Google Analytics, Data-Driven Decision Making, and Marketing Agility in West Java Higher Education

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Abstract

This study examined how Google Analytics (GA) shapes Data-Driven Decision-Making (DDDM) and Marketing Agility (MA) among private higher education institutions (PHEIs) in West Java, and whether DDDM mediates the GA–agility relationship. This study employed a quantitative explanatory cross-sectional survey design. Data were collected from PHEI marketing and admissions practitioners, consisting of 108 respondents from GA-adopting institutions analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4, while 19 respondents from non-adopting institutions were analyzed descriptively as a benchmark. The findings reveal that GA utilization significantly improves DDDM, and DDDM significantly enhances Marketing Agility. Furthermore, DDDM partially mediates the relationship between GA utilization and Marketing Agility, while GA also has a significant direct effect on agility. Non-adopting institutions demonstrate lower agility levels, with human resource analytics literacy identified as the main adoption barrier. Analytics-driven agility develops through both strategic decision-making processes and direct tactical responses to market signals. This study is limited by its cross-sectional design, single-province context, exclusive focus on GA4, and limited non-adopter sample size. This study extends Dynamic Capabilities theory by demonstrating the dual pathway mechanism between analytics utilization and institutional agility while providing practical guidance for PHEI leaders in developing analytics capabilities.

Keywords: *Data-Driven Decision Making, Google Analytics, Higher Education Marketing, Marketing Agility; PLS-SEM*

1. INTRODUCTION

Indonesia's higher education market has entered a period of intense competition. More than 300 Private Higher Education Institutions (PHEIs) operate in West Java alone, competing for a pool of prospective students whose growth has slowed, even as digital engagement has surged (Kemendikbudristek, 2023). With 185.3 million Internet users nationally and a 66.5% penetration rate, Generation Z and Alpha, as fully digital-native cohorts, drive roughly 80% of prospective students to begin their institutional search online. Thus, a PHEIs digital footprint has become a decisive competitive asset (We & Meltwater, 2024). This dynamic extends nationally: Indonesia hosts more than 3,000 higher education institutions, over 95% of which are privately operated by Kemendikbudristek (2023), with student growth persistently outpacing institutional supply. This makes West Java, with its dense PHEI concentration and highly digital-native applicant pool, a representative rather than an isolated case of this structural pressure (Bonilla, Perea, del Olmo, & Corrons, 2020).

Web analytics platforms, chiefly Google Analytics (GA), have become the standard instrument through which PHEIs sense digital behavior. Although as many as 87% of PHEIs in West Java have installed GA, only a minority use it routinely to inform marketing decisions (Saksono, Sugiono, Lestari, Hasanudin, & Nurwulandari, 2025), a pattern consistent with recent analytics-management research showing that institutions often possess the technological capacity to collect market signals but lack the organizational culture and routines to convert those signals into deliberate action (Karaboga, Zehir, Tatoglu, Karaboga, & Bouguerra, 2023; Chong, Khalid, & Ramayah, 2024). Data-Driven Decision-Making (DDDM) in Indonesian PHEIs is similarly applied unevenly, concentrated among a small number of technically capable staff rather than embedded as an institutional routine (Amalia, Rosalina, & Anggita, 2026).

This condition creates a two-part theoretical problem: First, the mechanism by which raw analytics translate into an institution's Marketing Agility and its capability to sense and respond quickly to shifts in prospective student behavior (Kalaignanam, Tuli, Kushwaha, Lee, & Gal, 2021) remains empirically under-specified in the PHEI context, since existing analytics-agility research is concentrated in corporate and western settings (Vesterinen, Tarkiainen, & Luoma-aho, 2024; Zhou, Mavondo, & Saunders, 2019). Second, prior literature has largely treated GA adoption and DDDM maturity as parallel, loosely connected phenomena rather than testing DDDM as a formal mediating mechanism between analytics utilization and agility outcomes (Kowalczyk, & Siuta-Tokarska, 2021; Troilo, & Guenzi, 2022). This gap is compounded by a structural feature that distinguishes higher-education marketing from most commercial contexts: the prospective-student decision journey unfolds over months or years rather than a single transaction, and institutional responses are constrained by academic-calendar cycles, accreditation requirements, and semi-bureaucratic governance, which are rarely present in corporate settings (Peruta, & Shields, 2017; Stathopoulou, Siamagka, & Christodoulides, 2019). Therefore, analytics frameworks built for fast-moving commercial markets may not be applicable to PHEIs.

A preliminary qualitative exploration conducted at a single PHEI in Bandung examined how the marketing team operationalized GA4, how DDDM developed at the managerial level, and how these processes contributed to institutional agility. The exploration revealed a recurring pattern in which tactical responses to market anomalies occurred more rapidly (within two to three days) than strategic decisions processed through formal DDDM mechanisms (within two to four weeks). This finding suggests that analytics may influence organizational agility through multiple pathways. However, this qualitative exploration is used solely as contextual motivation for developing the constructs and research model examined in the present study and is not included as part of the empirical analysis.

Building on this background, this study investigates how Google Analytics (GA) utilization influences Data-Driven Decision Making (DDDM) among GA-adopting Private Higher Education Institutions (PHEIs) in West Java, how DDDM contributes to Marketing Agility, and whether DDDM serves as a mediating mechanism in the relationship between GA utilization and Marketing Agility. In addition, this study explores the barriers experienced by non-adopting PHEIs and compares their Marketing Agility profiles with those of GA-adopting institutions. Accordingly, this research aims to empirically examine the structural relationship between GA utilization, DDDM, and Marketing Agility using PLS-SEM, while providing a comparative assessment of non-adopting institutions as a benchmark for understanding the value of analytics adoption.

The novelty of this study lies in three key aspects. First, it examines DDDM as a partial mediator rather than assuming a single pathway through which GA utilization influences Marketing Agility. Second, it extends analytics-agility research, which has predominantly been developed in corporate and Western contexts, to the unique and resource-constrained environment of Indonesian private higher education institutions. Third, it provides an empirical comparison between GA-adopting and non-adopting institutions to demonstrate the practical value of analytics adoption rather than treating its benefits as a theoretical assumption.

2. LITERATURE REVIEW

2.1 Resource-Based View and Dynamic Capabilities

This study is anchored in the Resource-Based View (RBV), which holds that sustained competitive advantage originates from resources that are valuable, rare, inimitable, and organizationally embedded (Barney, 1991). RBV identifies four key criteria, namely Valuable, Rare, Imperfectly Imitable, and Non-substitutable (VRIN), which determine whether a resource can generate a sustained competitive advantage. Institutional analytics infrastructure plausibly satisfies these criteria. It is valuable because it enables evidence-based recruitment decisions, rare because most PHEIs have not yet integrated it into routine organizational practices, imperfectly imitable because its effectiveness depends on institution-specific configurations and staff interpretive capabilities rather than the software itself, and non-substitutable because intuition-based decision-making cannot provide the same level of analytical granularity. (Kero, & Bogale, 2023; Mailani, Hulu, Simamora, & Kesuma, 2024).

However, much of this literature applies the VRIN criteria narratively rather than testing which criterion binds most tightly in a given context. This study empirically addresses that gap by treating institution-specific configuration imperfect imitability as the criterion most directly operationalized through DDDM's mediating role, rather than asserting all four as equally load-bearing. However, RBV explains why a resource is valuable but not how that value is realized under changing conditions. Dynamic Capabilities theory fills this gap through the sensing–seizing–reconfiguring cycle (Teece, 2019; Kero and Bogale, 2023; Khasanova, 2025). In this cycle, GA functions as the sensing infrastructure that detects shifts in prospective student behavior, DDDM serves as the seizing mechanism through which analytical signals are transformed into managerial decisions, and Marketing Agility represents the reconfiguring capability that enables institutions to adapt their actions accordingly ((Almheiri, Jabeen, Kazi, & Santoro, 2025); Muna, Yasa, Ekawati, Wibawa, Sriathi, & Adi, 2022; Yi, Oh, & Amenuvor, 2023).

2.2 Marketing Information System as a Middle-Range Bridge

Between this strategic-level theorizing and the applied tool under study lies a middle-range construct rarely made explicit in marketing agility research: the Marketing Information System (MKIS), which is understood as the people, equipment, and procedures that gather, sort, analyze, and distribute timely information to marketing decision-makers, decomposed into internal records, marketing intelligence, marketing research, and a decision-support subsystem (Rosário, 2021; Nugroho, & Susanti, 2026). Positioned this way, Google Analytics is a contemporary instantiation of the marketing intelligence and decision support subsystems of an institution's MKIS, continuously capturing behavioral signals and structuring them for decision-making (Ratnaningtyas, Martaleni, & Wijayanti, 2026; Hasan, 2026).

Prior marketing agility studies have rarely made this middle-range layer explicit, instead moving directly from strategic theory to tool-level discussions of specific platforms (Homburg & Wielgos, 2022), which leaves underexplained why a specific tool such as GA should count as a strategic resource in the first place. Inserting MKIS as an explicit bridge clarifies the logical chain linking theory to tool: RBV explains why analytics-derived information is a strategic resource, Dynamic Capabilities explains how it is operationalized, and MKIS theory explains the organizational infrastructure through which GA performs its function before being translated into DDDM (Rosário, 2021).

2.3 Conceptual Framework

Synthesizing the theoretical strands above, this study conceptualizes a sequential-with-bypass model: Google Analytics utilization functions as the sensing input into an institution's Marketing Information System; this input is predominantly, but not exclusively, processed through data-driven decision-making before shaping Marketing Agility, while a secondary direct pathway allows operational staff to act on analytics signals without full deliberation. This framework, detailed further in hypotheses H_1, H_2, H_3a, and H_3b, treats DDDM as a partial rather than an obligatory mediator, distinguishing this study's approach from prior models that assume analytics affects organizational outcomes solely through a single formal decision-making channel (Mikalef & Pateli, 2017).

2.4 Web Analytics, DDDM, and Marketing Agility

Web analytics is the measurement, collection, analysis, and reporting of web data to understand and optimize web usage. GA4 extends this through event-based tracking, cross-platform measurement, and predictive metrics, and is conceptualized here across traffic/audience monitoring, behavioral and funnel analysis, conversion tracking, cross-domain integration, and predictive feature utilization (McGuirk, 2023; Vollrath, & Villegas, 2022). Data-driven decision-making refers to grounding managerial decisions in systematic data analysis rather than intuition, encompassing data quality, analytical capability, formal integration into decision forums, and an evidence-based culture Karaboga, Zehir, Tatoglu, Karaboga, and Bouguerra (2023); it operationalizes the Dynamic Capabilities seizing stage (Kowalczyk, & Siuta-Tokarska, 2021; Troilo, & Guenzi, 2022; Faisal, Ngaliman, & Khaddafi, 2026).

Marketing Agility is the institutional capability to sense and respond rapidly and flexibly to market shifts (Kalaignanam, Tuli, Kushwaha, Lee, & Gal, 2021; Zhou, Mavondo, & Saunders, 2019). It is operationalized here across response speed, strategic flexibility, cross-functional coordination, learning orientation, and proactive anticipation Yang and Salameh (2023), each capturing a distinct facet of institutional responsiveness, from how quickly a PHEI acts on an emerging signal to whether outcomes are systematically fed back into future campaigns. This operationalization departs from Mikalef and Pateli (2017), who model analytics-to-outcome effects as flowing exclusively through a single formal decision-making channel. By explicitly testing a secondary direct pathway, the present framework examines rather than assumes the full mediation premise that has gone largely unexamined in prior analytics agility models.

2.5 Hypothesis Development

Each hypothesis below is developed by tracing the theoretical argument drawn from the framework above and the supporting empirical evidence before arriving at the formal hypothesis statement. In the sensing–seizing–reconfiguring cycle, GA constitutes the sensing input that must be deliberately seized through managerial processing to become an action (Teece, 2019). Institutions that utilize GA more extensively accumulate richer behavioral intelligence, which prior studies have linked to more structured, evidence-grounded decision routines (Karaboga, Zehir, Tatoglu, Karaboga, & Bouguerra, 2023). This process indicates that GA utilization alone does not automatically generate organizational value because its effectiveness depends on the institution's ability to transform analytical insights into systematic decision-making practices that support adaptive capabilities. Therefore, this study proposes:

H_1: Google Analytics utilization has a positive and significant effect on Data-Driven Decision-Making.

As the seizing stage of this cycle, a mature DDDM process converts sensed signals into decisions calibrated closely enough to market conditions to enable rapid reconfiguration. This is consistent with prior theories and empirical evidence linking a more mature DDDM process to faster and better-calibrated marketing responses (Homburg, & Wielgos, 2022; Vesterinen, Tarkiainen, & Luoma-aho, 2024; Dehta, & Alfarizy, 2026). This capability enables institutions to respond more effectively to dynamic environmental changes by ensuring that managerial actions are supported by timely, accurate, and relevant information. Accordingly, this study proposes:

H_2: Data-driven decision-making has a positive and significant effect on Marketing Agility.

Dynamic Capabilities theory further suggests that a sensed signal need not always pass through formal seizing before triggering a reconfiguring response, as operational staff may act on analytics signals directly under time pressure, bypassing the pathway built into this study's conceptual framework. Kalaignanam, Tuli, Kushwaha, Lee, and Gal (2021) similarly theorize that agility-relevant actions can occur outside formal deliberation channels when frontline actors have direct signal access. Beyond its direct influence, Google Analytics utilization may also enhance Marketing Agility through the development of DDDM capabilities. DDDM acts as an intermediate mechanism that transforms analytical insights into coordinated and adaptive organizational actions. Therefore, this study proposes:

H_3a: Google Analytics utilization has a positive and significant direct effect on marketing agility

H_3b: Data-Driven Decision-Making mediates the relationship between Google Analytics utilization and Marketing Agility

3. RESEARCH METHODOLOGY

This study employed a quantitative explanatory cross-sectional survey design. The population comprised marketing and admissions practitioners at PHEIs across West Java, a province with the second-highest concentration of PHEIs in Indonesia and correspondingly intense recruitment competition (Kemendikbudristek, 2023). Purposive sampling was used, with respondents recruited through institutional and professional networks and screened by a filter question into one of the two segments.

Purposive sampling was chosen over probability sampling because no complete sampling frame distinguishing GA-adopting from non-adopting PHEI marketing staff exists in West Java. Constructing an artificial frame for probability sampling would have introduced at least as much bias as the criterion-based recruitment used in this study. Respondents were required to (a) hold an active marketing or admissions role, (b) have at least six months' tenure to ensure sufficient exposure to their institution's data practices, and (c) be directly involved in or accountable for their institution's PMB (admissions) digital marketing activity.

Segment A comprised respondents from PHEIs that had adopted Google Analytics, yielding 108 usable responses (against a target of 200; a 54% realization rate attributable to access and response-rate constraints typical of institutional survey research). This segment constituted the primary analytical sample and was analyzed using PLS-SEM in SmartPLS 4 to test the hypothesized causal model. Its realized sample satisfies the widely applied "10-times rule" for PLS-SEM, ten times the largest number of structural paths directed at a single construct (Hair et al., 2019). With a maximum of two paths converging on Marketing Agility, the minimum required sample was 20, well below the 108 achieved.

Segment B comprised respondents from PHEIs that had not adopted GA, yielding 19 usable responses against a target of 80–100 responses. The low realization is informative, reflecting the near-saturation of GA adoption among West Java PHEIs. This falls markedly below the threshold required for valid inferential estimation. Segment B was analyzed descriptively rather than through inferential comparative testing (Mann-Whitney U) and is presented explicitly as a qualitative-style benchmark rather than a statistically powered comparison group.

Two structured survey instruments (Instrument A and Instrument B) were developed using 5-point Likert scales, built from the literature reviewed above, and contextualized through prior exploratory fieldwork before being reviewed and revised by the supervising faculty. Instrument A measured three latent constructs, including GA utilization, DDDM, and Marketing Agility, corresponding to the hypothesized model. Instrument B measured adoption barriers and the same Marketing Agility dimensions for descriptive comparison. Both instruments underwent a pilot test with 15 marketing and admissions practitioners outside the final sampling frame to assess item clarity and face validity before full deployment. Feedback from this pilot led to minor wording revisions on three items in Instrument A that pilot respondents found ambiguous particularly around the distinction between "using GA data" and "having GA installed" and to the addition of a screening question to more reliably classify respondents into Segment A or Segment B at the outset of the survey. All respondents were informed of the study's academic purpose, the voluntary nature of participation, and the anonymity of their responses prior to completing the survey. No personally identifiable information was collected, and the data were used exclusively for aggregate analysis in accordance with the ethical research standards of the supervising institution.

Illustrative items were used to represent each construct. For GA Utilization, an example item was "Our institution reviews GA4 traffic and conversion data at least weekly." For DDDM, an example item was "Marketing decisions in our institution are formally discussed using analytics data rather than based primarily on past experience." Meanwhile, for Marketing Agility, an example item was "Our institution can modify an active recruitment campaign within days of detecting a shift in prospective-student behavior." All items were measured using a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

Construct validity and reliability were evaluated using Average Variance Extracted (AVE) and Composite Reliability (CR) for convergent validity and internal consistency, and the

Heterotrait-Monotrait ratio (HTMT) for discriminant validity, following the thresholds recommended by Hair et al. (2019). Structural model evaluation used the coefficient of determination (R^2) to assess predictive strength and bootstrapping with 10.000 resamples to evaluate path coefficient significance (T-statistics>1.96; $p<0.05$). Mediation was assessed through the specific indirect effect of GA on Marketing Agility via DDDM, benchmarked against the direct effect to classify the type of mediation (Hair et al., 2019; Nitzl et al., 2016).

4. RESULTS AND DISCUSSION

4.1 Respondent Profile

The majority of the 108 Segment A respondents held tactical-to-strategic marketing roles, including Digital Marketing Manager, *Penerimaan Mahasiswa Baru* (PMB) (New Student Admission) Data Analyst, PMB Coordinator (New Student Admission Coordinator), and IT Web & Analytics Staff, with an average tenure exceeding one year, indicating sufficient institutional exposure to reliably assess their institution's Marketing Agility condition.

Table 1. Sample Realization: Planned Target vs. Actual

Segment	Planned Target	Realized Sample	Share of Total (n=127)
Segment A (GA users)	200 respondents	108 respondents	85.04%
Segment B (non-users)	80–100 respondents	19 respondents	14.96%

Table 1 summarizes the realized sample against the planned target for both segments of the study. Segment A, representing GA-adopting institutions, contributed 108 respondents, accounting for 85.04% of the total sample, while Segment B, representing non-adopting institutions, contributed 19 respondents, accounting for 14.96% of the total sample. The difference in sample realization reflects the accessibility of respondents and the higher availability of participants from institutions that have implemented Google Analytics. Although the number of non-adopting institutions was relatively limited, this segment was retained as a descriptive benchmark to provide additional insight into differences in Marketing Agility profiles between GA-adopting and non-adopting institutions.

4.2 Measurement Model Evaluation

Table 2. Reliability and Convergent Validity

Construct	Cronbach Alpha	Composite Reliability	AVE	Remark
GA Utilization	0.997	0.997	0.960	Valid & Reliable
DDDM	0.997	0.997	0.959	Valid & Reliable
Marketing Agility	0.998	0.998	0.975	Valid & Reliable

Convergent validity and internal consistency exceeded the recommended thresholds for all three constructs, as presented in Table 2. The results show that all constructs achieved excellent reliability, with Cronbach's Alpha and Composite Reliability values above the recommended threshold of 0.70. In addition, the Average Variance Extracted (AVE) values for GA Utilization (0.960), DDDM (0.959), and Marketing Agility (0.975) exceeded the minimum criterion of 0.50, indicating strong convergent validity. Therefore, all constructs were confirmed as valid and reliable and were appropriate for further structural model evaluation.

Table 3. Heterotrait-Monotrait Ratio (HTMT)

Construct Pair	HTMT Value
GA ↔ DDDM	0.731
MA ↔ DDDM	0.766
MA ↔ GA	0.680

Discriminant validity via the Heterotrait-Monotrait ratio (HTMT) confirmed that the constructs were empirically distinct, as presented in Table 3. The results show that all HTMT values were below the recommended threshold of 0.90, with the highest inter-construct ratio between GA Utilization and

DDDM at 0.731 (Henseler, Ringle, & Sarstedt, 2015). This indicates that each construct represents a distinct concept and that no substantial overlap exists among the variables in the research model. Therefore, the measurement model demonstrates adequate discriminant validity and supports further structural model evaluation.

4.3 Structural Model Evaluation

The model explained 53.2% of the variance in DDDM and 61.6% of the variance in Marketing Agility, indicating a moderate-to-substantial level of explanatory power. Bootstrapping with 10,000 resamples supported all three hypothesized paths.

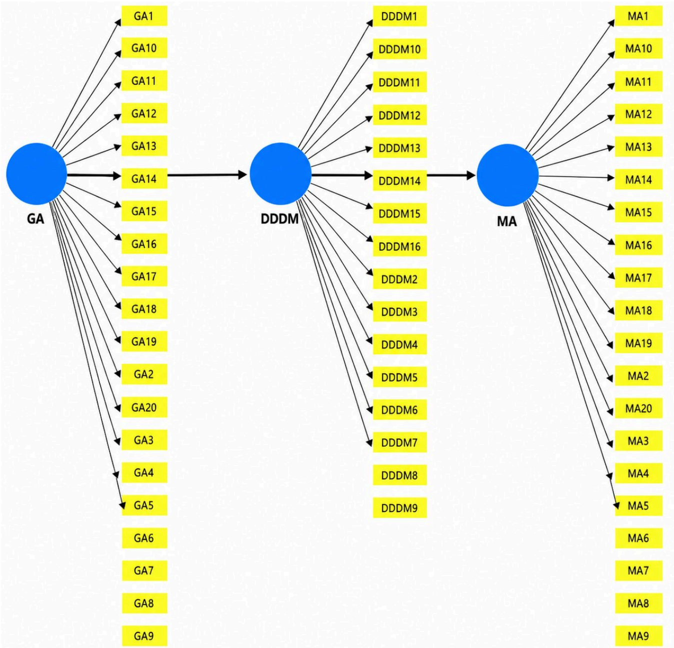

Figure 1. Structural Model: GA → DDDM → Marketing Agility (SmartPLS 4 Output)

Figure 1 illustrates the structural model evaluation results generated using SmartPLS 4. The model demonstrates the hypothesized relationships among Google Analytics (GA) utilization, Data-Driven Decision-Making (DDDM), and Marketing Agility (MA). The measurement model shows that each construct is represented by its respective indicators, while the structural model presents the proposed causal paths between the latent variables. The results provide the basis for evaluating the significance and strength of the relationships among constructs in the subsequent structural model analysis.

Table 4. Path Coefficient Significance Test

Hypothesis	Path	β	T-Statistics	P-Values	Decision
H_1	GA → DDDM	0.729	16.292	0.000	Supported
H_2	DDDM → MA	0.576	6.330	0.000	Supported
H_3a	GA → MA (direct)	0.259	2.711	0.007	Supported

Table 4 presents the results of the path coefficient significance test for the direct relationships among the research constructs. The bootstrapping analysis with 10,000 resamples indicates that all proposed direct hypotheses are supported. Google Analytics utilization has a positive and significant effect on Data-Driven Decision-Making (β=0.729, T-statistics=16.292, p<0.001), supporting H_1. Furthermore, Data-Driven Decision-Making significantly influences Marketing Agility (β=0.576, T-statistics=6.330, p<0.001), supporting H_2. The direct effect of Google Analytics utilization on Marketing Agility is also positive and significant (β =0.259, T-statistics=2.711, p=0.007), confirming H_3a. These findings demonstrate that analytics utilization contributes to institutional agility both through improved decision-making processes and through a direct pathway.

4.4 Mediation Analysis

Table 5. Mediation Test (Specific Indirect Effect - H3b)

Hypothesis	Mediation Path	Path Coefficient	T-Statistics	P-Values	Type of Mediation
H_3b	GA → DDDM → MA	0.42	5.773	0.000	Partial Mediation - Supported

Table 5 shows that the specific indirect effect of GA utilization on Marketing Agility through DDDM was positive and significant (β=0.420, T-statistics=5.773, $p<0.001$), confirming that DDDM meaningfully transmits the effect of analytics utilization on institutional agility and supporting H_3b. Since the direct effect of GA utilization on Marketing Agility remained significant after considering the indirect pathway (Table 4), the mediation effect was classified as partial rather than full mediation. This finding indicates the existence of two complementary pathways, namely a strategic pathway in which analytical insights are processed through DDDM before informing broader strategic adjustments and a tactical pathway in which operational staff directly utilize GA-derived signals to enable rapid and localized responses.

4.5 Descriptive Comparison: GA-Adopting versus Non-Adopting Institutions

Table 6. Descriptive Comparison of Marketing Agility: Segment A (GA Users) vs. Segment B (Non-Users)

Marketing Agility Dimension	Segment A Mean (n=108)	Segment B Mean (n=19)	Gap Indication
Market response speed	3.8 (High)	2.3 (Low)	Segment A responds faster to enrollment anomalies
Strategic flexibility	3.6 (High)	2.0 (Low)	Segment B is rigid, struggles to modify campaigns mid-cycle
Cross-functional coordination	3.9 (High)	2.4 (Low)	GA data enables more objective cross-unit communication in Segment A
Learning orientation	3.7 (High)	2.2 (Low)	Segment B evaluation is reactive, only triggered when targets are missed
Proactive anticipation	3.4 (Moderate)	1.8 (Very Low)	Absence of detection tools makes Segment B unable to predict future trends

Table 6 shows the descriptive comparison of Marketing Agility dimensions between GA-adopting and non-adopting institutions. Segment B respondents (n=19) reported that the principal barrier to GA adoption was not financial cost but a shortage of staff with the technical literacy to install, manage, and interpret web analytics data, compounded by a decision culture still anchored in historical experience and prior-year enrollment patterns rather than real-time behavioral signals. The descriptive comparison across the five Marketing Agility dimensions showed a consistent and substantial gap, the widest of which was in proactive anticipation. As noted in the Methodology, this comparison is descriptive rather than statistically inferential given Segment B's limited sample size, but the consistency and magnitude of the gap across all five dimensions reinforces the substantive value of analytics adoption observed in the Segment A structural model.

4.6 Discussion

These findings empirically confirm, within the PHEI context, the sensing-seizing-reconfiguring logic of Dynamic Capabilities theory (Teece, 2019). GA operates as a sensing infrastructure whose intelligence is substantially, though not exclusively, seized through DDDM before manifesting as institutional agility. The partial mediation result extends prior work that has typically framed DDDM as a full or singular pathway from analytics to organizational outcomes (Kowalczyk, & Siuta-Tokarska, 2021; Homburg, & Wielgos, 2022) by showing that a meaningful share of agility-relevant action bypasses formal deliberation altogether, consistent with evidence that IT-enabled customer agility often depends on the capacity for immediate, decentralized response rather than solely on centralized decision processes (Zhou, Mavondo, & Saunders, 2019; Osei, Amankwah-Amoah, Khan, Omar, & Gutu, 2019).

The comparative profile of non-adopting institutions lends further support to the RBV proposition that GA-derived intelligence functions as a valuable, rare, and difficult-to-replicate resource (Barney, 1991; Kero, & Bogale, 2023).Institutions lacking this resource were not simply slower but structurally more reactive across every dimension of Marketing Agility, with the barrier concentrated in human capital rather than cost, echoing Safi, Suef, and Karningsih (2025) on the uneven digital and analytical maturity of Indonesian higher education institutions and suggesting that closing the adoption gap requires investment in analytical literacy at least as much as in the technology itself. Taken together, these results have distinct practical implications for each confirmed pathway. The H_1 finding implies that PHEI leadership should treat GA proficiency as a core marketing-staff competency rather than an optional technical skill, since its effect on DDDM is the strongest and most tightly estimated relationship in the model. The H_2 finding suggests that formalizing DDDM, for example, through a recurring analytics review meeting integrated into the admissions calendar, is likely to yield a larger agility payoff than ad hoc reporting. The H_3a or H_3b findings jointly imply that institutions should not treat formal DDDM infrastructure and frontline analytics literacy as substitutes because a meaningful share of agility (the direct path) bypasses formal deliberation; restricting analytics access to a centralized data team would forfeit the tactical responsiveness identified in this study as a significant and distinct contributor to institutional agility.

These patterns broadly parallel the findings of marketing agility research conducted outside Indonesia. Zhou et al. (2019), studying South African firms, similarly found that the agility-performance relationship strengthened under conditions of market turbulence rather than stability, consistent with the West Java context, where sustained competitive pressure appears to reward institutions capable of both deliberate and rapid tactical responses. Osei et al. (2019), examining Marketing Agility deployment in an emerging-economy firm, reported that agility was built through decentralized frontline responsiveness rather than centralized strategic planning alone, echoing this study's finding that a substantial share of GA's effect on marketing agility operates outside the formal DDDM channel. The consistency of this pattern across an African commercial firm, a South African cross-industry sample, and Indonesian PHEIs suggests that the coexistence of deliberate and tactical agility pathways may be a more general feature of resource-constrained, emerging-market organizations than a sector-specific artifact of higher education.

5. CONCLUSIONS

5.1 Conclusion

This study set out to answer four research questions concerning the relationship between Google Analytics utilization, Data-Driven Decision Making, and Marketing Agility among private higher education institutions in West Java. GA utilization was found to be a strong and significant antecedent of DDDM, confirming that analytics utilization functions as a genuine driver of an institution's data-driven decision culture rather than a parallel, disconnected activity. DDDM significantly enhanced Marketing Agility, confirming that the maturity of an institution's decision-making process is a substantive driver of recruitment responsiveness. DDDM was further confirmed as a partial mediator of the GA-Marketing Agility relationship: both the indirect strategic pathway through DDDM and the direct tactical pathway from GA to agility were significant, indicating that institutional agility is produced through two complementary mechanisms rather than a single deliberative channel. Finally, the descriptive comparison of non-adopting institutions revealed that their principal barrier is human resource literacy rather than financial cost, corresponding to a consistently weaker Marketing Agility profile across all five measured dimensions, most acutely in proactive anticipation.

Theoretically, this study contributes by explicitly bridging the Resource-Based View and Dynamic Capabilities theory to the applied use of a specific analytics tool through the middle-range lens of Marketing Information System theory and by empirically demonstrating partial rather than full mediation in the analytics-to-agility pathway. Practically, the findings translate into four recommendations for PHEI marketing leadership: formalize a recurring analytics review cycle that integrates GA4 data directly into admissions decision forums; build GA proficiency as a distributed competency across marketing and admissions staff rather than concentrating it in a single data-specialist role; prioritize staff training and literacy-building among institutions currently without GA, ahead of or alongside platform adoption itself; and periodically benchmark analytics-marketing maturity, for instance, using the EDMAC and IPA-GAPM instruments developed in this study to identify whether the institutional gap lies in the sensing, seizing, or reconfiguring stage, since the appropriate intervention differs across each.

5.2 Research Limitations

This study is limited by its cross-sectional design, geographic focus on West Java, exclusive focus on the GA4 platform, and small size of the non-adopting comparison sample, which precluded inferential statistical testing.

5.3 Suggestions and Directions for Future Research

Future research should pursue a longitudinal design to strengthen causal inference across multiple recruitment cycles, replicate the model across other Indonesian provinces to extend external validity, and explore the automation of the underlying assessment instrument through direct GA4 API integration to reduce reliance on self-reported survey data.

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AUTHOR CONTRIBUTIONS

RR contributed to the conceptualization, research design, methodology, data collection, data analysis, interpretation of findings, and manuscript preparation. PS was responsible for supervision, theoretical framework development, validation, critical revision of the manuscript, and research guidance. All authors contributed to the development of this study, critically reviewed the manuscript, and approved the final version for publication.

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