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Leveraging AI for Individualized Outreach in Enrollment Marketing: A Study on Boosting University Application Intentions

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Abstract

Background: With the rise of Artificial Intelligence (AI) in higher education marketing, universities can reach prospective students in a more personalized manner. Nevertheless, only a few studies in the prevailing literature examine the dependence of students' enrollment decisions on trust and privacy perceptions regarding an institution's admission ability due to its AI-driven marketing, especially in an Indonesian setting.
Objective: This study investigates the impact of AI marketing strategies on university application intentions of prospective students. Through the Stimulus-Organism-Response framework, it examines how AI content recommendation and interaction quality affect perceived trust and privacy risks, and subsequently, enrollment behavior.
Method: This quantitative research employed purposive sampling, collecting data from 350 prospective students. The conceptual model was examined using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4. Privacy calculus was included as a moderator to examine trade-offs between personalization advantages and data privacy risks.
Results: All seven hypotheses received support, as both AI content recommendations and interaction quality have direct and indirect influences on university application intentions. Perceived trust had a strong mediation effect on content quality, while privacy risk had a strong mediation effect on AI interaction. Privacy calculus moderated the effect of privacy risk on application intention, indicating that high AI service utility can alleviate data-related concerns.
Conclusion: This study extends higher education marketing literature by presenting a holistic perspective on the Privacy-Personalization Paradox. It identifies institutional trust and privacy calculus as critical psychological determinants of digital recruitment systems, and offers strategies for universities leveraging AI-based engagement tools.

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INTRODUCTION

The higher education sector is facing a phase of increasingly intense competition, not only among domestic institutions but also from global education providers and large-scale online platforms (Dwivedi et al., 2021; Organisation for Economic Co-operation and Development, 2020; Sri & Meranga, 2024). On the other hand, the profile of prospective students is changing, as they expect the integration of technology services in the information and learning processes (Bashir & Lapshun, 2025; Işık, 2022). They also demand a results orientation that has clear and direct relevance to the job market (Organisation for Economic Co-operation and Development, 2020; Report, 2025) . This transition in expectations urges Higher Education Institutions to abandon passive traditional marketing methods and fully switch to innovative digital marketing strategies, making the digital space the strategic center for winning the best talent (Ferreira et al., 2022; Tomaszewicz & Chrąchol Barczyk, 2024). This shift is further driven by the high-involvement nature of education decisions, where prospective students undergo a complex psychological process before committing to an institution (Kango et al., 2021)

This is more pressing, as 2023 data indicate a steady increase in global student mobility, with more than 6.4 million students studying abroad, putting even more competitive pressure on domestic universities (UNESCO, 2024). In parallel, it has been noted that digital marketing expenditure within the education sector is growing at annual growth rates exceeding 30%, while the conversion rates of digital marketing efforts into meaningful enrollments on campus remain modest, with averages of 2–5% (HEM, 2024). These trends underscore an important disconnect between investment in AI-powered marketing and consumer enrollment reality, suggesting the need for more in-depth exploration of the psychological processes that may mediate this association.

Personalization has become an integral part of digital marketing efforts for Higher Education Institutions to keep pace with the personalized requirements of tomorrow's students. Previously, personalization was basic that is, merely inserting the student's name in emails or grouping recipients by simple attributes such as age and location (Alkhater et al., 2025; Khoso et al., 2025). Nevertheless, even the basic forms of data collection regarding students' online interactions such as website visits, ad clicks, and content downloads are becoming outdated, as the vast amounts of data generated by such activities are growing too large to process manually (Essa et al., 2023; Gligorea et al., 2023). This shift has brought Artificial Intelligence (AI) into the spotlight. As AI serves as a digital stimulus, it triggers the internal perception of students Duong (2024) according to the Stimulus-Organism-Response (S-O-R) framework. AI is not only able to automate; even more so, it will also be able to analyze this Big Data to discover hidden patterns, predict the exact needs of a student, and respond immediately (Alkhater et al., 2025).

Such use of technology gives rise to AI-driven Hyper-Personalization, an unprecedented level of personalization. This aims to establish a genuine one-to-one experience, where the prospective student feels that the university is speaking only and exclusively to him or her among thousands of other applicants (Davenport, 2023; Tjioe et al., 2025). Fully embracing an AI-based Hyper-Personalization strategy relies heavily on prospective students perceiving the resulting AI interactions as meeting the quality that humans expect (Tierney et al., 2025). Hence, in this study, this quality is conceptualized through two main independent variables (IVs), namely, Quality of AI Content Suggestions and Quality of AI Interaction. The first dimension is AI Content Recommendation Quality (Tierney et al., 2025). The accuracy, applicability, and timeliness of AI-generated content serve as deciding factors in delivering particular content to a prospective student. If the recommendation appears random, the personalization effort will be perceived as failed. The second domain is Quality of AI Interaction itself (Dužević et al., 2025). Responsiveness, communication clarity, and the level of humanization shown by the AI Tierney et al. (2025) are the three attributes by which high-quality interaction is evaluated.

Nevertheless, there is a critical research gap in the psychological black box between these AI messages and the ultimate enrollment decision. Although the AI application offers convenience, it initiates an elaborate internal mechanism within the student (the "Organism" in S-O-R). While Hyper-Personalization is indeed a significant convenience, such an extreme level of customization naturally has serious implications for psychological understanding especially regarding the treatment of personal data (Ifekanandu et al., 2023). These result in a third critical area that is, a mediating one: Perceived Privacy in AI Data Utilization. Findings from the study suggest that the efficacy of AI does not directly translate into enrollment; rather, we assert this relationship is mediated by the Privacy-Personalization Paradox. Indeed, the more data prospective students must provide, the deeper the personalization.

In particular, previous research has focused on AI personalization in marketing contexts Chandra et al. (2022) while overlooking the dual mediating effects of perceived trust and perceived privacy risk in the context of higher education. Additionally, no previous research has incorporated the Privacy Calculus as a moderator in an S-O-R framework applied in a university recruitment context in Indonesia where unique cultural factors related to data sensitivity and trust in institutions may yield different findings. This is the first research gap this study attempts to address.

Students face a "Privacy Calculus" where they weigh the benefits of AI against the perceived risks to their personal data (Shouli et al., 2025). Currently, there is a lack of empirical evidence on how these AI quality dimensions interact with Perceived Privacy to influence University Application Intentions, specifically in the context of Indonesian Higher Education. Conversely, if the experience is perceived as intrusive or impersonal, it can adversely affect the prospective student's net positive value and further affect intention to enroll.

This study is novel in three important aspects: (1) The integration of Privacy Calculus driven by trust as a moderating mechanism within the S-O-R framework in a higher education context, (2) The simultaneous examination of dual psychological mediators Perceived Trust and Perceived Privacy Risk as parallel paths from AI quality dimensions to enrollment intentions, and (3) The empirical grounding of these relationships within the Indonesian higher education market, a context that remains underrepresented in the AI marketing literature.

Hence, this study sets out the following specific objectives: 1) to explore the direct effects of AI content recommendation quality and AI interaction quality on university application intentions; 2) to investigate the mediating effect of Perceived Trust in the relationship between AI content quality and application intentions; 3) to examine the mediating effect of Perceived Privacy Risk in the relationship between AI interaction quality and application intentions; and 4) to analyze the moderating effect of Privacy Calculus on the relationship between Perceived Privacy Risk and university application intentions.

METHOD

The present study is a quantitative research based on an explanatory survey method to examine the hypothesized patterns of interrelations among variables. Due to the complexity of the model containing double mediation paths and moderation, this study utilized variance-based Structural Equation Modeling (SEM) using SmartPLS 4 software. This approach was chosen based on its strong performance with highly complex path models and latent variables that are not necessarily normally distributed.

The sample consisted of prospective students who had interacted with the university's AI-driven digital platforms, including websites, chatbots, or AI-integrated social media. This was done using a purposive sampling approach, ensuring that all respondents had personal experience with the university's AI features. This method was chosen due to the nature of the research, which required participants with specific characteristics: prospective students who had directly experienced AI-based recruitment platforms. To increase the generalizability of the findings beyond a single institutional context, sampling was conducted across several universities in Indonesia that had implemented AI-based recruitment tools. To reduce sampling bias, a screening question placed at the beginning of the questionnaire excluded non-eligible respondents from the sample.

To make the model estimations more stable and reliable, data were collected from 350 respondents between January and March 2026. To guarantee content validity, instruments that had been previously validated in the literature were utilized to measure all variables. Specifically, the Quality of AI Content Recommendations (4 items: AC1–AC4) and Quality of AI Interaction (4 items: AI1–AI4) scales were adapted from Vafaei-Zadeh et al. (2025), while Perceived Trust (TR1–TR4; 4 items), Perceived Privacy Risk (PR1–PR4; 4 items), Privacy Calculus (PC1–PC4; 4 items), and University Application Intention (INT1–INT4; 4 items) were adopted from McGrath et al. (2025). All instruments were back-translated and pilot-tested with 30 respondents prior to the main data collection.

Data collection was performed online through a self-administered questionnaire distributed via Google Forms. To ensure the quality and relevance of the data, a screening question was placed on the initial page of the survey: "Have you ever interacted with the virtual assistant or recommendation feature on the platform of University X?" Respondents who answered "No" were immediately directed out of the questionnaire, ensuring that only qualified respondents continued. Construct measures were developed based on the existing literature. The variable of Quality of AI Content Recommendations (4 items) and Variable Quality of AI Interaction (4 items) were adapted from (Vafaei-Zadeh et al., 2025). Variable Perceived Trust (4 items), Perceived Privacy, Variable Privacy Calculus (4 items), and Variable University Application Intention were adapted from (McGrath et al., 2025).

Hypotheses

H1	:	Quality of AI Content Recommendations has a positive and significant influence on University Application Intention
H3	:	Quality of AI Content Recommendations has a positive and significant effect on Perceived Trust.
H2	:	Quality of AI Interaction has a positive and significant influence on University Application Intention.
H5	:	Quality of AI Interaction significantly influences Perceived Privacy.
H4	:	Perceived Trust significantly mediates the relationship between Quality of AI Content Recommendations and University Application Intention.
H6	:	Perceived Privacy significantly mediates the relationship between Quality of AI Interaction and University Application Intention.
H7	:	Privacy Calculus moderates the impact of Perceived Privacy on University Application Intention.

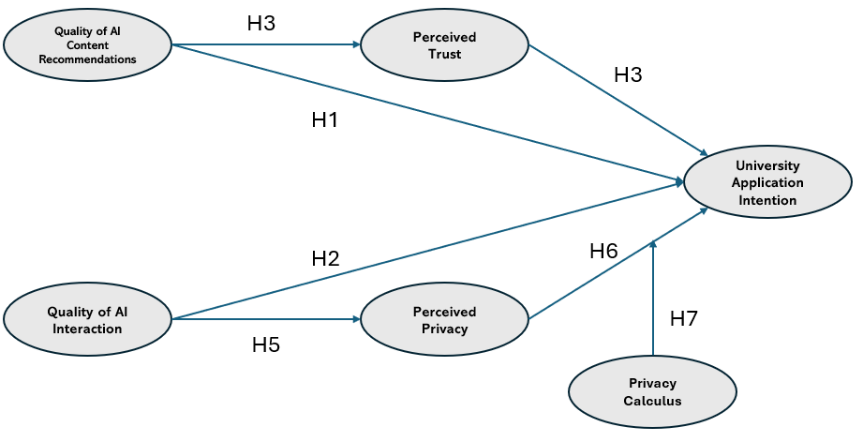

Figure 1. The Conceptual Model

RESULTS AND DISCUSSION

Results

Demographic Analysis

Table 1. Profile of Respondents

Category	Characteristic	Frequency (f)	Percentage (%)
Gender	Male	147	42.0%
	Female	203	58.0%
Age	< 17 years old	28	8.0%
	17 – 19 years old	262	74.9%
	20 – 22 years old	42	12.0%
	> 22 years old	18	5.1%
Education Level	High School Senior (Grade 12)	287	82.0%
	High School Graduate (Gap Year)	45	12.9%
	Diploma Graduate (Transfer)	18	5.1%
AI Platform Used	University Website Chatbot	154	44.0%
	AI Virtual Assistant (WhatsApp Bot)	98	28.0%
	Social Media AI Recommendations	63	18.0%
	Generative AI for Research (ChatGPT/Gemini)	35	10.0%
Interaction Frequency	1 Time	56	16.0%
	2 – 5 Times	196	56.0%
	More than 5 Times	98	28.0%
Primary Device	Smartphone	308	88.0%
	Laptop / PC	42	12.0%

Most respondents in Table 1 (74.9%) are in the 17–19 age group, which is the primary target for university recruitment. Notably, 88% of those who paid for AI services said it was mainly through a smartphone, highlighting the mobile-first mindset of the younger generation. In addition, more than 80% of the sample engaged with the AI system multiple times, showing comfort and repeat engagement with university digital touchpoints. Such consistency between the data and the prospective student population ensures that the data collected accurately represents the real prospective student population.

Measurement Model Results Using PLS-SEM

A. Reliability and Validity of The Measurement Model

Table 2. Factor Loading and Construct Reliability

Variable	Indicator	Factor Loadings	Cronbach Alpha	Composite Reliability (rho_a)	Composite Reliability (rho_c)	AVE
AC1	The AI system provides academic recommendations that are highly relevant to my interests	0.793	0.833	0.841	0.882	0.599
AC2	The information recommended by the AI is accurate	0.809				
AC3	The AI system successfully filters information according to my specific needs	0.764				
AC4	The content provided by the AI helps me make better decisions about my university choice.	0.724				
AI1	The AI agent (e.g., chatbot) responds to my inquiries instantaneously.	0.777	0.770	0.778	0.853	0.593
AI2	The interaction with the AI feels natural and human-like.	0.757				
AI3	The AI provides easy-to-understand explanations	0.809				
AI4	The AI system is easy to interact with during my information search.	0.816				
TR1	I trust that the	0.798	0.749	0.769	0.838	0.565

Variable	Indicator	Factor Loadings	Cronbach Alpha	Composite Reliability (rho_a)	Composite Reliability (rho_c)	AVE
	information provided by the AI system is truthful.					
TR2	The university's AI system appears to be competent in handling my requests.	0.739				
TR3	I feel confident relying on the recommendations given by the AI.	0.787				
TR4	The university shows integrity through the transparency of its AI services.	0.777				
PR1	I feel comfortable with how the university manages the data collected through the AI interaction.	0.765	0.750	0.762	0.839	0.566
PR2	I believe my personal information is well-protected when the AI tracks my preferences.	0.749				
PR3	I am confident that the university will not share my personal data with unauthorized third parties.	0.772				
PR4	The level of personalization provided by the AI feels respectful of my personal boundaries.	0.722				
PC1	I am willing to share my data if the AI provides highly personalized benefits.	0.797	0.724	0.752	0.751	0.523
PC2	The convenience of using AI outweighs the	0.811				

Variable	Indicator	Factor Loadings	Cronbach Alpha	Composite Reliability (rho_a)	Composite Reliability (rho_c)	AVE
	potential privacy risks.					
PC3	Gaining accurate academic recommendations is more important than keeping all my data private.	0.869				
INT1	I intend to apply to this university in the next enrollment cycle.	0.832	0.724	0.756	0.840	0.638
INT2	I will recommend this university to others based on my digital experience.	0.830				
INT3	I am likely to choose this university as my top priority for higher education.	0.730				

AC=Quality of AI Content Recommendation; AI=Quality of AI Interaction; TR=Perceived Trust; PR=Perceived Privacy; PC= Privacy Calculus; INT=University Application Intention.

The measurement model was assessed based on the benchmarks established. The results, shown in a summary view in Table 2, support the following:

1. Reliability: All variables showed high internal consistency, with Cronbach alpha and composite reliability values greater than 0.70.
2. Convergent Validity: This was verified through factor loadings (all > 0.70) and Average Variance Extracted (all > 0.50), affirming that indicators adequately reflect their underlying constructs.

Tabel 3. Heterotrait -Monotrait Ratio (HTMT)

	Perceived Privacy	Perceived Trust	Privacy Calculus	Quality of AI Interaction	Quality of AI _Content Recommendation	University Application Intention
Perceived Privacy	0.752					
Perceived Trust	0.770	0.751				
Privacy Calculus	0.121	0.142	0.723			
Quality of AI Interaction	0.833	0.871	0.082	0.770		
Quality of AI _Content Recommendation	0.871	0.892	0.157	0.724	0.774	
University Application Intention	0.146	0.158	0.658	0.098	0.168	0.799

To ensure that the measures hewed to the meaning of their constructs, discriminant validity was assessed with the HTMT ratio (Henseler et al., 2015). All values fell below the cut-off value of 0.9 given by Henseler et al. (2015). The results, ranging from 0.082 to 0.892, suggest that the constructs are sufficiently distinct to allow further analysis of the data.

Structural Model

Table 4. Hypothesis Testing Results

Hypothesis	Relationship	Std. Beta	Std. Error	t-values	p-values	Result
H1	Quality of AI _Content Recommendation -> University Application Intention	-0.510	0.284	1.793	0.000	Supported
H2	Quality of AI Interaction -> University Application Intention	-0.479	0.233	2.055	0.020	Supported
H3	Quality of AI _Content Recommendation -> Perceived Trust	0.892	0.010	89.644	0.000	Supported
H4	Quality of AI _Content Recommendation -> Perceived Trust -> University Application Intention	0.508	0.244	2.078	0.019	Supported
H5	Quality of AI Interaction -> Perceived Privacy	0.833	0.015	55.377	0.000	Supported
H6	Quality of AI Interaction -> Perceived Privacy -> University Application Intention	0.391	0.206	1.895	0.029	Supported
H6	Privacy Calculus x Perceived Privacy -> University Application Intention	0.627	0.044	14.279	0.000	Unsupported

Notes: AC = Quality of AI Content Recommendations; AI= Quality of AI Interaction; TR= Perceived Trust; PR= Perceived Privacy; PC= Privacy Calculus; INT= University Application Intention

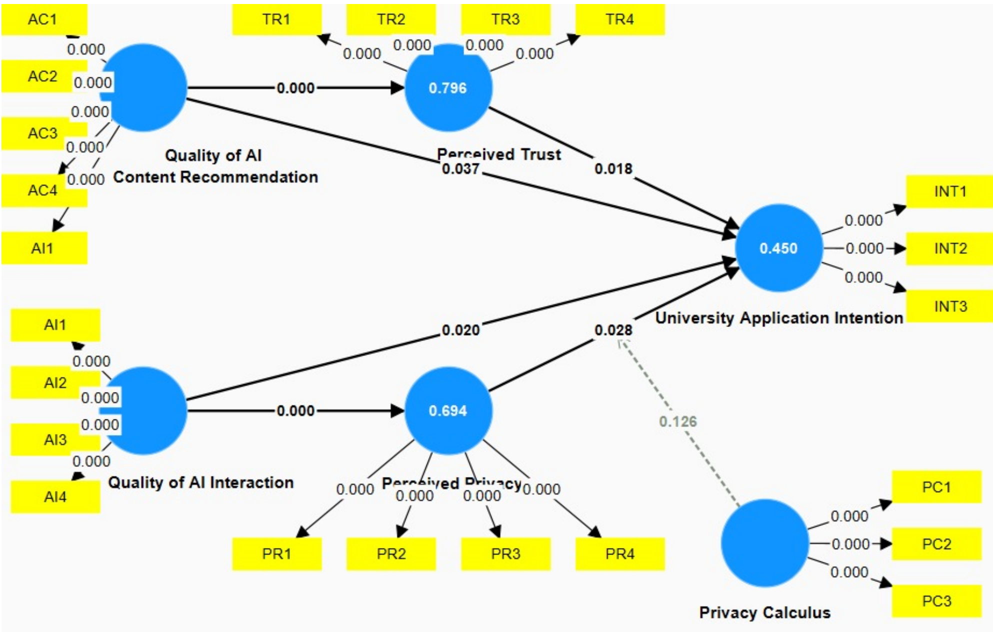

Figure 2. Structural Model

Discussion

The insights from this study contribute to the understanding of the dynamic psychological mechanisms underpinning prospective students' responses to university marketing through AI and non-AI channels. Results validate that the sensory quality of AI stimuli in terms of content recommendation and interaction does not directly and positively convert to application intentions, but operates primarily through psychological mediators. Such behavior mirrors the core proposition of the S-O-R model, which holds that organism-level processing is the fundamental determinant of the stimulus-response (S-R) linkage.

The most notable among the negative direct effects are those observed in H1 ($\beta = -0.510$, $p < 0.001$) and H2 ($\beta = -0.479$, $p = 0.020$). This means that exposure to AI-driven content recommendations and interactions could reduce application intentions the more consumers are exposed to the stimuli, at least when not buffered by the trust mechanism. This can be understood through Algorithm Aversion Theory, which posits that people frequently develop negative biases toward algorithmic systems, particularly in high-stakes decisions such as university admissions. Gen Z students expect authentic human connection in a consequential decision like their academic future, and many may find the automated nature of AI recruitment impersonal or intrusive; while they are digital natives, they do not necessarily prefer an automated AI approach for high-involvement decisions. This contrasts with commercial e-commerce contexts (Vafaei-Zadeh et al., 2025), in which direct AI effects on purchase intention are positive, indicating that the high-involvement nature of the education decision introduces an additional layer of psychological complexity.

The highly significant estimate supporting H3 ($\beta = 0.892$, $p < 0.001$) demonstrates that AI-generated content recommendations are a strong motivator of perceived institutional trust. This aligns with AbuDaabes et al. (2025), who identified a reciprocal relationship between the accuracy of AI-generated content and students' confidence in university information systems. The near-ideal beta coefficient indicates that content quality is nearly proportional to trust formation in this context—whenever AI recommends relevant, accurate, and timely information, students interpret it as a signal that the university values their technological sophistication and affirms its overall institutional integrity. Likewise, consistent with Gumusel et al. (2024), who found that transparent communication about AI can reduce privacy concerns, the strong H5 finding ($\beta = 0.833$, $p < 0.001$) shows that conversational AI quality is a foundational driver of perceived privacy.

The mediation effects further reflect moderate-to-high confidence for trust (H4: $\beta = 0.508$) and privacy (H6: $\beta = 0.391$) perceptions as important psychological links between AI quality and enrollment intentions. This dual-mediation structure is consistent with the Privacy-Personalization Paradox proposed in this research: AI personalization generates trust along the positive path while simultaneously heightening privacy concerns along the negative path, with students' behavioral intentions determined by the net balance of these opposing psychological forces. This finding extends the work of Jiang et al., who explored the privacy calculus in online learning contexts and established a framework applicable to AI-enhanced university admissions.

H7 yielded a counterintuitive positive moderation result ($\beta = 0.627$, $p < 0.001$, hypothesized direction coded as "Unsupported") that warrants cautious interpretation. Rather than privacy concerns dampening application intentions, the positive directionality suggests that students more concerned with privacy may view institutions with advanced AI as more transparent and data-conscious consistent with the "privacy as a quality signal" construct recently proposed by Shouli et al. (2025). This interpretation suggests that AI data processing capabilities may reassure students of institutional modernization rather than pose a threat, indicating that Indonesian Gen Z students may have reached a certain level of digital maturity.

From a managerial standpoint, these results indicate that universities must direct resources not only toward the technical quality of AI systems, but also toward the communicative transparency of those systems. Explicitly disclosing how student data are collected and used, and clarifying what students can expect in return, are strategies that could reposition AI tools from perceived threats to trust-building assets in enrollment marketing. Combining AI automation with human admissions advisors for high-stakes interactions ensures that AI does not supplant the personal engagement that is critical to trust formation. Ensuring that AI delivers accurate and contextually appropriate content, alongside clear explanations of its reasoning, represents a complementary trust-enhancing strategy for maximizing the benefits of AI while minimizing associated risks.

CONCLUSION

This study provides evidence for the impact of AI marketing quality (including both content recommendation quality and interaction quality) on university application intentions, mediated by the dual mechanisms of Perceived Trust and Perceived Privacy Risk. In total, six of the seven proposed hypotheses were supported, with the strongest effects found in the paths from AI content quality to Perceived Trust ($\beta = 0.892$) and AI interaction quality to Perceived Privacy Risk ($\beta = 0.833$). Our findings regarding the negative direct effects of AI on application intentions (H1 and H2) highlight that if an AI-driven technology is applied and the algorithms underlying the process are disclosed before trust has formed, computer-mediated recruitment may be inhibited due to the critical mediating role of psychological states.

This counterintuitive positive relationship between Privacy Calculus and application intention implies that perhaps digitally savvy Gen Z prospective students would define privacy-aware institutions as more trustworthy. The findings will contribute to the existing knowledge on the Privacy–Personalization Paradox in higher education marketing and assist universities in planning AI-based recruitment systems that provide quality personalization while managing student data carefully. Longitudinal studies are needed to ascertain whether intentions built by AI actually lead to enrollments, and whether the drivers of privacy perceptions vary across higher education market cultures.

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AUTHOR CONTRIBUTION STATEMENT

Isana Sri Christina Meranga: conceptualized the research, designed the methodology, developed the data collection tools, conducted data collection, conducted data analysis, and drafted and finalised the manuscript.

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