

The Role of AI Personalization in Shaping Students' Decision-making: The Mediating Role of Students' Intentions and the Moderating Effect of Academic Technology Experience in Higher Education

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Abstract

Purpose: This study investigates the impact of Al-driven personalization on university students' decision-making, with a particular focus on the mediating role of intention to apply and the moderating effects of experience with academic technology. By exploring these relationships, the research aims to offer insights into how personalized communications influence program choice and foster institutional trust.

Design/methodology/approach: A quantitative approach was employed, with data collected through surveys completed by 425 university students. Structural Equation Modeling (SEM) was applied to analyze the relationships between the variables.

Findings: The findings indicate that Al-powered personalization significantly influences students' decision-making directly. However, it does not have a direct effect on intention to apply. The mediating role of intention to apply is crucial, linking Al personalization to decision-making. Furthermore, experience with academic technology moderates the relationship between Al personalization and intention to apply, with higher levels of experience strengthening this connection.

Originality: This study provides insights into how Al-powered personalization shapes student decision-making in higher education. The results show that while Al personalization may not directly drive students' intention to apply, it plays a key role in fostering trust and engagement, which ultimately influences their decisions. Students with more experience in academic technology are particularly responsive to personalized content, emphasizing the importance of tailoring communication strategies to different technological proficiency levels. These findings offer valuable guidance for institutions looking to enhance student engagement and create more meaningful interactions through Al-driven personalization.

Keywords: Al-Powered Personalization, Intention to Apply, Higher Education, Student Engagement, Technology Experience, Program Selection.

Introduction

The education sector has undergone a significant shift facilitated by the incorporation of artificial intelligence (AI) technologies (George & Wooden, 2023). These advancements are redefining how educational institutions engage with students (Aithal & Maiya, 2023), particularly through personalized interactions (Ayeni et al., 2024). AI-powered tools are increasingly being used for tailored communication, including automated emails (AlAfnan et al., 2023), targeted advertisements (Kedi et al., 2024), and customized program recommendations (Dudekula et al., 2023). This shift enhances the educational experience by creating more engaging and relevant environments for students (Abendan et al., 2023). By delivering personalized content, institutions can address the diverse needs of their student populations, improving satisfaction and retention rates (Aithal et al., 2024).

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At the same time, the competitive landscape among educational institutions has intensified (Hart & Rodgers, 2024), requiring innovative strategies to attract and retain prospective students (Fanani & Syafrudin, 2024). In this context, Al-driven marketing techniques have become essential tools, not only for enhancing institutional visibility (Angelen & Siddik, 2023), but also for creating meaningful connections with students to influence their enrollment decisions (Cingillioglu, 2024). By leveraging data on student behaviors and preferences, institutions can optimize their communication efforts, ensuring messages resonate with the intended audience (Purcărea, 2023). This strategic use of Al highlights the critical role of personalization in educational marketing, enabling institutions to distinguish themselves in a crowded marketplace (Aithal & Maiya, 2023).

Al-powered personalization refers to the ability of Al systems to tailor interactions to individual preferences and behaviors (Raji et al., 2024). Within the educational context, this capability significantly influences students' choices, including program selection and trust in institutions. By providing targeted information and support, Al facilitates a more informed decision-making process, aligning choices with students' unique needs (Saaida, 2023). This personalized approach increases the likelihood of students identifying programs that match their goals while fostering loyalty and connection with the institution (Serrano, 2023). By understanding the role of personalization, institutions can refine their strategies to support students effectively at each stage of the application process (Song et al., 2024).

Despite growing interest in Al-powered personalization, its specific effects within the educational sector remain underexplored (Mintii, 2024). While previous studies have examined Al's influence on consumer behavior in various industries (Bulchand-Gidumal et al., 2024; Raji et al., 2024), limited attention has been given to how personalized interactions shape intention to apply and decision-making among students (Cho & Jeon, 2023; Wu et al., 2024).

This study aims to achieve three primary objectives: to assess the influence of AI-powered personalization on students' intentions to apply and decision-making; to analyze how intentions to apply mediate the relationship between personalization and decision-making; and to explore the moderating effects of academic technology experience on the relationship between personalization and intentions to apply.

This paper follows a structured format to comprehensively examine the research topic. The literature review discusses the Theory of Planned Behavior (TPB) and prior research on AI in education. The methodology section details the data collection methods and analytical techniques, followed by a presentation of key findings. The discussion section contextualizes these findings within existing literature. Subsequently, the theoretical and practical implications are addressed. The paper concludes by outlining the study's contributions and providing suggestions for future research.

Literature Review

Al-Powered Personalization in Higher Education

The adoption of AI-powered personalization is transforming higher education by enabling institutions to create individualized interactions with students, drawing from various data sources such as behavioral patterns, academic records, personal preferences, and engagement levels (Ellikkal & Rajamohan, 2024). This advanced customization allows for the delivery of highly tailored experiences, including personalized email campaigns, targeted program recommendations, and customized advertisements (Bhuiyan, 2024). By harnessing machine learning algorithms, institutions can better segment student populations and deliver content that meets students' unique needs, ultimately enhancing engagement and increasing application rates (Chinnadurai et al., 2024).

Despite its advantages, the growing reliance on AI has raised **significant concerns about privacy and the ethical handling of data** (Raji et al., 2024). When algorithms are not carefully designed, there is a risk of creating a sense of manipulation or exclusion among students. Moreover, biases-such as those linked to race or socioeconomic status-can inadvertently become embedded in recruitment practices, compounding

ethical dilemmas (Modi, 2023). To mitigate these risks, institutions must prioritize fairness, transparency, and accountability in the design and implementation of AI systems (Akinrinola et al., 2024).

Practical examples highlight the transformative impact of AI personalization. Georgia State University implemented an AI-powered chatbot and predictive analytics to enhance student engagement, resulting in a 30% increase in application rates (Mainstay, 2024). While such initiatives underscore the potential benefits of AI, they also reinforce the importance of balancing personalization efforts with rigorous ethical standards (Patel, 2024).

Theory of Planned Behavior (TPB)

The Theory of Planned Behavior (TPB) provides a foundational framework for understanding how personalized communication strategies impact student decision-making (Hamad et al., 2024). TPB posits that personalization influences students by shaping their attitudes toward academic programs, reinforcing social norms, and enhancing their perceived control over decisions (Wang et al., 2024). For example, tailored messages emphasizing program achievements or career opportunities can increase students' intention to apply-defined as the likelihood of engaging in the university application process through Al-driven communication strategies. Furthermore, Al-powered campaigns showcasing alumni success stories can strengthen students' confidence in their own ability to succeed, ultimately leading to higher application rates (Ashraf et al., 2024).

This study leverages TPB to investigate how AI-personalized communication affects students' intention to apply by influencing their attitudes, social influences, and perceived ease of decision-making. However, TPB does not fully account for the additional complexities presented by AI in digital environments, such as varying levels of perceived control or skepticism about algorithmic trustworthiness (Anwar & Herayono, 2024; Wang et al., 2024).

By expanding TPB, this study examines Al-powered personalization in the context of student decision-making. Although prior research has applied TPB to general student behaviors, limited studies have explored how Al-driven interactions shape application intent. This research addresses that gap by demonstrating that Al personalization affects students' attitudes and social norms, particularly in how they perceive institutions and make enrollment decisions. Integrating Al-specific insights into TPB offers a more comprehensive understanding of how digital tools impact higher education choices.

Consumer Decision-Making & Al Personalization

Al-powered personalization plays a fundamental role in shaping students' decision-making processes, encompassing the cognitive and behavioral steps through which students assess options, select programs, and finalize their application choices based on Al-driven recommendations. By simplifying the information search, evaluation, and selection stages, Al tools help guide students toward programs that align with their preferences (Naqvi et al., 2023). Personalized emails or advertisements can direct students to programs suited to their goals, making the information search process more efficient (lyelolu et al., 2024; Kaswan et al., 2024). During the evaluation stage, Al tools offer tailored program comparisons, enabling students to weigh options based on their academic and career objectives (Majjate et al., 2023). In the final selection stage, personalized follow-ups and reminders provide support, increasing the likelihood of application submission (Lee & Xiong, 2023). Research highlights that Al-driven personalization enhances conversion rates, affirming its impact on higher education marketing (Reddy & Nalla, 2024).

Al-Powered Personalization and Intention to Apply

Personalized communication plays a crucial role in shaping students' intention to apply, acting as a key driver in their decision-making journey (Liao et al., 2023). By delivering content aligned with students' individual interests, institutions can foster greater engagement and inspire actions such as attending infor-

mation sessions or completing applications (Zitha et al., 2023). Research consistently shows that customized content positively influences application behavior (Yang & Ogata, 2023). For example, Al-powered follow-up messages that highlight application deadlines and offer additional program insights help sustain momentum and improve completion rates (Kivinen, 2023).

Moderating Role of Experience with Academic Technology

Access to technology and digital literacy play crucial roles in shaping how students interact with Al-powered personalization tools (Zhang & Zhang, 2024). Experience with academic technology refers to the degree of familiarity and comfort students have with Al-powered tools used for educational purposes, including digital literacy and prior exposure. **Digital literacy is a key factor in enabling students to engage effectively with Al tools.** Students with higher access to technology and greater digital literacy are more likely to effectively engage with Al-powered systems, enhancing their overall experience (Naamati-Schneider & Alt, 2024). However, students with limited digital access or lower digital skills-often from lower socioeconomic backgrounds-may struggle with these technologies, leading to exclusion or frustration (Martins et al., 2024).

To bridge this gap, institutions must prioritize inclusive AI-driven strategies that account for diverse digital competencies. For example, improving user interfaces and providing digital literacy training can help make AI tools more accessible (Olabiyi, 2025). Without such measures, AI-powered personalization runs the risk of benefiting only digitally proficient students, further widening inequalities in higher education.

This literature review highlights the significant role of AI-powered personalization in shaping student engagement and decision-making. The application of TPB and consumer decision-making models underscores how AI influences students' perceptions, behaviors, and overall application intent. However, factors such as privacy concerns, digital literacy gaps, and trust in AI algorithms must be considered to ensure equitable adoption. Future research should explore how AI can be optimized to support students with diverse technological backgrounds, enhancing its role in student recruitment and decision-making. By leveraging AI responsibly and inclusively, institutions can ensure that personalized communication strategies not only increase application rates but also foster meaningful and equitable engagement for all students.

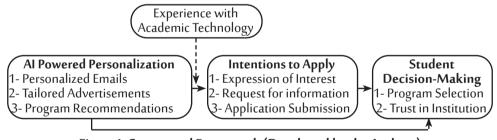


Figure I: Conceptual Framework (Developed by the Authors)

Research Questions, Objectives, Hypotheses, and Justifications

Building on the insights gained from the literature review, this study seeks to address several key questions:

- 1- How does Al-powered personalization influence students' intentions to apply to a university?
- 2- How do students' intentions to apply impact their decision-making process when choosing a university?
- 3- Does Al-powered personalization directly affect student decision-making, independent of application intent?
- **4-** Does students' intention to apply act as a mediating factor between Al-powered personalization and their decision-making process?
- 5- Does prior experience with academic technology influence the relationship between Al-powered personalization and students' intentions to apply?

The primary objectives of this study are:

- To examine the direct impact of Al-powered personalization on students' intentions to apply to a university.
- To investigate the role of intention to apply as a mediating factor between AI-powered personalization and student decision-making.
- To assess whether AI-powered personalization has a direct effect on student decision-making, independent of application intent.
- To explore how students' experience with academic technology moderates the relationship between Al-powered personalization and their intentions to apply.
- To provide practical insights for universities on how to optimize personalized communication strategies to enhance student engagement, application rates, and decision-making.

Based on these objectives, the following hypotheses are proposed:

- H1: Al-powered personalization positively influences students' intention to apply.
- H2: Students' intention to apply positively influences students' decision-making process.
- H3: Al-powered personalization directly enhances student decision-making.
- H4: Students' intention to apply mediates the relationship between Al-powered personalization and student decision-making.
- H5: Students' familiarity with academic technology moderates the relationship between AI-powered personalization and students' intention to apply.

Despite the increasing recognition of Al-powered personalization in higher education, critical gaps persist, particularly in understanding the role of intention to apply in shaping student decision-making. While existing research highlights the value of personalized communication in boosting student engagement (Hanaysha et al., 2023), few studies have explored how intention to apply mediates the relationship between Al-powered personalization and key outcomes, such as program selection and institutional trust (Cho & Jeon, 2023; Wu et al., 2024). This gap is significant for designing effective communication strategies that not only engage students but also drive application rates.

Additionally, **students' familiarity with academic technology** plays a crucial role in how they interact with AI-powered tools. However, there is limited research on how varying levels of technology experience moderate the effectiveness of AI-personalized communication (Ofosu-Ampong, 2023; Wang et al., 2023). Understanding these differences is essential for designing tailored messages that maximize engagement and influence student decisions (Chan-Olmsted et al., 2024; Obeagu & Obeagu, 2024).

This study addresses these gaps by examining how AI-powered personalization influences students' intention to apply and decision-making, whether intention to apply mediates the relationship between personalization and decision-making, and the moderating effect of academic technology experience on AI-powered personalization. Findings from this research will provide practical insights for universities to optimize their AI-driven communication strategies, ensuring that personalized outreach efforts are more effective, inclusive, and aligned with student needs.

Methodology

This research adopts a quantitative method to investigate the connection between Al-powered personalization and student decision-making in higher education. By employing systematic data collection and analysis, the study aims to provide empirical insights into how Al-driven communication strategies influence students' academic choices.

Population and Sample

The study focused on university students who were either in the process of selecting an academic program or had recently made their decision. To achieve a diverse and representative sample, a stratified sampling method was applied. The target population was divided into distinct academic disciplines, ensuring representation across various fields of study. Participants were grouped into five major academic categories: Management/Business, Supply Chain & Logistics, Engineering, Computing & Information Technology, and Arts & Design.

Within each academic discipline, participants were further stratified based on their level of experience with technology. This approach captured perspectives from both highly tech-savvy students and those with limited exposure to Al-driven tools. A total of 425 participants were targeted, following established methodological guidelines to ensure sufficient statistical power while accounting for practical constraints (Cohen, 1988; Fritz & MacKinnon, 2007). By stratifying participants across academic fields and technology experience levels, the study achieved a balanced and comprehensive representation of students' experiences with Al-powered personalization in university decision-making. A stratified random sampling method was adopted to ensure diversity in age, field of study, and technology use, acknowledging the significance of these factors in prior educational behavior research (e.g., Adeyemi & Adeyemi, 2014; Liu & Cheng, 2022).

Measures

The study utilized well-established scales, each adapted to the higher education context and Al-driven personalization. Al-powered personalization was measured using the scale from Tsai & Men (2017), which assessed students' perceptions of the relevance and customization of Al-driven interactions, such as program recommendations and targeted advertisements.

Intention to apply was measured using Ajzen's TPB framework (1991), focusing on students' intentions to engage with university programs, such as expressing interest or submitting applications. Decision-making processes were assessed with scales from McKnight et al. (2002) and Soutar & Turner (2002), which explored how trust is built and the factors influencing program selection. Additionally, the study investigated experience with academic technology to examine its potential moderating effects on the relationships between Al-powered personalization and intention to apply.

Data Collection

An online survey was administered via Google Forms to gather data. The survey contained structured questions designed to measure students' exposure to Al-powered tools, such as personalized emails, tailored advertisements, and program recommendations, and assess their impact on intention to apply, program selection, and institutional trust. To ensure the clarity and reliability of the survey, a preliminary pilot study involving 50 participants was conducted before the full-scale data collection. This initial test helped identify ambiguities, refine wording, and improve overall accuracy. Based on the feedback, minor modifications were made to enhance the survey's effectiveness and ease of comprehension before wider distribution.

Data Analysis

The collected data were analyzed using statistical techniques to examine the relationships between Al-powered personalization, intention to apply, and student decision-making. Descriptive statistics were used to summarize participant demographics and technology experience levels, while structural equation modeling (SEM) was employed to test the hypothesized relationships. SEM was chosen due to its ability to analyze complex relationships between multiple variables and to assess both direct and indirect effects within the model. Reliability and validity checks were performed using Cronbach's alpha and Confirmatory Factor Analysis (CFA) to ensure the consistency and accuracy of the measurement scales. Additionally, mod-

eration and mediation analyses were conducted to evaluate the moderating role of technology experience and the mediating role of intention to apply in student decision-making.

Ethical Considerations

This study was conducted in adherence to ethical research guidelines to ensure participant confidentiality and informed consent. Ethical approval was secured from the Institutional Review Board (IRB) of Badr University in Cairo (BUC) before data collection. Participants received comprehensive information regarding the purpose of the study and their right to withdraw at any time. Before completing the survey, they provided explicit consent to participate. To protect privacy, all responses were anonymized, and no personally identifiable information was collected. The data were analyzed in aggregate to prevent individual identification, ensuring a secure and ethical research process.

Results

The study sample comprised 425 participants. The majority (79.1%) were aged 18–20, followed by 15.5% under 18, 5.2% between 21 and 23, and 0.2% over 23. In terms of academic focus, most participants (61.6%) were studying or intending to study Management/Business, followed by 16.5% in Computing & Information Technology, 13.9% in Engineering, and 4.0% in Supply Chain & Logistics. A smaller group (0.9%) pursued Arts & Design, while 3.1% indicated "Other". Regarding experience with academic technologies, 39.8% were beginners, 47.3% had intermediate experience, and 12.9% were advanced users. When asked about the frequency of using technology for academic tasks, 32.0% reported daily usage, 36.0% used it a few times a week, 19.1% occasionally a few times a month, and 12.9% rarely, using it once a month or less.

Reliability and Validity Analysis

To evaluate the consistency and accuracy of the study's measures, Cronbach's alpha and validity coefficients were computed. The outcomes demonstrated high reliability and validity, confirming the robustness of the study's instruments and supporting the dependability of the data gathered.

Correlation Analysis

Pearson correlation tests were conducted to investigate the associations between the constructs. The findings revealed significant positive relationships between Al-powered personalization, intention to apply, and student decision-making. As Al personalization increased, students' intention to apply also rose. A similar pattern was observed between intention to apply and decision-making, suggesting that higher intention to apply leads to more decisive outcomes. Additionally, Al-powered personalization was found to positively influence student decision-making, underscoring its role in shaping decision outcomes.

The structural equation modeling (SEM) analysis indicated that the model fit the data well, with multiple indices

Table I: Reliability and Validity of Constructs

| Construct | ltem(s) | Cronbach's Alpha | Validity |
|---|-------------------------|---------------------|----------|
| Al-Powered | Personalized Emails | 0.819 | 0.905 |
| Personalization | Tailored Advertisements | 0.885 | 0.941 |
| Personalization | Program Recommendations | 0.875 | 0.935 |
| Overall AI-Powered Personalization Intention to Apply | (All items) | 0.923 | 0.961 |
| | Expression of Interest | 0.738 | 0.859 |
| | Request for Information | 0.731 | 0.855 |
| | Application Submission | 0.869 | 0.932 |
| Overall Intention to Apply | (All items) | 0.865 | 0.930 |
| Overall Intention to Apply Student Decision-Making | Program Selection | 0.770 | 0.877 |
| | Trust in Institution | 0.851 | 0.922 |
| Overall Student | (All items) | 0.879 | 0.938 |
| Decision-Making | (All Itellis) | 0.079 | 0.330 |

Source: Results from sample survey data analyzed using AMOS

Table II: Correlations between Constructs

| Constructs | AI-Powered Personalization | | Student Decision-Making |
|----------------------------|----------------------------|---------|----------------------------|
| Al-Powered Personalization | 1.000 | | |
| Intention to Apply | 0.623** | 1.000 | |
| Student Decision-Making | 0.599** | 0.700** | 1.000 |
| | | | |

Source: Results from sample survey data analyzed using AMOS

confirming its adequacy. The key fit indices showed that the model exhibited a strong fit, meeting established thresholds for model quality and demonstrating sensitivity to the sample size. These results support the robustness of the model and its capacity to represent the data accurately.

Regarding the hypothesized relationships, the SEM analysis revealed that Al-powered personalization did not have a significant direct effect on inten-

Table III: Goodness-of-Fit Indices for Model Evaluation

| Fit Index | Value | Threshold |
|---|--------|-----------|
| Chi-square (χ²) | 47.095 | p<0.05 |
| Degrees of Freedom (df) | 15 | |
| Goodness of Fit Index (GFI) | 0.974 | >0.90 |
| Adjusted Goodness of Fit Index (AGFI) | 0.938 | >0.90 |
| Root Mean Square Error of Approximation (RMSEA) | 0.071 | ≤0.08 |
| Comparative Fit Index (CFI) | 0.983 | >0.95 |

Source: Results from sample survey data analyzed using AMOS

tion to apply, meaning H1 was not supported. However, intention to apply significantly impacted student decision-making, supporting H2. Additionally, a significant direct effect was found between Al-powered personalization and student decision-making, confirming H3.

Although Al-powered personalization did not have a significant direct effect on intention to apply, a significant indirect effect was observed. Specifically, Al-powered personalization influenced student decision-making through intention to apply, suggesting that while Al personalization directly impacts decision-making, its influence is stronger when students have a higher intention to apply. Therefore, intention to apply partially mediates the relationship between Al personalization and decision-making, supporting H4 and highlighting its role in shaping students' decisions.

Table IV: Path Analysis Results for AI-Powered Personalization and Student Decision-Making

| Path | Estimate | Standardized Estimate | p- value | Supported? |
|--|----------|-----------------------|----------|------------|
| H1 AI-Powered Personalization → Intention to Apply | 0.142 | 0.107 | 0.168 | No |
| H2 Intention to Apply → Student Decision-Making | 0.867 | 0.790 | < 0.001 | Yes |
| H3 AI-Powered Personalization → Student Decision-Making | 0.957 | 0.788 | < 0.001 | Yes |
| H4 Indirect Effect (Al-Powered Personalization → Intention | 0.622 | | | Yes |
| to Apply \rightarrow Student Decision-Making) | 0.022 | | | ies |

Source: Results from sample survey data analyzed using AMOS

Moderation Analysis

The moderating effects of experience with academic technology on the relationship between Al-powered personalization and intention to apply were tested using SPSS and the PROCESS macro (Hayes, 2022). The results revealed that individuals with advanced technology experience showed a stronger relationship between Al-powered personalization

Table V: Effects of Technology Experience on Al-Powered Personalization

| Tech Experience | Effect | SE (HC3) | Т | Р | LLCI | ULCI |
|--------------------|--------|----------|------|------|--------|--------|
| Beginner | 0.4811 | 0.1083 | 4.44 | 0.00 | 0.2683 | 0.6939 |
| Intermediate | 0.6155 | 0.0873 | 7.05 | 0.00 | 0.4439 | 0.7871 |
| Advanced | 0.8446 | 0.1214 | 6.95 | 0.00 | 0.6059 | 1.0833 |

Source: Results from survey data analyzed using SPSS.

and their intention to apply, supporting H5. Those familiar with tools like learning management systems, research databases, and statistical software found AI personalization more impactful in shaping their decisions. Conversely, the effect was weaker for participants with beginner or intermediate technology experience, highlighting the importance of tailoring AI systems for users with varying levels of technological proficiency.

Discussion

This study explored the relationship between AI-powered personalization, intention to apply, and student decision-making in higher education, focusing on the moderating role of experience with academic technology. The lack of support for H1 suggests that AI-powered personalization may not significantly influence intention to apply in this context. This finding contrasts with previous research, such as du Plooy et al. (2024), which emphasizes the effectiveness of personalized communications in engaging prospective students. Research has shown that tailored messages, like personalized emails and targeted advertisements,

can enhance perceived relevance and foster a connection with institutions, motivating students to express interest (Alamri et al., 2020). Although this study did not find a significant effect, factors like the quality or timing of personalization efforts may be influential, necessitating further exploration in future research.

H2, which hypothesized that intention to apply positively influences student decision-making, was supported. This result aligns with studies highlighting intention as a key driver of decision-making behaviors (Newell & Shanks, 2014). This research contributes by demonstrating how personalized communications increase intention to apply, which, in turn, leads to favorable outcomes such as program selection and trust in the institution. It underscores that intention to apply is a crucial step in the decision-making process, rather than a passing consideration.

Support for H3 indicates that Al-powered personalization has a direct positive effect on student decision-making, independent of intention to apply. This result builds on existing research by showing that personalization can directly impact decision-making, rather than being solely mediated by intention (Zanker et al., 2019). While much of the literature has focused on indirect effects, this study reveals that personalized communications help build trust and credibility, which directly influence students' decisions, such as program selection. These findings call for further investigation into the specific aspects of personalization that foster trust and reduce perceived risks in decision-making.

Support for H4 adds depth to the understanding of the decision-making process, establishing that intention to apply mediates the relationship between Al-powered personalization and student decision-making. While the role of intention in decision-making has been acknowledged in prior research (Kim et al., 2008), this study provides new empirical evidence linking personalized communications to increased intention to apply, which subsequently affects decision-making outcomes. This finding highlights the importance for educational institutions to not only implement personalized strategies but also enhance students' intention to apply as a critical step in their decision-making journey.

Lastly, the support for H5 indicates that **experience with academic technology significantly moderates the relationship between AI**-powered personalization and intention to apply. Students with higher levels of technology experience-those categorized as having intermediate or advanced proficiency-responded more strongly to personalized communications. **This finding aligns with existing literature that highlights the** role of digital literacy in influencing how individuals interact with technology (McGuinness & Fulton, 2019). It suggests that students who are more comfortable with academic technologies are more likely to find AI-powered personalization engaging and relevant, thereby affecting their intention to apply. This underscores the importance of considering students' varying levels of technology experience when designing personalized communication strategies in higher education.

Implications

Theoretical Implications

Theoretical Implications This study makes a notable contribution to advancing the understanding of how AI-powered personalization affects student decision-making in higher education. By applying TPB, this research opens new avenues for future inquiry. The findings suggest that while AI personalization may not always directly impact students' intention to apply, it plays a crucial role in shaping decision-making by enhancing trust and engagement.

TPB provides a valuable framework for understanding how intentions guide behaviors. In this study, the role of intention as a step before decision-making aligns with TPB's premise that intentions drive actual behavior. The data supports the notion that AI personalization influences decision-making, but this influence is often mediated through students' intention to apply. **This underscores the significance of** intention as a key factor, rather than merely an outcome of personalization.

This research also adds to the relatively limited body of literature on AI-powered personalization in education. While previous studies have primarily focused on general technology use in education, fewer have

addressed the specific impact of Al-driven personalization. The findings suggest that personalized communications, when implemented effectively, can significantly increase students' intentions to apply, which, in turn, affects their decisions. This provides new insights into how Al can not only influence attitudes but also play a fundamental role in guiding critical decisions like program selection. Furthermore, the identification of intention to apply as a mediator enhances the understanding of decision-making processes in educational contexts. This aligns with earlier models of decision-making, such as those proposed by Ajzen (1991), and highlights the essential role of intention. The study demonstrates that Al-powered personalization, by enhancing students' intentions, influences their ultimate decisions regarding education. This reinforces the value of personalized interactions that are **customized to meet individual needs and preferences.**

Finally, the moderating effect of technology experience suggests that students' prior exposure to academic technologies shapes their response to Al-powered personalization. Students with advanced technological skills found personalized communications more relevant, which suggests that digital literacy is a significant factor in the effectiveness of Al tools. **This finding emphasizes the importance of considering individual variations in technology** experience, particularly in educational settings where such disparities are common. It encourages further exploration of how educational institutions can **refine their** Al strategies to accommodate the needs of diverse student populations.

Practical Implications

The findings of this study offer valuable insights for educational institutions aiming to improve student engagement and decision-making through Al-powered personalization. While the study did not find a significant direct effect of Al-powered personalization on intention to apply, it highlights the indirect influence personalized communication can exert on students' decision-making processes. Institutions should prioritize the development of communication strategies that leverage Al to personalize content. Al systems can analyze student data to create dynamic strategies, such as personalized emails, targeted advertisements, and program recommendations customized to align with the unique needs and preferences of individual students. Although personalization may not directly drive intention to apply, it can still significantly impact student attitudes or perceptions of an institution, thereby influencing their decision-making process.

The research also highlights the mediating role of intention to apply in the decision-making process. Even without a direct effect on intention to apply, AI personalization influences decision-making through this mediation. As such, institutions should focus on engaging prospective students early in their decision-making process. Interactive tools, such as chatbots or virtual advisors, can be used to provide personalized responses to student inquiries, creating a supportive and engaging experience that helps build a sense of community and belonging with the institution. This could increase the likelihood of students following through with their intention to apply.

Moreover, the study reveals that students' experience with academic technology affects how they respond to AI-powered personalization. Institutions should take a refined approach to marketing strategies by recognizing the varying levels of technology experience among students. For instance, students with less experience may respond better to communications that emphasize ease of use and support services, while more advanced users may be more engaged by innovative features. Tailoring marketing materials to reflect these differences will enhance the effectiveness of personalized communications across diverse student groups.

Transparency in the personalization process is another key takeaway. Institutions should clearly communicate how student data is used to tailor messages, which can help build trust and encourage deeper engagement. Transparency can strengthen the relationship between students and institutions, even when the direct effect of AI personalization on intention to apply remains unclear. Long-term engagement strategies, such as providing regular updates, inviting students to webinars, and offering opportunities for interaction with current students and faculty, can help **nurture a sense of community and ongoing support.**

To implement Al-driven personalization effectively, it is essential that staff receive adequate training and possess the necessary skills and knowledge to use these technologies. Investing in training for marketing and admissions teams on how to use Al tools and data effectively is essential. Staff should be capable of interpreting engagement data to adapt strategies, ensuring personalized communications align with institutional goals and student needs. A collaborative approach between departments, such as admissions, marketing, and academic advising, will enhance the quality and impact of student engagement efforts.

Finally, conducting longitudinal studies to measure the impact of personalization on enrollment and retention rates will help refine marketing approaches, ensuring institutions remain responsive to the evolving needs of prospective students.

Conclusion

This study highlights the significant role of Al-powered personalization in influencing student decision-making in higher education. While the findings suggest that Al-driven personalization does not directly impact students' intention to apply, it plays a crucial indirect role in shaping their final decisions. This reinforces the importance of crafting personalized communication strategies that cater to students' unique preferences and academic aspirations. Institutions looking to enhance student engagement should focus on designing Al-powered interactions that resonate with prospective students at different stages of their application journey. Moreover, this research supports key theoretical perspectives, particularly TPB, by demonstrating that students' experience with academic technology significantly affects their engagement with Al-driven personalization. Universities must recognize that not all students have the same level of comfort or familiarity with technology. To maximize engagement, institutions should develop more inclusive approaches that consider varying levels of digital literacy and exposure to Al-powered tools.

Limitations

Although this study offers important insights into the role of Al-powered personalization in student decision-making, several scientific and practical constraints should be acknowledged. One key limitation relates to the measurement of key constructs. Since the study relies on self-reported data, there is a possibility of response bias, where students' perceptions may not fully align with their actual behaviors. Additionally, intention to apply was measured based on students' stated intentions rather than actual application behavior, which may introduce a gap between perception and action. Future research could integrate longitudinal tracking or institutional application data to validate these findings.

Another challenge is the complexity of isolating causal relationships. While SEM was used to analyze the relationships among Al-powered personalization, intention to apply, and student decision-making, causality cannot be definitively established due to the cross-sectional nature of the study. Experimental or longitudinal designs would help determine the directionality and long-term effects of Al-driven personalization in higher education.

From a practical standpoint, the study faced constraints in survey design and data collection. Although a pilot test was conducted to refine the questionnaire, some students may have misinterpreted certain Al-related terms or concepts, leading to variation in responses. Additionally, the study depended on students' access to digital platforms for participation, which may have influenced the sample composition by favoring those who are already engaged with technology.

Finally, the research was conducted in a rapidly evolving technological landscape. As AI-powered personalization tools continue to advance, new features and student expectations may shift, potentially affecting the relevance of the findings over time. Future studies should account for emerging AI technologies and their evolving impact on student decision-making.

Future Research

Building on these findings, future research should address several key areas to enhance understanding of Al-powered personalization in higher education.

First, longitudinal studies should be conducted to assess the long-term effects of AI-personalized communication on student decision-making. Since this study captures only a snapshot in time, tracking students over multiple academic cycles would provide deeper insights into how AI-driven personalization influences their choices beyond initial application intent.

Second, future research should integrate qualitative approaches, such as in-depth interviews or focus groups, to better understand the motivations and concerns students have regarding Al-powered personalization. This would complement quantitative findings by uncovering subjective experiences, perceptions, and emotional responses to Al-driven recruitment efforts.

Third, expanding the research to different educational settings and international contexts would provide a more comprehensive understanding of AI personalization's impact across diverse student populations. Since higher education institutions differ in their use of AI technologies, comparing results across various universities would help identify best practices and contextual challenges in AI-driven student engagement.

Additionally, future studies should explore the intersection between technology access and experience, examining how students with varying levels of digital literacy engage with AI-driven university communications. Understanding this relationship could help institutions refine their personalization strategies to be more inclusive and effective.

Finally, as emerging technologies such as adaptive learning systems and Al-driven academic advising continue to evolve, future research should investigate how these innovations shape student decision-making. Examining how Al-powered personalization extends beyond recruitment-into areas like student retention, academic performance, and career planning-would further enhance our understanding of Al's role in higher education.

By addressing these areas, future research can contribute to more effective, data-driven, and student-centered AI personalization strategies, ensuring that universities can better connect with prospective students and support them in making informed academic decisions.

List of Declarations

- **Ethics approval and consent to participate:** This research obtained full ethical approval from the Institutional Review Board (IRB) of Badr University in Cairo (BUC). Informed consent was secured from all participants before their participation in the study.
- **Consent for publication:** The authors confirm that all participants provided appropriate consent for the publication of this research, with identifying information anonymized to uphold participant privacy.
- Data availability: The data produced and/or analyzed during this study are accessible from the first author upon reasonable request.
- Competing interests: The authors declare that they have no competing financial or non-financial interests.
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| App | pendix: Survey |
|------|--|
| Der | nographics |
| 1- | What is your Age? ☐ Under 18 ☐ 18—20 ☐ 21—23 ☐ More than 23 |
| 2- | What is your current field of study or intended major? Management/Business Supply Chain & Logistics Engineering Computing & Information Technology Arts & Design Other (please specify): |
| Tec | h Experience |
| 3- | How would you describe your experience with academic technology? |
| | Academic technology refers to tools such as learning management systems (e.g., Moodle, Blackboard) arch databases (e.g., Google Scholar, JSTOR), or any software used for research and assignments (e.g. el, SPSS, citation managers). |
| | \square Beginner (Limited experience with academic technology and often need assistance) |
| | ☐ Intermediate (Comfortable using academic technology with occasional help) |
| | ☐ Advanced (Confident using a wide range of academic technologies independently) |
| 4- | How frequently do you use technology for academic research and assignments? |
| | Technology includes using computers, research software, citation management tools, and other digita |
| reso | urces. Rarely (Once a month or less) Occasionally (A few times a month) Frequently (A few times a week) Daily (Used for most academic tasks) |
| 1=9 | Please indicate your level of agreement with the following statements using a scale from 1 to 5, where Strongly Disagree and 5 = Strongly Agree. |
| AI-I | Powered Personalization |
| 1- | Personalized Emails |
| | - Personalized emails from the university align with my academic interests. |
| | - Receiving personalized emails from the university makes me feel like they value my application. |
| | - Information in personalized emails from the university is usually relevant to me. |
| | - I am more likely to open and read personalized emails from the university. |
| | - Personalized emails enhance my overall perception of the university. |
| 2- | Tailored Ads |
| | - Tailored ads from the university are relevant to my program preferences. |

I find tailored ads from the university more engaging than generic ads.

- Tailored ads from the university reflect an understanding of my educational goals.
- I am more likely to click on tailored ads about university programs.
- Tailored ads from the university influence my decision-making process.

3- Program Recommendations

- Program recommendations from the university match my academic aspirations.
- I find Al-generated program recommendations from the university helpful.
- Program recommendations show that the university understands my academic needs.
- I am more inclined to consider programs recommended by the university.
- Program recommendations improve my overall satisfaction with the university.

Application Intent

1- Expression of Interest

- I have shown interest in applying to this university.
- I have sought information about the application process from the university.
- I have attended virtual or in-person sessions about this university's programs.

2- Request for Information

- I have requested detailed information about specific programs from the university.
- I have contacted the university's admissions office for more details.
- I frequently visit the university's website to gather information.

3- Application Submission

- I have completed the application form for this university.
- I have uploaded all required documents for my application.
- I have paid the application fee for this university.

Student Decision-Making

1- Program Selection

- I chose this university's program based on its specific curriculum.
- The faculty at this university influenced my decision to apply.
- The reputation of this university's program played a role in my choice.

2- Trust in Institution

- I trust this university to provide a high-quality education.
- I believe this university is honest and transparent in its communication.
- I feel confident in the support services offered by this university.