

# Evaluating The Impact of Digital Marketing Strategies on Enrollment Decisions through PLS-SEM Analysis: Insights from Private University X

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## Abstract

This study evaluates the effectiveness of digital marketing strategies in influencing enrollment decisions at Indonesian private universities. With the increasing reliance on digital platforms, higher education institutions (HEIs) have adapted their marketing approaches to engage digitally-savvy prospective students. The aim of this research is to identify the most impactful strategies and their contribution to student enrollment decisions. Utilizing Partial Least Squares Structural Equation Modeling (PLS-SEM), the study compares three models: one derived from prior research and two newly proposed by the authors. Data collected from 325 respondents revealed that social media engagement and personalized direct messaging significantly enhance enrollment decisions, with the highest  $R^2$  value (0.772) observed for social media engagement in Model 2. The Bayesian Information Criterion (BIC) indicated Model 2 as the best fit (-255.774) for explaining enrollment decisions. These findings suggest that strategies emphasizing social media engagement and personalized communication yield the greatest impact on prospective students. This study contributes to the growing field of digital marketing in higher education by offering actionable insights for enhancing online visibility and optimizing enrollment outcomes in a competitive market.

**Keywords:** *digital marketing; student enrollment; higher education; social media; PLS\_SEM*

## 1. Introduction

In recent years, the higher education landscape has undergone significant transformations due to advancements in technology and the increasing reliance on digital platforms. Private universities, particularly in Indonesia, face intense competition in attracting prospective students, which has led to the widespread adoption of digital marketing strategies. According to Kotler and Keller (2016), digital marketing involves leveraging online channels such as social media, search engines, email marketing, and websites to connect with potential customers effectively. For private universities, these strategies are becoming crucial in addressing declining student enrollment caused by demographic shifts and the emergence of alternative educational institutions offering flexible and cost-effective programs.

Despite the widespread adoption of digital marketing strategies, their effectiveness in influencing student enrollment decisions remains a critical area of inquiry. This study seeks to address this gap by evaluating which strategies yield the highest impact on enrollment outcomes. These methods include running targeted social media campaigns, optimizing websites for search engine visibility, and utilizing data analytics to refine recruitment efforts. For example, Facebook and Instagram have been widely used platforms to

showcase campus life, highlight unique academic programs, and directly interact with inquiries from prospective students. However, the effectiveness of such strategies in influencing student enrollment decisions remains a critical area of inquiry. Studies by Chaffey and Smith (2022) suggest that while digital marketing creates awareness, the impact on decision-making may be moderated by factors such as brand reputation, financial aid availability, and perceived quality of education.

This study aims to evaluate the effectiveness of digital marketing strategies implemented by Private University X in influencing student enrollment decisions. As a leading private institution in Indonesia, Private University X has adopted various digital marketing strategies to attract prospective students. By identifying which strategies yield the highest return on investment, the findings aim to guide the university in optimizing its marketing efforts. This research also seeks to provide actionable insights into improving communication and engagement with potential students through digital platforms.

While existing literature often emphasizes technical aspects of digital marketing, such as click-through rates and user engagement, these studies rarely examine how these metrics influence actual enrollment decisions. This study fills this gap by

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investigating the direct impact of digital marketing strategies on student enrollment outcomes at a private university in Indonesia.

## 2. Literatur Review

Recent years have seen a dramatic change in higher education marketing, mostly due to changes in customer behavior, increased rivalry among institutions, and technological breakthroughs. Traditionally, universities relied on conventional marketing techniques such as print media, campus fairs, and direct mail to engage prospective students. These methods, however, have gradually been supplemented—or in some cases, replaced—by digital marketing tools, in response to the changing dynamics of the education sector (Markovic et al., 2017). Higher education institutions (HEIs) are increasingly realizing the value of connecting, and this shift is part of a larger trend with a digitally-savvy generation. Digital platforms and data analytics have become integral in establishing a competitive advantage in a crowded educational market (Williamson, 2021). By utilizing websites, social media, email campaigns, and online advertising, A larger audience can be reached by HEIs and foster more meaningful interactions with prospective students (Neacsu and Armasar, 2018). On a global scale, HEIs have been able to serve global audiences by implementing digital marketing tactics, driving the globalization of education (University spiritu santo et al., 2017). The marketization of higher education is another key trend, where institutions employ business-oriented strategies to remain competitive on a global stage (Zhu, 2019). Digital marketing usage was further driven by the COVID-19 epidemic, as traditional in-person recruitment events were disrupted. In response, universities used digital content and social media to interact with potential students, stressing the need of having a strong online presence (Rawat et al., 2022). Additionally, the rise of e-learning platforms and MOOCs underscores the digital transformation of educational services, meeting the needs of a digitally proficient student population (Klave and Cane, 2024; Polianovskyi et al., 2021).

In Indonesia, digital marketing is being used more and more by Private University X as a way to stay competitive in a dynamic higher education landscape. The growing reliance on digital platforms by it is now crucial for educational institutions to improve their internet presence in order to attract prospective students (Farida, 2024; Julita et al., 2024). Given the highly competitive nature of the Indonesian higher education market, private universities must distinguish themselves through effective branding and digital marketing strategies. These strategies can significantly bolster a university's reputation and attract students, with social media platforms such as Instagram and Facebook playing a crucial role in building brand awareness and engaging prospective

students through targeted campaigns (Rajagukguk et al., 2023; Vidyawati and Rosyidah, 2022). Digital media also allows universities to directly engage with prospective students, providing personalized communication through social media platforms, which is essential for building strong relationships and fostering a sense of connection with the institution (Riofita, 2022). Video marketing and interactive content have become particularly important tools for showcasing university programs and connecting with a younger, more digitally-inclined audience (Farida, 2024). Furthermore, an important factor in establishing a university's brand identity is digital marketing, which is crucial for long-term sustainability. Universities can manage their reputation and highlight their academic strengths, success stories, and community involvement, thereby enhancing their credibility and appeal to prospective students (Munir et al., 2023; Rajagukguk et al., 2023).

A variety of components contribute to a successful digital marketing strategy in higher education. Search engine optimization (SEO) is fundamental in enhancing the visibility of university websites on search engines, which directly impacts the volume of organic traffic and the credibility of the institution ("Investigating Digital Marketing Strategies in Influencing Student Enrollment Decisions in Tertiary Education," 2023). Complementing SEO, paid advertising allows universities to reach broader audiences through targeted ads, but without interactive elements, such strategies can be less effective in fostering long-term engagement with prospective students (Puluhulawa et al., 2022). Social media marketing, on the other hand, has become a key strategy in driving engagement, building brand recognition, and generating leads. Through strategic campaigns on platforms like Facebook, Instagram, and Twitter, universities can maintain an ongoing dialogue with potential students, ultimately increasing the likelihood of enrollment (Magdalena et al., 2022). Direct messaging, which offers personalized communication, has also proven to be highly effective in influencing enrollment intentions, as it fosters a more direct and personal connection with prospective students (Abdol Ghani et al., 2023; Odle and Delaney, 2022). Affiliate marketing and public relations also play crucial roles in expanding a university's reach and strengthening its reputation. Through partnerships with influencers, educational consultants, and other organizations, universities can leverage affiliate marketing to tap into established networks and gain access to new audiences (Puluhulawa et al., 2022). PR campaigns further enhance the university's public image, establishing trust and shaping perceptions, which are vital for attracting students (Harrison, 2024; Silaban, 2023).

The influence of digital marketing tactics on students' decision-making has been the subject of numerous research, many focus on individual

components rather than offering a holistic analysis of the collective impact of various strategies. (Kusumawati, 2019) and Fierro et al. (2017) have assessed how digital marketing affects enrollment choices, yet there is a lack of comprehensive comparative studies that use advanced analytical methods to assess multiple strategies simultaneously (Wijaya et al., 2023). Furthermore, while quantitative methods like Structural Equation Modeling (SEM) and Partial Least Squares (PLS) are commonly used in higher education marketing studies (Kaushal et al., 2023), these studies often suffer from methodological limitations, including narrow variables and insufficient integration with qualitative insights (Harada, 2022; Seeber, 2020). There remains a need for more rigorous and context-sensitive research methodologies that assess the efficacy of digital marketing tactics more thoroughly.

Theories of consumer behavior, such as the Technology Acceptance Model (TAM), the Theory of Planned Behavior (TPB), and the Consumer Decision-Making Process Model, offer a theoretical framework for comprehending how digital marketing affects student choices. For example, TPB has been used to examine how behavioral intentions, such as students' choice of educational institutions, are influenced by attitudes, subjective norms, and perceived control (Wong et al., 2018). Similarly, the Consumer Decision-Making Process Model outlines the stages that students go through when selecting a university, TAM emphasizes the significance of usability and simplicity of use in the adoption of technology, both of which are critical to students' engagement with digital marketing platforms (Evans et al., 2022; Rajkumar et al., 2022). These theories have been widely applied in previous studies, such as those by (Jiang et al., 2022), (Duffy and Ney, 2015), and (Darmawansyah et al., 2023), to explore how digital experiences influence students' decisions and behaviors. By integrating these theoretical models, researchers are better able to comprehend how student enrollment decisions and digital marketing tactics are related.

Finally, SEM-PLS has proven to be an effective analytical tool in higher education marketing research due to its flexibility in handling complex models, ability to address non-normal data distributions, and suitability for small to medium sample sizes. SEM-PLS focuses on prediction and can accommodate exploratory research, making it particularly useful for analyzing the multifaceted relationships between digital marketing strategies and student behavior (Deepa, 2020; Safeer et al., 2021). Several studies, including those by (García et al., 2023), and (Singh, 2022), have successfully employed SEM-PLS to evaluate factors influencing student enrollment decisions and engagement with online learning platforms. These studies highlight the effectiveness of SEM-PLS in exploring the dynamic relationships

between various marketing strategies and student behaviors.

In summary, while substantial progress has been made in understanding the role of digital marketing in higher education, there remain significant gaps in the literature. Few studies have undertaken comprehensive comparative analyses of multiple marketing strategies, particularly in the context of private universities in Indonesia. Additionally, existing research often faces methodological limitations and lacks integration with qualitative insights. Addressing these gaps will be crucial for advancing our understanding of how digital marketing strategies collectively impact student enrollment decisions and for developing more effective marketing strategies for HEIs in Indonesia and beyond.

### 3. Methodology

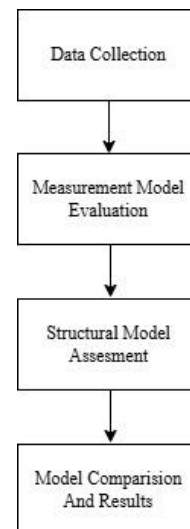


Figure 1. Research Method.

#### 3.1 Research Design

This study employs a quantitative research approach using Partial Least Squares Structural Equation Modeling (PLS-SEM) to investigate causal links among latent variables. PLS-SEM was chosen over CB-SEM due to its ability to handle complex models with small to medium sample sizes, as well as its robustness in analyzing non-normally distributed data (Hair et al., 2014). Unlike CB-SEM, which focuses on model fit, PLS-SEM is more suitable for exploratory research that aims to predict key drivers of student enrollment (Bollen and Noble, 2011; Hair, 2014). The research process follows a systematic flow as illustrated in Figure 1, which outlines the key stages: data collection, measurement model evaluation, structural model assessment, and model comparison.

Three models are analyzed to assess the effectiveness of digital marketing strategies: Model 1,

derived from prior research, and Models 2 and 3, newly proposed by the authors. The Bayesian Information Criterion (BIC) is utilized to evaluate model fit, with lower BIC values indicating better predictive relevance and overall model performance. These models are compared to identify the strategies that most effectively influence student enrollment decisions.

### 3.2 Population, Sample, and Data Collection Procedures

The population of this study consists of prospective students who registered for enrollment at Private University X during a specified period. A minimum sample size of 316 respondents was determined using Slovin's formula with a 5% margin of error, based on a population of 1,500 students. A straightforward random sampling method was used to guarantee a representative sample, giving every potential student an equal chance of being chosen. A total of 400 questionnaires were distributed, with 325 completed responses received, resulting in an 81.25% response rate.

This response rate was deemed sufficient to ensure the sample represented the diverse demographic characteristics of the target population, including gender, age, region of origin, and year of enrollment. Data were collected through a structured questionnaire designed to assess students' perceptions of various digital marketing strategies implemented by the university. Utilizing a 5-point Likert scale, the survey examined elements related to the students' enrollment choices, including website features, search engine optimization (SEO), click-based advertising, public relations, affiliate marketing, social networks, and direct messaging. Prior to distribution, the instrument underwent expert validation and reliability testing, with composite reliability values above 0.70, ensuring strong internal consistency.

### 3.3 Measurement of Variables

Based on the literature, the constructs and the indicators that go along with them were meticulously created and modified for the study's setting.

Table 1. Constructs and Indicators

Code	Factor	Code	Indicator
W1	Website	W1	Academic Information
		W2	Attractive Content
		W3	Good Interface
Y2	SEO	SEO1	Content Indexing
		SEO2	Structured Layout

		SEO3	Keywords
		SEO4	Access Speed
Y3	Click-Based Advertising	CB1	Simplicity of Promotion
		CB2	Advertising
		CB3	Pay-per-Click
Y4	Public Relations	PR1	Partnership Programs
		PR2	Community Involvement
		PR3	Program Socialization
		PR4	Scheduled Promotional Programs
Y5	Affiliate Marketing	AM1	Inter-University Collaboration
		AP2	Commissions
		AP3	Partner Evaluation
		AP4	Launching New Affiliate Programs
		AP5	Number of Partners
Y6	Social Networks	SN1	Number of Followers
		SN2	Active Interaction
		SN3	Service Interaction
		SN4	Information Completeness
Y7	Direct Messaging	DM1	Email or WhatsApp
		DM2	Email/ WhatsApp for Promotion
		DM3	Contact List
		DM4	Information Dissemination via Email / WhatsApp
Y8	Enrollment Index	IP1	Intention to Enroll
		IP2	Influence of Enrollment Information

Table 1 the constructs were measured using items on a five-point Likert scale. The questionnaire items were carefully adapted from established instruments, ensuring that they aligned with the theoretical

constructs and the specific context of Private University X.

### 3.4 Data Analysis Procedures

The collected data were analyzed using PLS-SEM with SmartPLS version 3.2.9 (Hair et al., 2019; Sarstedt et al., 2016). The analysis process includes two main stages: the evaluation of the measurement model and the structural model. PLS-SEM was chosen for this study due to its ability to handle complex models involving multiple constructs, including formative constructs. It is also capable of addressing non-normal data distributions and provide robust results even with smaller sample sizes (Muhammad Nusrang et al., 2023; Sayyida, 2023). The procedures for data analysis as follow:

1. Developing the Conceptual Framework: The first step involved formulating structural models for the three models under comparison (Model 1, Model 2, and Model 3).
2. Evaluating the Measurement Model:
  - Reliability: Composite reliability was calculated to assess the internal consistency of the constructs. A value above 0.70 indicates acceptable reliability (Hair et al., 2019).
  - Convergent Validity: The Average Variance Extracted (AVE) was evaluated to measure the degree to which the items explain the variance of their respective constructs. An AVE value greater than 0.50 suggests adequate convergent validity.
  - Discriminant Validity: The Fornell-Larcker criterion was applied to ensure that constructs were sufficiently distinct. For discriminant validity to be acceptable, the square root of the AVE of each construct should be greater than the correlation with other constructs.
3. Evaluating the Structural Model:
  - Coefficient of Determination ( $R^2$ ):  $R^2$  was used to evaluate the variance explained by the model for the dependent variable (enrollment decision). Higher  $R^2$  values indicate a better model fit and a greater explanatory power.
  - Effect Sizes ( $f^2$ ): Effect sizes were calculated to assess the relative importance of each predictor variable. A value of  $f^2$  greater than 0.02, 0.15, and 0.35 is considered small, medium, and large, respectively.

### 3.5 Ethical Considerations and Limitations of the Methodology

Ethical considerations were thoroughly addressed throughout the study. Participants were fully informed about the study's purpose, procedures, and their rights before participation, and informed consent was obtained from all respondents. To ensure confidentiality and anonymity, no personal identifiers were collected, and all data were securely stored and used exclusively for research purposes. The study received ethical approval from the Institutional Review Board (IRB) or Ethics Committee of Private University X, adhering to ethical guidelines outlined in the Declaration of Helsinki.

Despite these efforts, the methodology has several limitations. Although a simple random sampling method was used, the sample may not fully represent the entire population of prospective students, limiting the generalizability of the findings. Additionally, while the survey methodology ensures robust data, self-reported responses could introduce biases, such as social desirability bias, affecting the accuracy of the data. Furthermore, the study's findings may be more specific to Private University X and may not be directly applicable to other institutions, which calls for caution when generalizing the results to broader contexts.

## 4. Result and Discussion

This section presents the findings of the model comparison for digital marketing strategies and their influence on students' enrollment decision (ED) at a private university in Indonesia. The analysis employs Structural Equation Modeling (SEM) with Partial Least Squares (PLS) to evaluate the effects of various digital marketing strategies: Affiliate Marketing (AF), Public Relations (PR), Social Media Engagement (SM), Click-Based Advertising (CB), Direct Messaging (DM), Search Engine Optimization (SEO), and Website Quality (WEB) on ED. The results are discussed in the context of the respondents' demographic profile, the evaluation of the reflective measurement model, and the structural model. These components provide a comprehensive understanding of how each digital marketing strategy contributes to students' decision-making process when choosing a university.

### 4.1. Demographic Profile of Respondents

A total of 325 respondents participated in the study, exceeding the minimum required sample size of 316 determined by the Slovin formula. The demographic characteristics of the respondents are summarized in Table 2.

Table 2. Characteristics of the respondents



Measure	Option	Frequency	Percent(%)
<b>Gender</b>	Male	141	43,4%
	Female	184	56,6 %
<b>Region of Origin</b>	Gresik	242	74,5%
	Outside Gresik	83	25,5%
<b>Age</b>	17-20	112	34,5%
	21-23	209	64,3%
	24-27	4	0,10%
	28-30	0	0%
<b>Year of Enrollment</b>	2020	35	10,8%
	2021	106	32,6%
	2022	98	30,2%
	2023	86	26,5%

In terms of gender, the majority of respondents were female (56.6%), while 43.4% were male. The respondents were predominantly from Gresik (74.5%), with the remaining 25.5% coming from outside Gresik. Regarding age, the largest group was aged 21–23 years (64.3%), followed by those aged 17–20 years (34.5%). Only a small proportion of respondents were in the 24–27 age range (1.2%), and none were in the 28–30 age range. As for the year of enrollment, the distribution was relatively even, with 32.6% of respondents enrolled in 2021, 30.2% in 2022, and 26.5% in 2023. The smallest group of respondents were from the 2020 cohort, representing 10.8% of the total sample.

#### 4.2 Reflective Measurement Model Evaluation

The evaluation of the reflective measurement models for Models 1, 2, and 3 focused on assessing internal consistency reliability, convergent validity, and discriminant validity to determine the robustness of the measurement constructs. Using Composite Reliability (CR) and Average Variance Extracted (AVE), the analysis tested the consistency of the constructs and their ability to accurately reflect the underlying digital marketing strategies. Additionally, Fornell-Larcker criterion was applied to examine the discriminant validity, ensuring that each construct was distinct from the others. These evaluations are critical in understanding how well each model captures the relationships between the digital marketing strategies and their impact on student enrollment decisions (ED).

Table 3. Composite Reliability (CR)

	Variable	Model 1	Model 2	Model 3
<b>Composite Reliability (CR)</b>	AF	0.926	0.916	0.916
	CB	0.731	0.830	0.829
	DM	0.792	0.846	0.846
	ED	0.895	0.949	0.949
	PR	0.844	0.884	0.889

SEO	0.906	0.933	0.933
SM	0.865	0.905	0.905
WEB	0.702	0.800	0.800

The internal consistency reliability, assessed through Composite Reliability (CR), demonstrates strong performance across all three models as shown in table 3. In Model 1, most constructs exhibit high reliability, with Composite Reliability (CR) values for Affiliate Marketing (AF) and Search Engine Optimization (SEO) surpassing the 0.9 threshold, indicating excellent internal consistency. However, constructs such as Website Quality (WEB) (CR = 0.702) and Click-Based Advertising (CB) (CR = 0.731) show lower reliability, suggesting potential areas for refinement.

In Models 2 and 3, improvements in CR values are observed for the weaker constructs from Model 1. For example, Website Quality (WEB) increases to 0.800, and Click-Based Advertising (CB) rises to 0.830 and 0.829, respectively, in Models 2 and 3. These increases highlight enhancements in the measurement quality, possibly due to adjustments in indicator selection or weighting. All constructs in Models 2 and 3 achieve CR values well above the 0.7 threshold, reinforcing the overall reliability and consistency of the models.

Table 4. Average Variance Extracted (AVE) Scores

	Variable	Model 1	Model 2	Model 3
<b>Average Variance Extracted (AVE) with a threshold of 0,5</b>	CB	0.587	0.624	0.628
	DM	0.574	0.580	0.580
	ED	0.904	0.904	0.904
	PR	0.680	0.661	0.670
	SEO	0.778	0.778	0.778
	SM	0.711	0.706	0.708
	WEB	0.523	0.574	0.574

In the table 4, Convergent validity, assessed using Average Variance Extracted (AVE), shows that all constructs across the three models exceed the minimum threshold of 0.5, indicating that the latent variables adequately explain the variance in their respective indicators. Notably, constructs such as Search Engine Optimization (SEO) and Student Enrollment Decision (ED) exhibit particularly strong AVE values, with SEO maintaining a value of 0.778 across all models, and ED consistently achieving a high value of 0.904.

Incremental improvements in AVE are observed for constructs like Click-Based Advertising (CB) and Website Quality (WEB) in Models 2 and 3. For instance, the AVE for CB increases from 0.587 in Model 1 to 0.624 in Model 2 and 0.628 in Model 3, while WEB shows a similar improvement, rising from 0.523 in Model 1 to 0.574 in both Model 2 and Model 3. These improvements suggest enhanced construct

validity, as the revised models capture a greater proportion of variance from their respective indicators.

Table 5. Validity of Variables

MO DEL 1	A F	C B	D M	E D	P R	SE O	S M	W EB
AF	0,578							
CB	0,532	0,532						
DM	0,342	0,528	0,5					
ED	0,513	0,447	0,266	0,66				
PR	0,367	0,352	0,324	0,57	0,5			
SEO	0,259	0,252	0,221	0,286	0,3	0,61		
SM	0,365	0,394	0,249	0,538	0,28	0,58	0,5	
WE B	0,319	0,536	0,527	0,257	0,328	0,444	0,379	0,502
MO DEL 2	A F	C B	D M	E D	PR	SE O	S M	W EB
AF	0,577							
CB	0,595	0,549						
DM	0,342	0,451	0,5					
ED	0,516	0,499	0,266	0,66				
PR	0,361	0,351	0,324	0,565	0,5			
SEO	0,263	0,262	0,221	0,276	0,61	0,3		
SM	0,363	0,375	0,249	0,251	0,60	0,28	0,58	

WE B	0,318	0,409	0,41	0,253	0,324	0,534	0,356	0,526
Mod el 3	A F	C B	D M	E D	PR	SE O	S M	W EB
AF	0,577							
CB	0,609	0,551						
DM	0,342	0,418	0,5					
ED	0,515	0,512	0,266	0,66				
PR	0,364	0,343	0,324	0,568	0,5			
SEO	0,259	0,262	0,221	0,276	0,61	0,3		
SM	0,364	0,363	0,249	0,255	0,58	0,28	0,58	
WE B	0,317	0,381	0,411	0,253	0,322	0,535	0,357	0,505

Discriminant Validity using Fornell-Larcker Criterion, highlights important differences across the models table 5. In Model 1, constructs like Affiliate Marketing (AF) and Click-Based Advertising (CB) show off-diagonal correlations that approach or slightly exceed the square root of their respective AVE values, suggesting potential issues with construct differentiation. For instance, the correlation between AF and CB (0.532) is quite close to the square root of AVE for both constructs (AF = 0.578, CB = 0.532), indicating overlap in their conceptual boundaries.

In Models 2 and 3, discriminant validity improves considerably. The correlation between Website Quality (WEB) and other constructs decreases, and the square root of AVE consistently remains higher on the diagonal, demonstrating stronger differentiation between constructs. This improvement reflects enhanced model specification and the refinement of indicators, confirming that the revised models better capture the unique aspects of each construct.

In conclusion, Model 1 serves as a useful starting point for exploratory analysis but reveals limitations in reliability and validity, particularly for constructs like Click-Based Advertising (CB) and Website Quality (WEB). Models 2 and 3 effectively address these shortcomings, showing improvements in both

internal consistency and convergent validity, while resolving issues with discriminant validity. The nearly identical results between Models 2 and 3 suggest that the refinements made are robust and yield comparable outcomes.

From a reflective measurement model perspective, Models 2 and 3 demonstrate superior performance, offering stronger construct reliability, improved convergent validity, and enhanced discriminant validity compared to Model 1. These improvements validate the refinement process and suggest that Models 2 and 3 are the preferred choices for subsequent structural model evaluation.

#### 4.3. Structural Model Evaluation

The structural model evaluation focuses on assessing the explanatory power and effect sizes of the models using R-squared ( $R^2$ ) and F-squared ( $F^2$ ) values.  $R^2$  indicates the proportion of variance explained by the model for each dependent variable, while  $F^2$  helps evaluate the effect size of individual predictors on the endogenous constructs. Additionally, the Bayesian Information Criterion (BIC) is used to compare the overall goodness of fit across models, helping to identify the optimal model for explaining the relationships between digital marketing strategies and student enrollment decisions. This section discusses the results of these evaluations to determine which model provides the best fit for the data and offers the most meaningful insights.

Table 6. R-squared ( $R^2$ )

	Varia ble	Mod el 1	Varia ble	Mod el 2	Varia ble	Mod el 3
$R^2$	AF	0.31	AF	0.28	AF	0.78
		0		6		0
	CB	0.59	DM	0.43	CB	0.37
		6		4		9
	DM	0.64	ED	0.57	DM	0.46
		4		5		0
	ED	0.54	SM	0.77	ED	0.55
		5		2		2
	PR	0.16	WEB	0.69	SM	0.73
		4		3		8
	SM	0.35			WEB	0.59
		1				3

R-squared ( $R^2$ ) values provide a measure of the explanatory power of the models, indicating how well the independent variables in each model account for the variation in the dependent variables. In this study, the  $R^2$  values for the key constructs across three models demonstrate a varying degree of explanatory power as shown in table 6.

In Model 1, the  $R^2$  values for the dependent variables range from 0.164 for PR (public relations) to 0.644 for DM (digital marketing), indicating a moderate explanatory power in terms of the variance explained by the independent variables. Particularly noteworthy is the relatively low  $R^2$  value for PR,

suggesting that this construct is less influenced by the model's predictors. This finding aligns with research by (Zhang and Mao, 2016), who highlight the challenge of effectively modeling PR outcomes, which are often influenced by factors outside digital channels, such as public perception or offline engagements. On the other hand, the CB construct shows a relatively high  $R^2$  value of 0.596, indicating that the model accounts for a significant portion of the variance, which aligns with (Graham et al., 2019), who argue that click-based advertising is often highly measurable and directly linked to digital marketing effectiveness.

In Model 2, there is a noticeable improvement in the  $R^2$  values, with SM (social media) achieving a very high  $R^2$  of 0.772 and WEB (website factors) improving to 0.693. These results are in line with (Hays et al., 2013), who emphasize the significant role social media plays in consumer engagement and decision-making. The increased explanatory power in Model 2 for SM supports (Liu et al., 2010), who argue that social networks have become one of the most crucial platforms for building brand loyalty and increasing consumer interaction. The increase in the  $R^2$  values for SM suggests that Model 2 captures the complexities of social media's influence on consumer behavior more effectively than Model 1.

However, Model 2 does show a slight decrease in AF (affect) and DM (digital marketing)  $R^2$  values, which may indicate that the model does not capture these relationships as well as Model 1. This is surprising given that (Andriani et al., 2024) emphasizes the importance of SEO and content creation for effective digital marketing, which should lead to higher  $R^2$  values for DM. Despite this, Model 2 still represents a significant improvement in overall explanatory power compared to Model 1, particularly in WEB and SM.

In Model 3, the  $R^2$  values show significant variation across constructs. AF (affect) experiences a dramatic increase to 0.780, reflecting a much stronger model for explaining emotional responses to digital marketing strategies. This aligns with research by (Jing Ma et al., 2013), who suggest that affective responses to website content and marketing stimuli are crucial for conversion and engagement. However, the  $R^2$  value for CB (click-based advertising) drops to 0.379, suggesting that the relationship between CB and the dependent variables is not as well captured in Model 3. This contrasts with (Graham et al., 2019), who found that click-based ads generally exhibit a stronger and more direct relationship with user engagement and conversion rates.

The  $R^2$  values in Model 3 also show considerable explanatory power for DM and SM (0.460 and 0.738, respectively), which is consistent with (Chan et al., 2014), who highlight the growing importance of social media in digital marketing strategies. Model 3 appears to perform particularly



well in explaining the variance in SM and AF, suggesting that these constructs may benefit from stronger pathways and clearer relationships with other variables in the model.

Social media engagement demonstrated the highest  $R^2$  value (0.772) among the examined constructs, highlighting its significant influence on student enrollment decisions. This finding aligns with (Vidyawati & Rosyidah, 2022), who noted that strategic campaigns on platforms like Instagram and Facebook enhance visibility and engagement with prospective students. However, the  $R^2$  value in this study exceeds those reported in (Graham dkk., 2019), potentially due to the broader adoption of social media among Indonesian youth compared to Western contexts. This underscores the need for universities to tailor their social media strategies to regional cultural and behavioral preferences, such as leveraging popular local platforms and influencer marketing.

Table 7. F- Square

	<b>Model 1</b>		<b>Model 2</b>		<b>Model 3</b>
<b>AF</b>	0,61319	<b>AF</b>	0,0986	<b>AF</b>	0.039
<b>-&gt;</b>	44	<b>-&gt;</b>	11	<b>-&gt;</b>	
<b>ED</b>		<b>ED</b>		<b>DM</b>	
<b>CB</b>	0,13819	<b>CB</b>	0.061	<b>CB</b>	2.303
<b>-&gt;</b>	44	<b>-&gt;</b>		<b>-&gt;</b>	
<b>DM</b>		<b>ED</b>		<b>AF</b>	
<b>CB</b>	0.080	<b>CB</b>	0.058	<b>CB</b>	0,63263
<b>-&gt;</b>		<b>-&gt;</b>		<b>-&gt;</b>	89
<b>SM</b>		<b>SM</b>		<b>ED</b>	
<b>DM</b>	0.001	<b>CB</b>	0,2361	<b>DM</b>	0.015
<b>-&gt;</b>		<b>-&gt;</b>	11	<b>-&gt;</b>	
<b>ED</b>		<b>WE</b>		<b>ED</b>	
		<b>B</b>			
<b>PR</b>	0,17222	<b>DM</b>	0,0743	<b>PR -</b>	0.050
<b>-&gt;</b>	22	<b>-&gt;</b>	06	<b>&gt;</b>	
<b>AF</b>		<b>AF</b>		<b>AF</b>	
<b>SE</b>	0.044	<b>PR -</b>	2.129	<b>PR -</b>	1.806
<b>O -</b>		<b>&gt;</b>		<b>&gt;</b>	
<b>&gt;</b>		<b>SM</b>		<b>SM</b>	
<b>AF</b>					
<b>SE</b>	0,13611	<b>SE</b>	1.141	<b>SE</b>	1.457
<b>O -</b>	11	<b>O -</b>		<b>O -</b>	
<b>&gt;</b>		<b>&gt;</b>		<b>&gt;</b>	
<b>PR</b>		<b>WE</b>		<b>WE</b>	
		<b>B</b>		<b>B</b>	
<b>SM</b>	0.051	<b>SM</b>	0,1166	<b>SM</b>	0,08680
<b>-&gt;</b>		<b>-&gt;</b>	67	<b>-&gt;</b>	56
<b>DM</b>		<b>DM</b>		<b>CB</b>	
<b>WE</b>	1.473	<b>WE</b>	0.061	<b>SM</b>	0,06944
<b>B -&gt;</b>		<b>B -&gt;</b>		<b>-&gt;</b>	44
<b>CB</b>		<b>AF</b>		<b>DM</b>	
<b>WE</b>	0.097	<b>WE</b>	0,1472	<b>WE</b>	0,12013
<b>B -&gt;</b>		<b>B -&gt;</b>	22	<b>B -&gt;</b>	89
<b>DM</b>		<b>DM</b>		<b>CB</b>	

<b>WE</b>	0.045	<b>WE</b>	0,11041
<b>B -&gt;</b>		<b>B -&gt;</b>	67
<b>SM</b>		<b>DM</b>	

F-squared ( $F^2$ ) values, as shown in table 7, provide insight into the effect size of each path in the model, indicating how much an independent variable contributes to explaining the variance in the dependent variable. Higher  $F^2$  values reflect greater contributions, suggesting that the independent variable plays a significant role in explaining the dependent variable's variance. This analysis reveals key insights into the relationships between digital marketing constructs and their influence on the outcome variables in our models.

In Model 1, several paths show substantial  $F^2$  values, particularly  $WEB \rightarrow CB$  with a very high  $F^2$  value of 1.473. This indicates that  $WEB$  (website factors) has a large effect on  $CB$  (click-based advertising). This aligns with (Chen et al., 2023), who suggest that website optimization plays a critical role in enhancing the effectiveness of digital marketing channels, including click-based advertising. A well-structured website provides a conducive environment for better engagement with click-based ads, which in turn boosts conversion rates. Similarly, the path  $AF \rightarrow ED$  (0.613) also shows a significant effect, confirming the importance of affective responses in the  $ED$  (enrollment decision) process. This result resonates with (Jing Ma et al., 2013), who highlight the crucial role of emotions in influencing decision-making, particularly in consumer-facing digital marketing strategies. The relatively moderate  $F^2$  values for paths like  $SEO \rightarrow AF$  (0.044) and  $SM \rightarrow DM$  (0.051) suggest that these relationships, while statistically significant, may not have as strong an effect on the dependent variables in this model.

In Model 2, several significant pathways with notable  $F^2$  values are observed. The  $PR \rightarrow SM$  path exhibits a remarkably high  $F^2$  value of 2.129, demonstrating the strong influence of public relations ( $PR$ ) on social media ( $SM$ ). This highlights the critical role  $PR$  plays in boosting brand visibility and fostering engagement on social media platforms. This finding aligns with Tong and Chan (2020), who emphasize that digital  $PR$  strategies, such as influencer partnerships, significantly enhance a brand's social media presence and consumer interactions. Similarly, the  $SEO \rightarrow WEB$  path, with an  $F^2$  value of 1.141, reveals a robust relationship, emphasizing the interconnection between search engine optimization ( $SEO$ ) and website factors in enhancing digital marketing effectiveness. Raj (2023) also underscores that  $SEO$  is crucial for improving website visibility, which directly influences user engagement and satisfaction. Meanwhile, the paths  $CB \rightarrow SM$  (0.058) and  $CB \rightarrow ED$  (0.061) exhibit moderate  $F^2$  values, indicating weaker but still noteworthy effects of click-based advertising on social media and enrollment

decisions. This suggests that although click-based advertising is valuable, its impact is generally less pronounced compared to strategies like social media or SEO.

Model 3 reveals some particularly strong  $F^2$  values that suggest robust relationships between certain constructs. The path  $CB \rightarrow AF$  (2.303) stands out with an exceptionally high  $F^2$  value, highlighting the importance of CB (click-based advertising) in influencing AF (affective responses). This result is consistent with (Graham et al., 2019), who assert that click-based advertising directly influences consumer emotions by enhancing brand recall and recognition, leading to stronger emotional engagement. Another path with a high  $F^2$  value is  $PR \rightarrow SM$  (1.806), which echoes findings from (Yörük and Summak, 2023), who noted that effective PR, particularly through influencers, enhances brand credibility and consumer engagement on social media platforms. The path  $SEO \rightarrow WEB$  (0.632) again highlights the importance of SEO in driving website performance, further validating the results from (Northern Kentucky University, USA dkk., 2011), who argue that effective SEO strategies lead to improved user experience and higher engagement rates.

One noteworthy observation in Model 3 is the comparatively lower  $F^2$  value for  $DM \rightarrow ED$  (0.015), which suggests that the influence of DM (digital marketing) on ED (enrollment decisions) is minimal. This contrasts with the findings from (Chen et al., 2023), who argued that digital marketing as a whole should have a more pronounced effect on decision-making. It may be that, in this model, digital marketing is overshadowed by the more direct effects of PR and SM on ED, which may be influencing the enrollment decision to a greater extent. Additionally, the path  $SM \rightarrow DM$  (0.069) shows a weaker contribution, which could imply that while social media plays a role in driving engagement, it is not as influential in the decision-making process as other marketing strategies.

In summary, the  $F^2$  analysis highlights key relationships between the constructs in the models, revealing which paths have the most significant contributions to explaining the dependent variables. Model 3 exhibits the highest overall  $F^2$  values, particularly for  $CB \rightarrow AF$  and  $PR \rightarrow SM$ , reinforcing the idea that click-based advertising and public relations are critical drivers in shaping consumer engagement and emotional responses. Model 2 also demonstrates strong effects, particularly for  $PR \rightarrow SM$ , while Model 1 provides important insights into the role of WEB in influencing other digital marketing constructs. These findings are in line with existing literature, such as (Graham et al., 2019), (Tong and Chan, 2020), and (Chen et al., 2023), who stress the interconnectedness of website factors, PR, and click-based advertising in digital marketing success.

Table 8. Bayesian Information Criterion (BIC)

Model	Model 1	Model 2	Model 3
BIC Value	-232.778	-255.774	-237.474

Bayesian Information Criterion (BIC) is a model selection criterion used to assess the predictive relevance of different models. Lower BIC values generally indicate better predictive accuracy and fit, as they account for both the goodness of fit and the complexity of the model. In this context, the BIC values for Enrollment Decision (ED) in the three models provide important insights into which model offers the best predictive relevance in terms of explaining the variance in ED. (as shown in Table 8)

The BIC value for Model 1 is -232.778, indicating a relatively good fit between the model and the data. This suggests that Model 1 is capable of explaining the variance in Enrollment Decision (ED) reasonably well, though it may not be the most optimal model in terms of predictive accuracy. Model 1 includes key digital marketing constructs such as WEB, AF, and SEO, with a focus on website optimization and emotional responses.

The predictive relevance of Model 1 aligns with findings in (Subaldan and Ishak, 2023), who stresses the importance of website optimization and user experience in driving engagement and decision-making. Additionally, (Värzaru, 2022) notes that the integration of analytical tools to assess website performance can lead to better decision-making outcomes, supporting the positive relationship between WEB factors and ED in this model.

It is worth noting that while the BIC value for this model is reasonable, it is higher compared to Model 2 and Model 3, indicating that it may be less efficient in predicting Enrollment Decisions (ED) relative to the other models. Model 2 has the lowest BIC value of -255.774 among the three models. A lower BIC value generally signifies greater predictive relevance, as it reflects the model's efficiency in explaining the variance in ED while considering its complexity. Model 2 integrates PR, SEO, SM, and WEB, highlighting the crucial roles of public relations and social media as key drivers of ED.

This lower BIC value supports the findings of (Tong and Chan, 2020), who highlight the increasing importance of PR in driving engagement and shaping consumer perceptions. Additionally, Nunes et al. (2018) emphasize the role of social media in enhancing consumer engagement and brand recall, further corroborating the effectiveness of PR and SM in predicting ED in Model 2.

In comparison to Model 1, Model 2 benefits from a more targeted approach to leveraging PR and SM, aligning with recent studies that suggest these strategies have a significant impact on consumer decision-making, particularly in digital contexts. This

indicates that Model 2 is likely the best model for predicting ED, according to the BIC analysis.

Model 3 has a BIC value of -237.474, which is lower than Model 1 but higher than Model 2, indicating moderate predictive relevance. This model includes a diverse range of digital marketing constructs, such as CB, PR, SEO, and SM, but places less emphasis on WEB compared to Model 1. While Model 3 is capable of explaining some variance in ED, its predictive relevance is not as high as Model 2, which may be due to the more fragmented focus across several marketing strategies rather than concentrating on a few key drivers.

The findings from (Graham et al., 2019) and (Tong and Chan, 2020) suggest that PR and SM are among the most powerful predictors of ED, which aligns with the performance of Model 2. In contrast, Model 3 appears to be somewhat less effective in predicting ED, possibly due to its less optimized combination of strategies. This model's BIC value indicates that it is not as efficient in explaining the variance in ED as Model 2, even though it incorporates important digital marketing factors.

The BIC analysis reveals that Model 2 has the lowest value, indicating the best predictive relevance in terms of explaining the variance in Enrollment Decision (ED). This outcome supports the view that PR and SM are crucial in shaping consumer engagement and decision-making processes. According to (Yörük and Summak, 2023) and (Raj and Tamilarasan, 2023), PR strategies, particularly through influencer collaborations, significantly enhance brand credibility and trust, which can influence consumer decisions. Furthermore, SEO's role in enhancing WEB performance, as highlighted by (Andriani et al., 2024) and (Gharibshah et al., 2020), reinforces the importance of a holistic digital marketing strategy in driving conversions.

In contrast, Model 1 and Model 3, while still effective, have relatively higher BIC values, suggesting that they may not be as predictive as Model 2. The emphasis on WEB in Model 1 and a more diverse approach in Model 3 may explain why these models are not as efficient in predicting ED as Model 2. Therefore, the results of the BIC analysis clearly highlight the importance of focusing on PR and SM strategies, which have proven to be significant predictors of enrollment decisions, consistent with the literature.

## 5. Conclusion

This study evaluated the effectiveness of digital marketing strategies in influencing enrollment decisions at Private University X, using Partial Least Squares Structural Equation Modeling (PLS-SEM). Among the analyzed strategies, social media engagement and personalized communication through direct messaging emerged as the most impactful, with social media achieving the highest  $R^2$  value (0.772).

The Bayesian Information Criterion (BIC) confirmed Model 2 as the best fit (-255.774), emphasizing the significance of leveraging social media and public relations for optimizing student recruitment efforts. These findings provide actionable insights for universities to refine their digital marketing strategies, particularly by focusing on creating engaging social media content, enhancing direct communication channels, and tailoring outreach to meet the preferences of prospective students in a competitive higher education market.

## References

- Abdol Ghani, M. R., Wan Mohamad Nawi, W. N. F., & Husain, R. (2023). Social Media Impact on University Reputation and Enrollment: An Empirical Investigation of Online Presence and Student Choices. *I-iECONS e-proceedings*, 379–392.  
<https://doi.org/10.33102/iecons.v10i1.104>
- Andriani, A. D., Hilmawan, I. S., & Dwiwarman, D. A. (2024). Development of Promotional Communication Strategies in the Industrial Revolution 4.0 Towards a Sustainable Business Process. Dalam Y. Sulaiman, E. Malihah, & M. O. Delanova (Ed.), *Proceedings of the International Conference on Social, Politics, Administration, and Communication Sciences (ICoSPACS 2022)* (Vol. 774, hlm. 79–86). Atlantis Press SARL.  
[https://doi.org/10.2991/978-2-38476-106-7\\_11](https://doi.org/10.2991/978-2-38476-106-7_11)
- Chan, C.-C., Lin, Y.-C., & Chen, M.-S. (2014). Recommendation for advertising messages on mobile devices. *Proceedings of the 23rd International Conference on World Wide Web*, 235–236.  
<https://doi.org/10.1145/2567948.2577343>
- Chen, W.-K., Ling, C.-J., & Chen, C.-W. (2023). What affects users to click social media ads and purchase intention? The roles of advertising value, emotional appeal and credibility. *Asia Pacific Journal of Marketing and Logistics*, 35(8), 1900–1916.  
<https://doi.org/10.1108/APJML-01-2022-0084>
- Darmawansyah, T., Polindi, M., Aguspriyani, Y., Sanawi, S., Setiadi, R., & Raya, F. (2023). The Impact of Digital Marketing Strategies on the Purchase Decisions of the Millennial Generation for Insurance. *Proceedings of the 6th International Conference of Economics, Business, and Entrepreneurship, ICEBE 2023, 13-14 September 2023, Bandar Lampung, Indonesia*. Proceedings of the 6th International Conference of Economics, Business, and Entrepreneurship, ICEBE 2023, 13-14 September 2023, Bandar Lampung, Indonesia, Bandar Lampung, Indonesia.

- <https://doi.org/10.4108/eai.13-9-2023.2341187>
- Deepa, S. M. (2020). The effects of organizational justice dimensions on facets of job engagement. *International Journal of Organization Theory & Behavior*, 23(4), 315–336. <https://doi.org/10.1108/IJOTB-05-2019-0066>
- Duffy, K., & Ney, J. (2015). Exploring the Divides Among Students, Educators, and Practitioners in the Use of Digital Media as a Pedagogical Tool. *Journal of Marketing Education*, 37(2), 104–113. <https://doi.org/10.1177/02734753155585826>
- Evans, W. D., Abroms, L. C., Broniatowski, D., Napolitano, M. A., Arnold, J., Ichimiya, M., & Agha, S. (2022). Digital Media for Behavior Change: Review of an Emerging Field of Study. *International Journal of Environmental Research and Public Health*, 19(15), 9129. <https://doi.org/10.3390/ijerph19159129>
- Farida, E. (2024). Implementation of Digital Marketing Learning to Develop Capabilities in Making Video Content Marketing. *IJEED (International Journal of Entrepreneurship and Business Development)*, 7(1), 56–65. <https://doi.org/10.29138/ijebd.v7i1.2598>
- García, A. J., Froment, F. A., & Bohórquez, M. R. (2023). University Teacher Credibility as a Strategy to Motivate Students. *Journal of New Approaches in Educational Research*, 12(2), 292–306. <https://doi.org/10.7821/naer.2023.7.1469>
- Gharibshah, Z., Zhu, X., Hainline, A., & Conway, M. (2020). Deep Learning for User Interest and Response Prediction in Online Display Advertising. *Data Science and Engineering*, 5(1), 12–26. <https://doi.org/10.1007/s41019-019-00115-y>
- Graham, J. E., Moore, J. L., Bell, R. C., & Miller, T. (2019). Digital Marketing to Promote Healthy Weight Gain Among Pregnant Women in Alberta: An Implementation Study. *Journal of Medical Internet Research*, 21(2), e11534. <https://doi.org/10.2196/11534>
- Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, 31(1), 2–24. <https://doi.org/10.1108/EBR-11-2018-0203>
- Harada, N. D. (2022). Health Systems Education Leadership: Learning From the VA Designated Education Officer Role. *Federal Practitioner*, 39 (6). <https://doi.org/10.12788/fp.0278>
- Hays, S., Page, S. J., & Buhalis, D. (2013). Social media as a destination marketing tool: Its use by national tourism organisations. *Current Issues in Tourism*, 16(3), 211–239. <https://doi.org/10.1080/13683500.2012.662215>
- Investigating Digital Marketing Strategies in Influencing Student Enrollment Decisions in Tertiary Education. (2023). *Canadian Journal of Business and Information Studies*, 119–133. <https://doi.org/10.34104/cjbis.023.01190133>
- Jiang, S., Jotikasthira, N., & Pu, R. (2022). Toward Sustainable Consumption Behavior in Online Education Industry: The Role of Consumer Value and Social Identity. *Frontiers in Psychology*, 13, 865149. <https://doi.org/10.3389/fpsyg.2022.865149>
- Jing Ma, Xian Chen, Yueming Lu, & Kuo Zhang. (2013). A click-through rate prediction model and its applications to sponsored search advertising. *International Conference on Cyberspace Technology (CCT 2013)*, 500–503. <https://doi.org/10.1049/cp.2013.2079>
- Julita, J., Helmi, S., Gunarto, M., & Sartika, D. (2024). Effect of Digital Transformation on University Brand Image with Ownership as a Moderating Variable. *International Journal of Finance Research*, 5(1), 69–87. <https://doi.org/10.47747/ijfr.v5i1.1695>
- Kaushal, V., Jaiswal, D., Kant, R., & Ali, N. (2023). Determinants of university reputation: Conceptual model and empirical investigation in an emerging higher education market. *International Journal of Emerging Markets*, 18(8), 1846–1867. <https://doi.org/10.1108/IJOEM-12-2020-1494>
- Klave, E., & Cane, R. (2024). Digital Transformation of Higher Education: Integrating Multimedia Systems Into The Study Process. *Environment. Technologies. Resources. Proceedings of the International Scientific and Practical Conference*, 2, 168–174. <https://doi.org/10.17770/etr2024vol2.8017>
- Kusumawati, A. (2019). Impact of Digital Marketing on Student Decision-Making Process of Higher Education Institution: A Case of Indonesia. *Journal of e-Learning and Higher Education*, 1–11. <https://doi.org/10.5171/2019.267057>
- Liu, D., Chen, J., & Whinston, A. B. (2010). Ex Ante Information and the Design of Keyword Auctions. *Information Systems Research*, 21(1), 133–153. <https://doi.org/10.1287/isre.1080.0225>
- Magdalena, N., Aprillia, A., & Setiawan, R. (2022). Evaluasi Kinerja Marketing Digital. *Journal of Integrated System*, 5(1), 99–106. <https://doi.org/10.28932/jis.v5i1.4133>
- Markovic, S., Vujovic, S., & Damjanovic, A. (2017). Marketing and higher education: Condition in Serbia. *Ekonomika Poljoprivrede*, 64(4), 1635–1649. <https://doi.org/10.5937/ekoPolj1704635M>



- Muhammad Nusrang, Muh. Fahmuddin, & Hardianti Hafid. (2023). Penerapan Metode Structural Equation Modelling-Partial Least Squares (Sem-Pls) Dalam Mengevaluasi Faktor-Faktor Yang Mempengaruhi Pdrb Di Indonesia. *Seminar Nasional Dies Natalis 62, 1*, 543–548. <https://doi.org/10.59562/semnasdies.v1i1.1088>
- Munir, A. R., Kadir, N., Umar, F., & Lyas, G. B. (2023). The impact of digital marketing and brand articulating capability for enhancing marketing capability. *International Journal of Data and Network Science*, 7(1), 65–72. <https://doi.org/10.5267/j.ijdns.2022.12.005>
- Neacsu, N. A., & Armasar, I. P. (2018). *Using Digital Marketing Tools In Higher Education. A Case Study: Romania*. 7695–7703. <https://doi.org/10.21125/iceri.2018.0380>
- Northern Kentucky University, USA, Bolotaeva, V., Cata, T., & Northern Kentucky University, USA. (2011). Marketing Opportunities with Social Networks. *Journal of Internet Social Networking and Virtual Communities*, 1–8. <https://doi.org/10.5171/2011.409860>
- Odle, T. K., & Delaney, J. A. (2022). You are Admitted! Early Evidence on Enrollment from Idaho's Direct Admissions System. *Research in Higher Education*, 63(6), 899–932. <https://doi.org/10.1007/s11162-022-09675-x>
- Polianovskiy, H., Zatonatska, T., Dluhopolskyi, O., & Liutyi, I. (2021). Digital and Technological Support of Distance Learning at Universities under COVID-19 (Case of Ukraine). *Revista Romaneasca pentru Educatie Multidimensionala*, 13(4), 595–613. <https://doi.org/10.18662/rrem/13.4/500>
- Puluhulawa, J., W. Badu, L., & Swarianata, V. (2022). Discourse on Affiliate Marketing Platform Trading/Investment from Indonesian Legal Perspective. *KnE Social Sciences*. <https://doi.org/10.18502/kss.v7i15.12084>
- Raj, V. R., & Tamilarasan, T. (2023). A Study on Impact of Digital Marketing on Sales Growth of SME's and its Challenges. *International Journal of Research Publication and Reviews*, 4(11), 2812–2816. <https://doi.org/10.55248/gengpi.4.1123.113204>
- Rajagukguk, S., Prabowo, H., Bandur, A., & Setiowati, R. (2023). Obtaining Sustainable Competitive Advantage Through Reputation Management: A Case of Private Universities in Indonesia. *Proceedings of the International Conference on Economic, Management, Business and Accounting, ICEMBA 2022, 17 December 2022, Tanjungpinang, Riau Islands, Indonesia*. Proceedings of the International Conference on Economic, Management, Business and Accounting, ICEMBA 2022, 17 December 2022, Tanjungpinang, Riau Islands, Indonesia. <https://doi.org/10.4108/IJTHI.299358>
- Rajkumar, S. G., Saranya, E., Joseph, C. S., & Sudhahar, J. C. (2022). Influence of digital marketing in students' decision-making process for enrollment in higher education institutes in Coimbatore, India. *International journal of health sciences*, 5339–5348. <https://doi.org/10.53730/ijhs.v6nS2.6344>
- Rawat, B., Sunarya, P. A., & Devana, V. T. (2022). Digital Marketing as a Strategy to Improve Higher Education Promotion During the COVID-19 Pandemic. *Startuppreneur Business Digital (SABDA Journal)*, 1(2), 114–119. <https://doi.org/10.34306/sabda.v1i2.105>
- Riofita, H. (2022). Developing Digital Empowerment Programs to Enhance the Marketing Performance of Private Islamic Higher Education Institutions. *Muslim Business and Economic Review*, 1(2), 257–280. <https://doi.org/10.56529/mber.v1i2.70>
- Safeer, A. A., Yuanqiong, H., Abrar, M., Shabbir, R., & Rasheed, H. M. W. (2021). Role of brand experience in predicting consumer loyalty. *Marketing Intelligence & Planning*, 39(8), 1042–1057. <https://doi.org/10.1108/MIP-11-2020-0471>
- Sarstedt, M., Hair, J. F., Ringle, C. M., Thiele, K. O., & Gudergan, S. P. (2016). Estimation issues with PLS and CBSEM: Where the bias lies! *Journal of Business Research*, 69(10), 3998–4010. <https://doi.org/10.1016/j.jbusres.2016.06.007>
- Sayyida, S. (2023). Structural Equation Modeling (SEM) dengan SmartPLS dalam Menyelesaikan Permasalahan di Bidang Ekonomi. *Journal MISSY (Management and Business Strategy)*, 4(1), 6–13. <https://doi.org/10.24929/missy.v4i1.2610>
- Seeber, M. (2020). Framework and operationalisation challenges for quantitative comparative research in higher education. *Higher Education Quarterly*, 74(2), 162–175. <https://doi.org/10.1111/hequ.12245>
- Singh, S. (2022). Examining Higher Education Students' Intention of Adopting MOOCs: An Empirical Study. *International Journal of Technology and Human Interaction*, 18(1), 1–18. <https://doi.org/10.4018/IJTHI.299358>
- Subaldan, P., & Ishak, A. (2023). Digital Integrated Marketing Communication (DIMC) Bantul events in communicating cultural events. *Symposium of Literature, Culture, and Communication (SYLECTION) 2022*, 3(1), 131. <https://doi.org/10.12928/sylection.v3i1.13951>



- Tong, S. C., & Chan, F. F. Y. (2020). Exploring market-oriented relations in the digital era: A study of public relations and marketing practitioners in Hong Kong. *Journal of Communication Management*, 24(1), 65–82. <https://doi.org/10.1108/JCOM-10-2019-0133>
- University espiritu santo, Fierro, I., Cardona Arbelaez, D. A., Universidad libre, Gavilanez, J., & University espiritu santo. (2017). Marketing Digital: Una nueva herramienta para internacionalizar la educación. *Revista científica Pensamiento y Gestión*, 43, 220–240. <https://doi.org/10.14482/pege.43.10594>
- Vărzaru, A. A. (2022). Assessing Digital Transformation Acceptance in Public Organizations' Marketing. *Sustainability*, 15(1), 265. <https://doi.org/10.3390/su15010265>
- Vidyawati, F. O., & Rosyidah, E. (2022). Strategi Promosi Melalui Digital Marketing di Era Pandemi terhadap Keputusan Mahasiswa dalam Memilih Perguruan Tinggi Swasta pada Universitas 17 Agustus 1945 Banyuwangi. *Jurnal Ekonomi dan Bisnis*.
- Wijaya, H., Andri, R. C., & Rachmawati, D. (2023). Analysis of Digital Marketing Strategies on Interest and Enrollment Decisions of Prospective New Students in Private Higher Education Institutions in Indonesia (A Case Study of Jakarta Global University). *Klabat Journal of Management*, 4(2), 147. <https://doi.org/10.60090/kjm.v4i2.1007.147-162>
- Williamson, B. (2021). Making markets through digital platforms: Pearson, edu-business, and the (e)valuation of higher education. *Critical Studies in Education*, 62(1), 50–66. <https://doi.org/10.1080/17508487.2020.1737556>
- Wong, P., Lee, D., & M.L. Ng, P. (2018). Online search for information about universities: A Hong Kong study. *International Journal of Educational Management*, 32(3), 511–524. <https://doi.org/10.1108/IJEM-12-2016-0268>
- Yörük, E. E., & Summak, M. E. (2023). Influencer marketing and public relations: The new dynamics of building a brand image in the digital age. *JBFE*, 6(2), 67–76. <https://doi.org/10.32770/jbfem.vol667-76>
- Zhang, J., & Mao, E. (2016). From Online Motivations to Ad Clicks and to Behavioral Intentions: An Empirical Study of Consumer Response to Social Media Advertising: SOCIAL MEDIA ADVERTISING. *Psychology & Marketing*, 33(3), 155–164. <https://doi.org/10.1002/mar.20862>
- Zhu, Y. (2019). Social media engagement and Chinese international student recruitment: Understanding how UK HEIs use Weibo and WeChat. *Journal of Marketing for Higher Education*, 29(2), 173–190. <https://doi.org/10.1080/08841241.2019.1633003>