.	University leadership, strategic planning committee
6. Provide training programs for faculty on AI and flexible learning tools	Organize workshops and certification courses on AI tool usage and flexible pedagogy; offer ongoing support through a helpdesk.	Human resources department, faculty development unit
7. Implement monitoring and evaluation systems for AI and flexible learning initiatives	Establish KPIs (e.g., success rates, engagement levels); use learning analytics to assess effectiveness and adjust strategies.	Quality assurance unit, IT department
8. Create feedback channels for students to improve AI and flexible learning tools	Set up online surveys, focus groups, and suggestion boxes; analyze feedback to refine tools and approaches.	Student affairs office, IT department
9. Expand the application of AI and flexible learning to governmental universities through pilot studies	Partner with governmental institutions to conduct pilot programs that test and adapt these tools in diverse contexts, sharing resources and best practices to inform broader implementation	University administration, external educational partners
10. Enhance student support services with AI-driven counseling tools: Deploy AI-based chatbots or virtual advisors to provide academic and psychological support, addressing probationary	Implementation includes integrating tools like Replika or Woebot into student portals, with training for counselors to oversee interactions	Student Affairs Office, Counseling Services).

students' stress and motivation challenges.		
11. Incorporate AI and flexible learning into institutional accreditation processes: Align AI and flexible learning initiatives with accreditation standards (e.g., NAQAAE in Egypt) to ensure quality and sustainability.	Implementation involves documenting intervention outcomes and integrating them into self-study reports	Quality Assurance Unit, University Leadership

These recommendations aim to create a supportive, technology-enhanced learning environment that addresses the needs of students on academic probation, enhances their academic outcomes, and supports exploratory expansion to diverse institutional contexts.

7. Theoretical implications of the study:

This study provides notable theoretical contributions by addressing a critical issue in higher education: the academic struggles of students on probation, who are at risk of dismissal. These students often face challenges such as cognitive overload, low engagement, and a lack of personalized learning support. By integrating AI-based educational tools and flexible learning techniques, this research highlights a modern approach to mitigating these challenges and enhancing academic performance.

A key theoretical insight is the role of student satisfaction and engagement as mediating factors in the relationship between AI-driven learning methods and academic outcomes. The findings confirm that AI and flexible learning do not merely provide direct academic benefits but also foster a more engaging and satisfying educational experience. This aligns with existing theories on the importance of emotional and behavioral engagement in student success (e.g., Fredricks et al., 2004) and extends them by demonstrating how technology can actively shape these psychological factors.

Furthermore, this study contributes to the evolving discourse on adaptive learning by emphasizing the capacity of AI-driven tools to personalize instruction, address individual learning gaps, and offer real-time feedback. These aspects are particularly crucial for students on academic probation, who require tailored interventions to regain confidence and improve their performance. The research thus reinforces the argument that integrating AI in education is not just an enhancement but a necessary evolution in addressing diverse student needs.

By providing empirical evidence on the effectiveness of AI-based educational interventions, this study adds to the growing body of literature on technology-enhanced learning and strengthens the theoretical foundation for exploring innovative educational strategies.

The study further advances theoretical models by integrating Tinto's (1993) retention theory with technology-mediated interventions, illustrating how AI and flexible learning can mitigate dropout risks through enhanced satisfaction and engagement. It also refines Kahu's (2013) engagement framework by specifying the role of AI-driven personalization in fostering cognitive and emotional engagement among probationary students. These contributions provide a foundation for future theoretical explorations of how technology can address systemic barriers in higher education, particularly in rigid systems like Egypt's. Additionally, the partial mediation model enriches mediation theories by highlighting the dual pathways (direct and indirect) through which educational interventions impact performance, offering a nuanced lens for studying at-risk populations.

8. Managerial applications of the study:

The findings of this study provide critical insights for decision-makers and academic administrators in Egyptian universities, offering a strategic perspective for integrating AI-based educational tools and flexible learning (FL) techniques to enhance academic performance. While the primary focus is on students on academic probation, the broader implications extend to improving overall educational quality, institutional effectiveness, and student engagement. To successfully implement these advancements, the following key actions are recommended:

- Establish clear policies and governance standards: Develop a well-defined set of policies to guide the ethical and effective implementation of AI and FL, addressing compliance with privacy laws, institutional values, and data security while ensuring transparency.
- Implement robust data governance and security protocols: Establish a strong framework to ensure the ethical collection, analysis, and protection of student data, adopting stringent security measures to safeguard personal and academic information.
- Foster interdepartmental collaboration and innovation: Encourage cooperation between academic departments, IT teams, and university leadership to drive an innovation-oriented culture, sharing best practices for AI and FL adoption across disciplines.
- Build strategic partnerships with industry and technology providers: Collaborate with leading Ed-Tech companies, AI research institutions, and industry experts to access cutting-edge tools and expertise, keeping universities at the forefront of AI-enhanced education.
- Develop a faculty incentive program for AI and FL adoption: Create reward systems (e.g., grants, teaching awards) to encourage faculty to integrate AI tools and flexible pedagogies, fostering widespread adoption. Implementation includes establishing criteria for innovation in teaching and monitoring uptake (Responsible Entity: Human Resources Department, Academic Affairs).
- Establish a centralized AI and FL resource hub: Create an online portal with tutorials, toolkits, and case studies to support faculty and students in using AI and flexible learning tools effectively. Implementation involves collaboration between IT and academic departments to maintain and update resources (Responsible Entity: IT Department, Faculty Development Unit).
- Engage stakeholders in policy development: Involve faculty, students, and external partners in crafting AI and FL policies to ensure buy-in and alignment with institutional needs. Implementation includes town hall meetings and feedback sessions (Responsible Entity: University Leadership, Student Affairs Office).

By implementing these managerial actions, Egyptian universities can create a more adaptive, inclusive, and technology-driven learning environment. This will not only support students on academic probation but also elevate the overall academic experience, fostering greater student success and institutional excellence.

9. Limitations and future scope of research:

While this study provides meaningful insights into the role of AI-based educational tools and flexible learning techniques in enhancing academic performance—particularly for students on academic probation—certain limitations must be considered when interpreting and generalizing the findings.

• Scope of AI tools and flexible learning techniques

This research examined a specific set of AI-driven educational tools, including Google Scholar, Coursera, Google Assistant, Google AI Education, Google AutoML, Google Classroom, and Grammarly, along with selected flexible learning techniques such as adaptive scheduling, flexible assessment standards, diverse learning resources, personalized assignments, and adaptable deadlines. However, the study did not explore the effects of other AI tools or alternative flexible learning methods that may offer additional advantages. For instance, generative AI tools, such as ChatGPT or other language models, which can generate personalized learning materials and provide real-time feedback, were not included in this study but hold significant potential for supporting at-risk students (Baidoo-Anu & Owusu Ansah, 2023). Future research could extend this investigation by incorporating a broader range of AI-driven innovations and pedagogical models, including generative AI, to fully understand their impact on academic performance and student engagement.

• Sampling approach and generalizability

The study employed a census approach, targeting all 240 students on academic probation enrolled in the summer term at CIC, out of a total of 660 probationary students across the college. This decision was driven by the limited availability of students during the summer term, precluding the use of random sampling. As a result, the findings may be biased toward the characteristics of this specific group and may not fully represent the broader population of probationary students. Future studies are recommended to adopt a stratified random sampling approach, utilizing established statistical tools to ensure a more representative sample and enhance the generalizability of the results.

• Limited moderating variables

The study assessed the moderating roles of students' satisfaction and engagement in the relationship between AI-based tools, flexible learning, and academic performance. However, it did not account for other potential moderating factors, such as self-efficacy, motivation, digital literacy, socio-economic status, or institutional support. Further research should examine these additional variables to develop a more comprehensive understanding of the mechanisms influencing student success.

• Absence of mediating variables

This study did not include mediating variables that could further explain how AI-based tools and flexible learning techniques impact academic performance. Future research could explore mediators such as cognitive load, self-regulated learning, metacognitive skills, or emotional well-being to provide deeper insights into the pathways through which these interventions affect student outcomes.

• Contextual and institutional limitations

The study was conducted only at Canadian International College (CIC), which is a private institution in Egypt. Consequently, the findings may not be directly generalizable to governmental universities, non-educational organizations, or institutions in different cultural or regulatory settings. Future studies should explore these relationships across diverse educational institutions, including governmental universities and international contexts, to assess the broader applicability of the findings.

• **Short-term focus**

The study focused on a single summer term, limiting insights into the long-term sustainability of AI and flexible learning interventions. Probationary students may require ongoing support to maintain academic progress, which was not assessed. Future research should employ longitudinal designs to evaluate sustained impacts on retention and graduation rates.

- **Faculty and infrastructure constraints**

The study did not account for variations in faculty readiness or institutional infrastructure (e.g., internet access, device availability), which may influence the effectiveness of AI and flexible learning. Future research should explore these factors to ensure equitable implementation across diverse settings.

Building on these limitations, future research could:

- Investigate the impact of a broader range of AI tools, including generative AI tools like ChatGPT, and flexible learning strategies beyond those covered in this study.
- Examine the role of other moderating and mediating variables to refine the understanding of the factors influencing academic performance.
- Expand the research to other types of universities beyond private institutions, such as public and national universities, to validate the findings in diverse contexts.
- Conduct longitudinal studies to evaluate the long-term effects and sustainability of AI and flexible learning interventions on academic performance, student retention, engagement, and career outcomes.
- Explore the scalability of AI and flexible learning interventions through multi-institutional collaborations, assessing their feasibility in resource-constrained settings. Investigate the role of faculty training and student digital literacy in optimizing intervention outcomes.

By addressing these areas, future research can contribute to a more nuanced and comprehensive understanding of how AI and flexible learning can enhance educational outcomes—particularly for students at risk of academic failure. This will ultimately aid in the development of more adaptive, inclusive, and data-driven educational strategies, fostering long-term improvements in student success and institutional effectiveness.

References

1. Aithal, P. S., Aithal, Shubhrajyotsna. (2023). The Changing Role of Higher Education in the Era of AI-based GPTs. International **Journal of Case Studies in Business, IT, and Education** (IJCSBE), 7(2), 183-197. ISSN: 2581-6942.
2. Alaswad, Z., & Nadolny, L. (2015). Designing for Game-Based Learning: The Effective Integration of Technology to Support Learning. **Journal of Educational Technology Systems**, 43(4), 389-402.
3. Al-Harbi, K. A. S. (2011). E-Learning in the Saudi tertiary education: Potential and challenges. **Applied Computing and Informatics**, 9(1), 31-46.
4. Allam H, Dempere J, Akre V &Flores P,.(2023). Artificial Intelligence in Education (AIED): Implications and Challenges. Proceedings of the **HCT International General Education Conference** (HCT-IGEC 2023,(Atlantis Highlights in Social Sciences, Education and Humanities 13, 126-140.
5. Alrubail, R., & Alqaryouti, I. (2020). The use of intelligent tutoring systems to support students with dyslexia: A systematic review. **Education and Information Technologies**, 25(6), 5281-5298.
6. Arshad Muhammad,Syed Muhammad Imran Haider Zaidi and Khalid Mahmood,. (2015). Self-Esteem & Academic Performance among University Students. **Journal of Education and Practice** .Vol.6, No.1.
7. Asif, M., Thomas, G., Awan, M.U. and Muhammad Din, A. (2021), "Enhancing student engagement through heterogeneous pedagogical approaches: action research in a university level course in Saudi Arabia", **International Journal of Educational Management**, Vol. 35 No. 1, pp. 1-28.
8. Austerschmidt, K. L., & Bebermeier, S. (2019). Implementation and effects of flexible support services on student achievements in statistics. **Zeitschrift für Hochschulentwicklung**, 14(3), 137-155.
9. Baidoo-Anu, D., & Owusu Ansah, L. (2023). Education in the era of generative artificial intelligence (AI): Understanding the potential benefits of ChatGPT in promoting teaching and learning. **Journal of AI in Education**, 1(1), 23-34.
10. Baker, R. S. (2021). "**Artificial Intelligence in Education: Promise and Implications for Teaching and Learning.**"
11. Bean, J. P. (1985). Interaction effects based on class level in an explanatory model of college student dropout syndrome. **American Educational Research Journal**, 22(1), 35-64.

12. Bergamin, P. B., Ziska, S., Werlen, E., & Siegenthaler, E. (2012). The relationship between flexible and self-regulated learning in open and distance universities. **The International Review of Research in Open and Distributed Learning**, 13(2), 101-123.
13. Bergamin, P., Ziska, S., & Groner, R. (2010). Structural equation modeling of factors affecting success in student's performance in ODL-programs: Extending quality management concepts. **Open Praxis**, 4(1), 18-25.
14. Chen, X., Wu, Q., and K. He.(2020) .Personalized federated learning for intelligent IOT applications: A cloud-edge based framework," IEEE Computer Graphics and Applications.
15. Chen, Y. S., Kao, T. C., & Sheu, J. P. (2003). A mobile learning system for scaffolding bird watching learning. **Journal of Computer Assisted Learning**, 19(3), 347-359.
16. Christenson, S. L., Reschly, A. L., & Wylie, C. (Eds.). (2012). **Handbook of research on student engagement**. Springer Science & Business Media.
17. Collis, B. & Van der Wende, M. (2002). Models of technology and change in higher education: an international comparative survey on the current and future use of ICT in higher education (Enschede, CHEPS).
18. Collis, B., Vingerhoets, J., and Moonen, J.(1997). Flexibility as a key construct in European training: experiences from the TeleScopia Project. British **Journal of Educational Technology**. 28 (3), 199–217.
19. Dennis, J. M., Phinney, J. S., & Chuateco, L. I. (2005). The role of motivation, parental support, and peer support in the academic success of ethnic minority first-generation college students. **Journal of College Student Development**, 46(3), 223-236.
20. Eisenberg, D., Lipson, S. K., & Posselt, J. (2016). Promoting resilience, retention, and mental health. **New Directions for Student Services** Volume 2016, Issue 156: College Student Mental Health, 87-95.
21. Fitria, T. N. (2024). The use of artificial intelligence in education (AIED): Can AI replace the teacher's role?. **Institut Teknologi Bisnis AAS**. Indonesia, vol: 20, 165-187. DO - 10.32722/epi.v20i2.5711.
22. Flannery, M., & McGarr, O. (2014). Flexibility in higher education: An Irish perspective. **Irish Educational Studies**, 33(4), 419-434. https://doi.org/10.1080/03323315.2014.978658

23. Fredricks, J. A., Blumenfeld, P. C., & Paris, A. H. (2004). School Engagement: Potential of the concept, state of the evidence. **Review of Educational Research**, 74(1), 59-109.
24. Fredricks, J. A., Parr, A. K., Amemiya, J. L., Wang, M.-T., & Brauer, S. (2019). What Matters for Urban Adolescents' Engagement and Disengagement in School: A Mixed-Methods Study**. Journal of Adolescent Research**, 34(5), 491-527.
25. Gaddis, S. M. (2014). Discrimination in the credential society: An audit study of race and college selectivity in the labor market. **Social Forces**, 93(4), 1451-1479.
26. Garrick, J., & Jakupec, V. (2000). **Flexible learning, work and human resource development**, (pp. 1-8). London: Routledge.
27. Heilporn, G., Lakhal, S., Bélisle, M., & St-Onge, C. (2020). Student engagement: A multidimensional measurement scale applied to blended course modalities at the university level. **Mesure et évaluation en éducation**, 43, 1–32.
28. Holmes, W., et al. (2022). Ethics of AI in education: Towards a community-wide framework. International **Journal of Artificial Intelligence in Education**, 32(2), 504-526.
29. Jayanthi S. Valli, Santhi Balakrishnan, Angela Lim Siok Ching, Noor Aaqilah Abdul Latiff, A.M.A. Nasirudeen,. (2014). Factors Contributing to Academic Performance of Students in a Tertiary Institution in Singapore, **American Journal of Educational Research**, 2014, Vol. 2, No. 9, 752-758.
30. Joelle C. Ruthig, Sonia Marrone, Steve Hladkyj, Nancy Robinson-Epp.(2011). Changes in College Student Health: Implications for Academic Performance **Journal of College Student Development**, 52(3), 307-320.
31. Jony, Md. Solaiman. (2022). Exploring the reasons of academic probation among private university students in bangladesh. **European Journal of Education Studies** , 9 (2), 256-267.
32. Kapur, R., (2018). Factors Influencing the Student's Academic Performance in Secondary Schools in India, https://www.researchgate.net/publication/324819919.
33. Khalil, R., Mansour, A. E., Fadda, W. A., Almihmadi, A. H., Aldeeri, R., Alkhalifah, A., & AlWassiti, A. (2020). The sudden transition to synchronized online learning during the COVID-19 pandemic in Saudi Arabia: a qualitative

study exploring medical students' perspectives. BMC medical education, 20(1), 1-10.

34. Kokoç, M., (2019). Flexibility in e-Learning: Modeling its Relation to Behavioral Engagement and Academic Performance. **Themes in eLearning**, 12, 1-16.
35. Kokoç, M., Ilgaz, H., & Altun, A. (2020). **Individual cognitive differences and student engagement in video lectures and e-learning environments**. In E. Alqurashi (Ed.), Handbook of Research on Fostering Student Engagement with Instructional Technology in Higher Education (pp. 78-93). Hershey, PA: IGI Global.
36. Kuh, G. D. (2009). What student affairs professionals need to know about student engagement. **Journal of College Student Development**, 50(6), 683-706.
37. Kuh, G. D., Cruce, T. M., Shoup, R., Kinzie, J., & Gonyea, R. M. (2007). Unmasking the effects of student engagement on first-year college grades and persistence. annual meeting of the American Educational Research Association, Chicago, April 2007, 1-50.
38. Lange S. R. (2014). How College Affects Students: A Third Decade of Research. Jossey-Bass. **Journal of Student Affairs in Africa**. 2(2), 47–50.
39. Lewis, P. A., Tutticci, N. F., Douglas, C., Gray, G., Osborne, Y., Evans, K., & Nielson, C. M. (2016). Flexible learning: Evaluation of an international distance education programme designed to build the learning and teaching capacity of nurse academics in a developing country. **Nurse Education in Practice**, 21, 59-65.
40. Li, K. C., & Wong B. Y. Y. (2018). Revisiting the definitions and implementation of flexible learning. In K. Li, K. Yuen & B. Wong (Eds.), Innovations in Open and Flexible Education (pp. 3-13). Singapore: Springer.
41. Ling, P., Arger, G., Smallwood, H., Toomey, R., Kirkpatrick, D. & Barnard, I. (2001) The effectiveness of models of flexible provision of higher education (Commonwealth of Australia).
42. Malouff, J. (2010). Use of motivational teaching techniques and psychology student satisfaction **Psychology learning and teaching**, Vol.9(1), pp. 39-44.
43. Martin AJ., (2007). Examining a multidimensional model of student motivation and engagement using a construct validation approach. **British Journal of Educational Psychology**;77:413-440 .

44. Martin AJ.,(2006).The relationship between teachers' perceptions of student motivation and engagement and teachers' enjoyment of and confidence in teaching. **Asia-Pacific Journal of Teacher Education** 34:73-93.
45. Martín-Rodríguez, Ó., Fernández-Molina, J. C., Montero-Alonso, M. Á., & González-Gómez, F. (2014). The main components of satisfaction with e-learning. Technology, **Pedagogy and Education**, 24(2), 267–277.
46. Mavroudi, A., Giannakos, M., & Krogstie, J. (2018). Supporting adaptive learning pathways through the use of learning analytics: developments, challenges and future opportunities. **Interactive Learning Environments**, 26(2), 206-220.
47. McGarry, B. J., Theobald, K., Lewis, P. A., & Coyer, F. (2015). Flexible learning design in curriculum delivery promotes student engagement and develops metacognitive learners: An integrated review. **Nurse Education Today**, 35(9), 966-973.
48. Means, B., Toyama, Y., Murphy, R., & Baki, M. (2013). The Effectiveness of Online and Blended Learning: A Meta-Analysis of the Empirical Literature. Teachers College Record, 115(3), 1-47.
49. Means, B., Toyama, Y., Murphy, R., Bakia, M., & Jones, K. (2009). Evaluation of evidence-based practices in online learning: A meta-analysis and review of online learning studies. US Department of Education.
50. Müller et al. (2023). Learning effectiveness of a flexible learning study program in a blended learning design: why are some courses more effective than others?. **Journal of Educational Technology in Higher Education**.20(10), 2-25.
51. Mushtaq Irfan & Shabana Nawaz Khan,. (2012). Factors Affecting Students' Academic Performance. **Global Journal of Management and Business Research**. Volume 12 Issue 9 Version 1.0.
52. Naidu, S. (2017). How flexible is flexible learning, who is to decide and what are its implications? Distance Education, 38, 269-272.
53. Nikolov, R., Lai, K. W., Sendova, E., & Jonker, H. (2018). Distance and flexible learning in the twenty-first century. In J. Voogt, G. Knezek, R. Christensen & K. W. Lai (Eds.), **International Handbook of Information Technology in Primary and Secondary Education** (2nd ed.), 1-16.
54. Nilsson, N. J. (2014). **The quest for artificial intelligence: A history of ideas and achievements**. Cambridge University Press.

55. Noble, J., & Sawyer, R. (2002). Predicting different levels of academic success in college using high school GPA and ACT composite score. ACT Research Report Series.4, 1-25.
56. Olufemi Oladebinu Tokunbo, Amos Adekunle Adediran and W.O. Oyediran,.(2018). Factors affecting students' academic performance in colleges of education in southwest, **Nigeria, British Journal of Education** Vol.6, No.10, pp.43-56.
57. Pardo, A., Han, F., & Ellis, R. A. (2016). Exploring the relation between self-regulation, online activities, and academic performance: A case study. In Proceedings of the sixth international conference on learning analytics & knowledge , 422-429.
58. Rahmawati, Y.,Taylor, E.; Taylor, P.C.; Ridwan, A.; Mardiah, A., (2022). Students' Engagement in Education as Sustainability: Implementing an Ethical Dilemma-STEAM Teaching Model in Chemistry Learning. **Sustainability** 14, 3554,1-15.
59. Shahzadi Erum and Zahoor Ahmad,. (2011). A study on academic performance of university students. Proc. 8th International Conference on Recent Advances in Statistics, Pakistan – February 8-9, 255-268.
60. Shi, Y., & Zheng, X. (2006). Artificial Intelligence in Education: Progress and Challenges**. Journal of Computing Sciences in Colleges**, 21(5), 810-821.
61. Soffer, T., Kahan, T., & Nachmias, R. (2019). Patterns of students' utilization of flexibility in online academic courses and their relation to course achievement. The International Review of Research in Open and Distributed Learning, 20(3).
62. Tadese, M., Yeshaneh A., & Mulu G.(2022). Determinants of good academic performance among university students in Ethiopia: a cross-sectional study. BMC Medical Education, 22:395, 1-9.
63. Tinto, V. (2012). **Leaving college: Rethinking the causes and cures of student attrition**. University of Chicago Press.
64. Tinto, V. (2017). Through the eyes of students. **Journal of College Student Retention: Research, Theory & Practice,** 19(3), 254-269.
65. Trowler, V. (2010). Student engagement literature review. The higher education academy, 11(1), 1-15.
66. Tzafilkou, K., Perifanou, M., Economides, A., & Xinogalos, S. (2021). Ethical considerations and challenges in the design and implementation of AI-

based educational technologies: A systematic literature review. Education and Information Technologies, 26(6), 7293-7319.

67. Veletsianos, G., & Houlden, S. (2019). An analysis of flexible learning and flexibility over the last 40 years of distance education., 1-15.
68. Wang, F. H. (2017). An exploration of online behavioral engagement and achievement in flipped classroom supported by learning management system. **Computers & Education**, 114, 79–91.
69. Wang, Y., Liu, C., Tu, Y.-F. (2021). Factors Affecting the Adoption of AI-Based Applications in Higher Education: An Analysis of Teachers' Perspectives Using Structural Equation Modeling. **Educational Technology & Society**, 24 (3), 116– 129.
70. Wim de Boer & Betty Collis (2005). Becoming more systematic about flexible learning: beyond time and distance, ALT-J, 13:1, 33-48.
71. Wintre, M. G., & Bowers, C. D. (2007). Predictors of persistence to graduation: extending a model and data on the transition to university model. **Canadian Journal of Behavioural Science**/Revue canadienne des sciences du comportement, 39(3), 220-248.
72. Woodfine, B. P., Nunes, M. B., & Wright, D. J. (2021). Text-to-speech technologies and children with dyslexia: An empirical investigation. **British Journal of Educational Technology**, 52(4), 1578-1597.
73. York, T. T., Gibson, C., & Rankin, S. (2015). Defining and measuring academic success. Practical Assessment, Research, and Evaluation, 20(1), 5.
74. Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education – where are the educators? International **Journal of Educational Technology in Higher Education**, 16(1), Article 1.
75. Zepke, N., & Leach, L. (2010). Improving student engagement: Ten proposals for action. **Active Learning in Higher Education**, 11(3), 167-177.
76. Zimitat, G. (2002) Benchmarking flexible learning: a pilot study, in A. Goody & D. Ingram (Eds) Proceedings of the 4th World Conference of the International Consortium for Educational Development (ICED) (Perth, Western Australia).

الدور الوسيط للمشاركة والرضا عن العملية التعليمية، في العلاقة بين الأدوات التعليمية القائمة على الذكاء الاصطناعي، تقنيات التعلم المرن، وأداء الطلاب المُنذَرون أكاديمياً

ملخص الدراسة :

تبحث هذه الدراسة تأثير الأدوات التعليمية القائمة على الذكاء الاصطناعي وتقنيات التعلم المرن على الأداء الأكاديمي للطلاب المنذرون اكاديميا، مع التركيز على الدور الوسيط لرضا هؤلاء الطلاب ومشاركتهم في العملية التعليمية.

مع استمرار الذكاء الاصطناعي في التأثير علي العملية التعليمية، تسعى هذه الدراسة إلى فهم كيفية تعزيز هذه الأدوات المبتكرة وطرق التعلم التكيفية لتجارب الطلاب ودعم التطور الأكاديمي للطلاب، أجريت الدراسة في الكلية الدولية الكندية (CIC) في مصر، واستهدفت جميع الطلاب المنذرون اكاديميا الفصل الصيفي باستخدام نهج الإحصاء الشامل، تم الاستعانة بالعديد من ادوات جمع البيانات، مثل الاستبيانات، والمقابلات شبه المنظمة، وتحليل السجلات الأكاديمية لاستكشاف هذه العلاقات. تظهر النتائج أن الأدوات القائمة على الذكاء الاصطناعي، مثل أنظمة التدريس الذكية ومنصات التعلم، إلى جانب تقنيات مرنة مثل الجدولة التكيفية، تؤثر إيجابيًا على رضا الطلاب ومشاركتهم، مما يحسن نتائجهم الأكاديمية. تؤكد الدراسة على قيمة دمج الأساليب التعليمية القائمة على الذكاء الاصطناعي والتعلم المرن في التعليم العالي لدعم الطلاب المعرضين لخطر الانذار الاكاديمي. وتقترح أن تبحث الدراسات المستقبلية في عوامل إضافية، مثل الدافع أو الثقافة الرقمية، وتوسيع النطاق ليشمل بيئات تعليمية متنوعة خارج مصر.

الكلمات المفتاحية: الأدوات التعليمية القائمة على الذكاء الاصطناعي، تقنيات التعلم المرن، الأداء الأكاديمي، الانذار الاكاديمي، رضا الطلاب عن العملية التعليمية، مشاركة الطلاب في العملية التعليمية.