MARKETING ANALYTICS EDUCATION AND DATA-DRIVEN DECISION-MAKING COMPETENCE AMONG UNIVERSITY STUDENTS IN NIGERIA

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Abstract

This study examined whether marketing analytics education is related to data-driven decision-making competence among Nigerian university students, and whether that competence differs by year of study, programme type, and institution type. A cross-sectional survey was administered in six universities (three public and three private), and 412 usable questionnaires were analysed. Marketing analytics education was measured through curriculum content, tool-based practice and applied learning, and decision-making competence through data literacy, analytical reasoning, interpretation and decision application. Students reported moderate levels of both marketing analytics education ($M = 3.17$, $SD = 0.53$) and decision-making competence ($M = 3.42$, $SD = 0.60$). Overall marketing analytics education positively predicted competence ($\beta = .61$, $p < .001$, $R^2 = .37$). When the three dimensions were entered together, tool-based practice ($\beta = .39$) and applied learning ($\beta = .37$) were statistically significant predictors, whereas curriculum content was not ($\beta = .08$, $p = .056$); the model explained 40% of the variance. Competence differed by year of study ($\eta^2 = .07$) and by programme type ($\eta^2 = .05$) but not between public and private universities ($p = .135$). The findings suggest that analytics teaching built around software practice and applied projects is more closely tied to students' competence than content coverage alone. The paper recommends adding tool-based practice and applied projects to analytics courses, extending introductory analytics to other programmes, resourcing practice-based teaching, and building industry partnerships, although the cross-sectional design and self-reported measures limit causal claims.

Keywords: Marketing analytics education, data-driven decision-making, decision-making competence, tool-based practice, Nigerian universities.

INTRODUCTION

Unemployment Marketing practice now depends on data to a degree that makes analytical skill a baseline expectation of new graduates, and employers recruiting for entry-level marketing roles expect familiarity with big data, analytics, and artificial intelligence (Grewal et al., 2024). Content analyses of job advertisements point in the same direction: an examination of more than 2,600 postings identified analytics, communication, visualization, data science, business requirements and problem-solving among the most sought-after skills (Levendis & Indika, 2025), and an industry assessment of entry-level requirements noted that firms have moved from seeking a specific degree towards recruiting based on skill sets (Stanton & Stanton, 2020).

Universities have responded by adding analytics content to marketing and business programmes, yet whether the resulting teaching matches what employers need is still disputed. A study that matched more than 14,000 job posts against 3,600 online courses reported gaps between the skills in demand and the learning opportunities available (Almgerbi et al., 2021), and an analysis of LinkedIn advertisements for data analysts raised the possibility of comparable gaps between employer expectations and what universities teach (Zhang et al., 2023). Kurtzke and Setkute (2021) argued that analytics capability in marketing education has to combine knowledge, soft skills, and technical skills with the ability to communicate insights from data to stakeholders, which implies that classroom exposure matters only to the extent that it prepares students to make decisions from data.

Most of the instructional literature describes how particular courses, tools, or projects were designed and how students reacted to them, and it says less about whether exposure to analytics education is associated with students' ability to decide on the basis of data. Python-based teaching in marketing courses, for instance, was reported to improve students' learning experience and their perception of teaching effectiveness (Teimourzadeh et al., 2022), and a comparison of simulations with client-based projects in digital marketing analytics courses found a slight advantage for simulations alongside benefits and difficulties for both (Zhang & Scribner, 2024). Both studies concern the delivery of a course rather than the competence that students carry into decisions. Evidence from developing countries is thinner still, and Diab and El Sayad (2025) observed that few studies had examined how data analytics enters business education in such settings.

Nigeria illustrates the difficulty well, because the study located for this paper that comes closest to the topic assessed data literacy among students in five southern Nigerian universities and reported moderate skills, with doctoral students ahead of master's and bachelor's students (Oguguo et al., 2020). That work did not ask how analytics education related to the skills it measured, and data literacy covers only part of what is needed to decide with data. As far as the sources reviewed here show, no study has examined whether marketing analytics education predicts decision-making competence among Nigerian university students, and none has separated the contribution of what is taught from the contribution of hands-on tool use and applied projects.

This study addresses that gap through a cross-sectional survey of undergraduates in six Nigerian universities. Marketing analytics education (MAE) is treated as three dimensions, namely curriculum content (CC), tool-based practice (TP), and applied learning (AL), and data-driven decision-making competence (DDMC) as four, namely data literacy (DL), analytical reasoning (AR), interpretation (IN), and decision application (DA). Four research questions guide the work. RQ1 asks what levels of MAE exposure and DDMC students report. RQ2 asks whether overall MAE predicts DDMC, RQ3 whether each MAE dimension does so, and RQ4 whether DDMC differs by year of study, programme type, and institution type (public or private).

Each of the last three questions is tested through directional or comparative hypotheses, which are stated here and derived from the literature later in the paper. H1 holds that overall MAE significantly and positively predicts DDMC. H2a, H2b and H2c hold that CC, TP and AL, respectively, each significantly and positively predict DDMC. H3a, H3b and H3c hold that DDMC

differs significantly by year of study, by programme type and between public and private universities.

The findings bear on curriculum designers, university managers, regulators, and employers, who need evidence on which parts of analytics teaching are associated with students' competence. The study is limited to undergraduates at the 200 to 400 level in six universities and relies on self-reported measures, so its results describe associations in this sample and do not settle questions of causation. The paper reviews the literature and derives the hypotheses, describes the methodology, reports the results, discusses them against earlier studies, and closes with conclusions and recommendations.

LITERATURE REVIEW

Marketing Analytics Education and Decision-Making Competence as Constructs

Marketing analytics education is treated in this paper as the set of learning opportunities through which marketing students acquire the capacity to collect, analyse and interpret marketing data. Practice-informed accounts describe that capacity as a blend of knowledge, technical skills and soft skills, including the ability to communicate what the data say to stakeholders (Kurtzke & Setkute, 2021), and this breadth motivates the three dimensions used here. Curriculum content (CC) covers what is taught, such as statistical and analytical concepts and the stages of the analytics process. Jaggia et al. (2020), for example, organise a business analytics course around the CRISP-DM framework, which runs from problem formulation to storytelling, while Johnson et al. (2020) and Paul and MacDonald (2020) approach the question from the side of the concepts, skills, knowledge and tools that analytics curricula should contain. Tool-based practice (TP) refers to hands-on work with software, e.g., Python libraries (Teimourzadeh et al., 2022), R and Excel (Sankaran et al., 2023), or dashboards (Hoang et al., 2025). Applied learning (AL) covers projects, cases, and industry exposure in which students work on realistic problems, as in the marketing analytics project model of Lim and Heinrichs (2021).

Data-driven decision-making competence is treated as the capacity to move from data to a justified decision. Data literacy supplies the starting point, and it has been described as a set of interrelated skills in data management, data analysis, and the interpretation and communication of results (Nath & Kirby, 2022), or more broadly as a competence spanning knowledge, skills, and attitudes (Schüller, 2020). Chung and You (2022) link data literacy to uncovering problems in raw data, interpreting meaning, communicating more effectively and making more rational decisions. Competence in this paper goes one step beyond reading data: besides DL, it includes analytical reasoning (AR), interpretation (IN) and decision application (DA). Judgement is a recurring element in work on decision-making and employability, where judgeability emerged as the most important decision-making employability factor and was influenced by self-efficacy, self-control and self-regulation (Huang et al., 2020).

Measurement choices follow from these definitions, because competence can be assessed through tests or through self-assessment, and self-efficacy scales have been used where the aim is to capture perceived ability across the components of data-driven decision-making. Qiao et al. (2025) built such a scale for teachers' data-driven decision-making that links data use with pedagogical and ethical issues, and Bakir et al. (2025) found that undergraduates' self-rated Excel skills were positively related to their job-related Excel performance. Self-rated competence is therefore used in this study, and the limitations that follow from it are taken up in the discussion.

Experiential Learning and Human Capital as Explanatory Perspectives

Two perspectives explain why education should build decision-making competence, and they point to somewhat different mechanisms. Experiential learning perspectives hold that competence develops through concrete engagement with problems followed by reflection and application, and the analytics education literature relies on this reasoning when it advocates real data and realistic tasks. Jaggia et al. (2020) describe experiential learning opportunities as effective for teaching applied and complex subjects such as business analytics, and they use a term-long project with real data to give students the whole analytics process rather than only the modelling stage. Anand and Mitchell (2022) designed a capstone course that combines self-directed learning, experiential learning, diverse teams, and structured mentoring around projects in commercial firms, and Zhang and Scribner (2024) compare two experiential formats, simulation and client-based projects, in digital marketing analytics courses.

Evidence on project-based approaches outside marketing is consistent with this reasoning, since industry-enriched project-based learning raised students' reported readiness for the workforce (Naseer et al., 2025), a review of project-based learning in engineering programmes reported gains in technical and non-technical competencies (Gaya-López & Lara-Bercial, 2024), and a multi-course project-based approach was associated with the development of critical thinking and collaborative decision-making skills (Khandakar et al., 2020). Seen through this lens, TP and AL are the dimensions most likely to build DDMC, because they give students repeated opportunities to choose methods, run them and interpret the results, whereas CC supplies concepts that students may or may not have put to use.

A human capital view adds the argument that education is an investment that raises skills and, through them, employability and career prospects. Xu et al. (2022) hypothesised that both soft and hard skills affect human capital, individual attributes, and career development among engineering students taking big data analytics courses, and Tello et al. (2025) examined how digital education experience related to engineering students' employability skills and their perception of big data analytics. This view says less about which components of education matter, but it supports the expectation that more exposure to analytics education goes with higher competence.

Marketing Analytics in Higher Education

Curriculum development in marketing and business analytics has been driven largely by concern over the fit between teaching and practice. Marketing educators have been urged to reconsider how they prepare students for technology-enabled roles (Grewal et al., 2024), and Sood and Pattinson (2023) argue for a big data curriculum for marketing that uses large language models. At programme level, Gharehgozli et al. (2023) set out a framework for creating an undergraduate business analytics programme in a state-funded business school, whereas Gerhart et al. (2024) found that business analytics courses in United States universities overlap in content while industry needs vary, which points to a need for tailored offerings. Kowalska-Styczeń and Juszczyk (2024) compared analytics-related specialisations in bachelor's and engineering programmes across Polish universities and reported that business-oriented provision should cover broader skill sets, including interpersonal and communication skills, while engineering programmes emphasise technical and analytical expertise.

Teaching methods and tools have received more attention than curriculum architecture. Furthermore, studies on them tend to report learning experience and satisfaction, as when Python-based case work in marketing courses was associated with a better learning experience and higher perceived teaching effectiveness (Teimourzadeh et al., 2022), student satisfaction with R in a data mining and business analytics course was related to intrinsic interest and career benefits (Sankaran et al., 2023), and undergraduates' self-rated Excel skills were positively related to their job-related

performance in the same tool (Bakir et al., 2025). Dashboard-based learning activities, designed through problem-based learning and constructive alignment, have been introduced in introductory analytics courses (Hoang et al., 2025), and project models that give marketing analytics students context-relevant experience address the skills gap directly (Lim & Heinrichs, 2021). Student reluctance is a recurring difficulty, since many marketing students avoid quantitative courses out of fear and hesitation, and Dingus et al. (2024) reported that a single class activity increased students' interest in marketing analytics and reduced their perceived intimidation.

Student and faculty perspectives add a further layer to this picture, since a mixed-methods study with 20 marketing educators and 480 marketing students found that ability, affective, and interest factors predicted students' interest in big data courses, whereas competitiveness traits and academic value did not (Elhajjar & Borna, 2022), and faculty intention to use marketing analytics technology was influenced by perceived technical support, time to integrate the technology, and administrative support (Keiper et al., 2023). Evidence from Africa among the sources reviewed concerns data reasoning and institutional uses of data more than marketing analytics teaching. University science education students in Ghana, for example, were studied for their reasoning about scientific data and for gender differences in that reasoning (Kumassah et al., 2025); diagnostic test data have been integrated into analytics reports to help educators tailor student support in South African higher education (Mudavanhu & Steyn, 2025); and a review of data literacy for teaching and learning in higher education institutions links data literacy to decision-making and recommends continuous reskilling (Enakrire, 2020).

Reviews of the wider literature on data in higher education give context for these studies but are concerned mainly with institutions. A systematic review of 75 papers found that big data and analytics in higher education mostly support learning and guide teaching, with limited use in administrative decision-making (Stojanov & Daniel, 2023), and a review of learning analytics concluded that such tools can support study success while more large-scale evidence is needed (Ifenthaler & Yau, 2020). Both reviews deal with the use of data to support learning, teaching and study success rather than with students' own competence in deciding from data.

Analytics Education and Decision-Making Competence: Empirical Evidence

Studies that connect analytics education to student outcomes mostly report favourable associations, although the outcomes they measure differ. A big data analytics course was associated with better hard and soft skills among engineering students, with soft skills carrying more weight for employability (Xu et al., 2022), and project-based learning in an undergraduate business analytics course improved students' analytical skills in solving and communicating business problems (Yazici, 2020). Digital education and e-learning experiences were related to engineering students' employability skills and to their perception of big data analytics (Tello et al., 2025), and learning analytics mediated the relation between the usefulness of online learning and knowledge in enhancing employability skills in a study of higher education students (Mittal et al., 2022). Closest to the present focus, Kosim et al. (2025) surveyed all 67 students of a management programme in Bekasi, Indonesia, and reported that quantitative analysis skills and statistical mastery influenced managerial decision-making, explaining 60.8% of its variance.

The favourable pattern needs qualification, because the outcome variable is seldom decision-making competence and is more often employability, satisfaction, or perceived learning, as in the Python study of Teimourzadeh et al. (2022) or the comparison of simulations and client projects by Zhang and Scribner (2024), where the differences between methods were slight. Interest and attitudes do not always follow the expected factors, since competitiveness traits and perceived academic value did not predict students' interest in big data courses (Elhajjar & Borna, 2022). Benefits also vary by delivery mode: graduates of a distance-learning university reported positive effects on analytical capacity, autonomy and communication, although concerns about

digital skills and teamwork remained (Abrantes et al., 2022). Table 1 summarises twelve studies that bear most directly on the relationships examined here.

Table 1
Summary of Prior Empirical Studies on Analytics Education, Data Literacy and Decision-Making

Study	Context and design	Main finding	Gap relative to the present study
Oguguo et al. (2020)	Five southern Nigerian universities; descriptive survey, *n* = 2,550	Moderate data literacy; doctoral students ahead of master's and bachelor's students	Data literacy only; no analytics education variable
Chung & You (2022)	Korean university students; scale validation and freshman survey	Freshman data literacy not high; differences among colleges and disciplines	Measurement focus; education exposure not modelled
Nath & Kirby (2022)	University students; cross-sectional survey with a data literacy benchmark	Three data literacy factors; scores varied by study area	Not linked to decision application
Kosim et al. (2025)	67 management students, Bekasi, Indonesia; census survey	Quantitative analysis skills and statistical mastery influenced managerial decision-making (60.8% of variance)	Small single-programme sample; skills rather than the education that builds them
Xu et al. (2022)	Engineering students; cross-sectional survey	Big data analytics courses improved hard and soft skills; soft skills mattered more for employability	Engineering sample; employability rather than decision-making competence
Yazici (2020)	Undergraduate business analytics course; project-based learning	Projects improved analytical skills in solving and communicating business problems	Course-level evidence; no Nigerian data
Zhang & Scribner (2024)	Digital marketing analytics courses; case study	Simulation had a slight edge over client-based projects; both had benefits and difficulties	Compares two teaching methods; no Nigerian data
Teimourzadeh et al. (2022)	Marketing students; cross-sectional survey	Python-based teaching improved learning experience and perceived teaching effectiveness	Perceptions of learning rather than measured competence
Elhajjar & Borna (2022)	20 marketing educators interviewed; 480 marketing students surveyed	Ability, affective and interest factors predicted interest in big data courses; competitiveness and academic value did not	Interest and attitudes rather than competence

Study	Context and design	Main finding	Gap relative to the present study
Keiper et al. (2023)	Marketing faculty; survey based on the concerns-based adoption model	Technical support, administrative support and time shaped intention to use analytics technology	Faculty side; student outcomes not examined
Diab & El Sayad (2025)	Egyptian business graduates; cross-sectional survey	Analytics in the curriculum seen as necessary; views shaped by work experience and profession	Perceptions only; competence not measured
Persaud (2020)	Job postings, executive interviews and university programmes; multimethod	Employers seek functional, cognitive and social competencies and often require extra training	Employer demand; student-level outcomes not examined

Note. Studies are listed in the order in which they bear on the research questions. n = sample size.

The Nigerian Higher Education Context

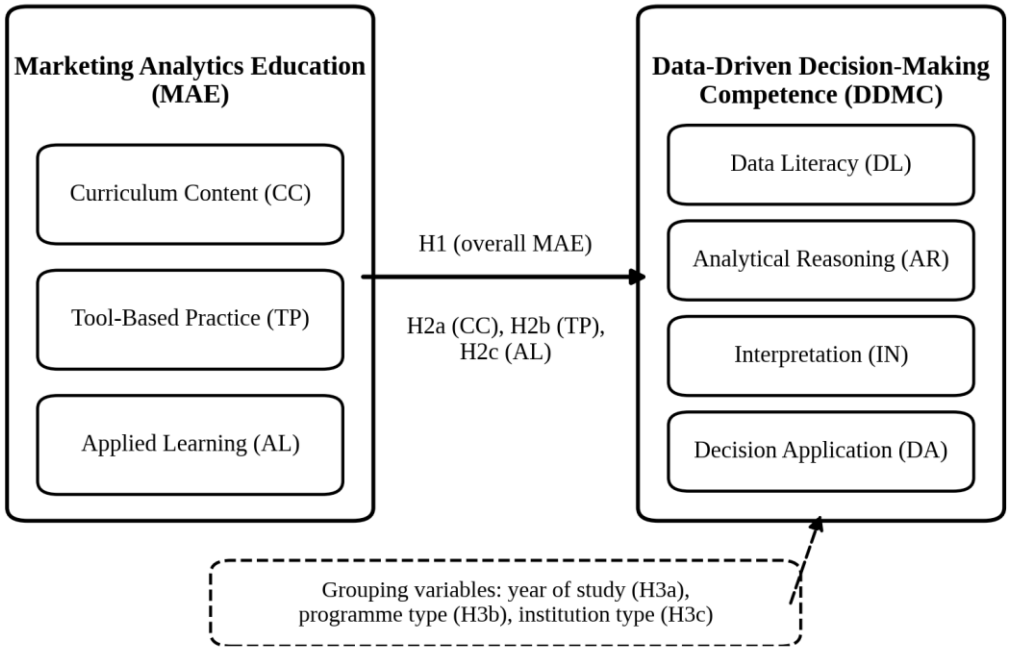
The Nigerian evidence in the reviewed sources is limited to one large survey of data literacy. Oguguo et al. (2020) drew a multi-stage sample of 2,550 students from five southern universities, used a Data Literacy Questionnaire whose reliability was established with Cronbach's alpha, and found moderate skills overall, with doctoral students ahead of master's and bachelor's students. The advantage of high-levelled students suggests that competence accumulates with progression, although a cross-sectional comparison across degree levels cannot separate exposure from selection. The study offers no direct view of marketing analytics teaching.

Questions about how well Nigerian universities can deliver tool-based and applied teaching have to be approached indirectly. Studies from other settings identify conditions that shape whether analytics technology reaches teaching: marketing faculty intention to use analytics technology depended on technical, administrative, and time resources (Keiper et al., 2023), and adoption of learning analytics tools in higher learning institutions was influenced by perceived usefulness, top management support, financial support, and government involvement (Mukred et al., 2024). Xing and Wang (2021) point to university-wide cultures of data use and professional development in data literacy as supports for students' effective use of data. Whether these conditions hold across Nigerian universities, and whether they differ between public and private institutions, is not documented in the sources reviewed. Business graduates in Egypt, another developing-country setting, considered data analytics necessary in the curriculum, with views shaped by work experience and profession (Diab & El Sayad, 2025), and industry partnerships have been proposed as a route to relevance in project-based learning (Naseer et al., 2025), which suggests that industry linkage is a plausible element of applied learning in Nigeria as well.

Conceptual Framework and Hypotheses

Taken together, the literature supports a positive association between analytics education and student outcomes but leaves three matters open for Nigerian students. The outcome is rarely decision-making competence, education is rarely separated into content, tool practice and applied learning, and the Nigerian evidence concerns data literacy alone. The conceptual framework in Figure 1 responds to these points by relating the three MAE dimensions to the four DDMC dimensions and by adding year of study, programme type and institution type as grouping variables.

Figure 1
Conceptual Framework of Marketing Analytics Education and Data-Driven Decision-Making Competence



Note. CC = curriculum content; TP = tool-based practice; AL = applied learning; DL = data literacy; AR = analytical reasoning; IN = interpretation; DA = decision application. The dashed arrow shows the grouping variables used for the group comparisons.

The hypotheses follow from this framework and from the evidence reviewed above, beginning with the positive associations reported between analytics courses, projects, and student skills (Xu et al., 2022; Yazici, 2020) and between quantitative skills and managerial decision-making (Kosim et al., 2025), which lead to H1: overall MAE significantly and positively predicts DDMC. Because experiential reasoning applies to each strand of education, H2a, H2b, and H2c state that CC, TP, and AL each significantly and positively predict DDMC. Grouping effects are expected from three sources. Competence was higher at higher degree levels in the Nigerian data literacy survey (Oguguo et al., 2020), and digital competence differed by grade level in a sample of 5,164 first-year and fourth-year students at a Chinese university (Zhao et al., 2021), which supports H3a: DDMC differs significantly by year of study. Data literacy differed among colleges and disciplines (Chung & You, 2022) and by study area (Nath & Kirby, 2022), supporting H3b: DDMC differs significantly by programme type. Resource conditions that shape analytics provision (Keiper et al., 2023; Mukred et al., 2024) may differ between ownership types, but no direct evidence on this was found, so H3c, that DDMC differs significantly between public and private universities, is stated without a predicted direction.

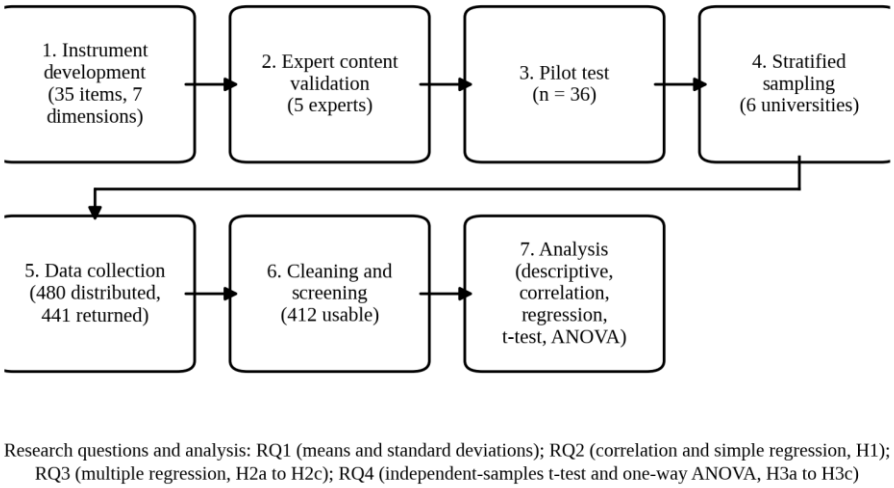
METHODOLOGY

Research Design and Approach

The study used a quantitative, cross-sectional survey design, which suits the aim of estimating how self-reported exposure to marketing analytics education is related to self-rated decision-making competence at a single point in time across several institutions. Figure 2 shows the sequence

followed, from instrument development through expert validation, piloting, sampling, data collection and screening to analysis. Each research question is linked in the figure to the technique used to answer it, and the same mapping is described in the analysis procedures below.

Figure 2
Research Design Flow



Note. RQ = research question; H = hypothesis. Counts in steps 5 and 6 are reported in the results.

Population, Sample, and Sampling Technique

The target population was undergraduate students at the 200, 300, and 400 level in Nigerian universities who had taken at least one course involving statistics, data analysis, or research methods, so that every respondent had some basis for rating analytics exposure. First-year students were excluded because their exposure to such courses was expected to be minimal. The sampling frame consisted of six universities, three public and three private, and respondents were drawn through stratified sampling with institution type and programme type as strata. Programme type had three categories: marketing and business, computing and information systems, and other programmes, such as social sciences and engineering. Within each university, questionnaires were distributed to intact classes at the three levels in each stratum that the university offered, so that year of study reflects class availability and not proportional allocation.

The sample size was set with the standard formula for estimating a proportion in a large population at 95% confidence and a 5% margin of error, which gives about 384 respondents. To allow for non-response and unusable returns, 480 questionnaires were distributed, 80 in each university. This target is also ample for a regression with three predictors.

Instrument

Data were collected with a structured questionnaire in three parts, the first of which recorded gender, year of study, programme type and institution type. The second part contained 15 items on MAE, five each for CC, TP and AL, and the third contained 20 items on DDMC, five each for DL, AR, IN and DA. All 35 items were rated on a five-point Likert scale from 1 (strongly disagree) to 5 (strongly agree), and dimension scores were computed as the mean of the five items. Overall MAE is the mean of the three MAE dimension scores, and overall DDMC is the mean of the four DDMC dimension scores. Items were written for this study using the literature as a guide to content, as set out in Table 2, and DDMC is measured as self-rated competence.

Table 2
Measurement Instrument

Construct	Dimension	Items	Sample item	Basis for item development
MAE	Curriculum content (CC)	5	My programme teaches statistical and analytical methods that can be applied to marketing problems	Kurtzke & Setkute (2021); Jaggia et al. (2020); Johnson et al. (2020)
	Tool-based practice (TP)	5	I have used software such as Excel, R or Python to analyse data in my courses	Teimourzadeh et al. (2022); Sankaran et al. (2023); Bakir et al. (2025)
	Applied learning (AL)	5	I have worked on a project that used real organisational data	Yazici (2020); Lim & Heinrichs (2021); Naseer et al. (2025)
DDMC	Data literacy (DL)	5	I can identify the data needed to answer a business question	Nath & Kirby (2022); Chung & You (2022); Schüller (2020)
	Analytical reasoning (AR)	5	I can choose an analytical technique that fits a marketing question	Johnson et al. (2020); Kosim et al. (2025)
	Interpretation (IN)	5	I can explain what the results of an analysis mean for a marketing decision	Nath & Kirby (2022); Qiao et al. (2025)
	Decision application (DA)	5	I use the results of data analysis when choosing between marketing options	Huang et al. (2020); Qiao et al. (2025)

Note. All items were rated from 1 (strongly disagree) to 5 (strongly agree). MAE = marketing analytics education; DDMC = data-driven decision-making competence.

Validity and Reliability

Content validity was assessed by five experts: three lecturers in marketing or business analytics, one measurement specialist, and one analytics practitioner. Each rated the relevance of every item; items with an item-level content validity index below .80 were revised or removed, and the scale-level average index was .93. Two items were reworded after expert comments. The revised questionnaire was piloted with 36 students at a university outside the main sample, and Cronbach's alpha in the pilot ranged from .78 to .89 across the seven dimensions. Only minor wording changes followed.

For the main sample, internal consistency was judged by Cronbach's alpha and composite reliability, with .70 as the minimum, and convergent validity by average variance extracted (AVE), with .50 as the minimum. Loadings for these indices came from one-factor solutions for each dimension. Discriminant validity between the two constructs was checked by comparing the square root of each dimension's AVE with its correlations with the dimensions of the other construct.

Data Collection Procedure

Questionnaires were administered on paper in class sessions with the permission of lecturers over six weeks, and trained research assistants explained the purpose of the study and collected completed forms on the spot. Returned questionnaires were screened for completeness and for invariant response patterns before analysis.

Data Analysis Techniques

Analyses were conducted in Python 3 with SciPy and statsmodels, using two-tailed tests at the .05 level. Means and standard deviations answered RQ1, and mean scores were read against three equal bands of the five-point scale: low (1.00 to 2.33), moderate (2.34 to 3.67), and high (3.68 to 5.00). Pearson correlations described the associations among the variables. H1 was tested with a simple linear regression of DDMC on overall MAE, and H2a to H2c with a multiple regression in which CC, TP, and AL were entered together. Multicollinearity was checked with variance inflation factors, independence of residuals with the Durbin-Watson statistic, and normality of residuals with skewness, kurtosis, and the Shapiro-Wilk test. H3a and H3b were tested with one-way analysis of variance followed by Tukey post hoc comparisons, and H3c with an independent-samples *t* test. Homogeneity of variance was checked with Levene's test, and effect sizes were reported as η^2 and Cohen's *d*.

Ethical Considerations

Participation was voluntary and anonymous, and each respondent received an information sheet describing the purpose of the study and gave informed consent before completing the questionnaire. No personal identifiers were recorded, and completed questionnaires were stored securely and used only for this research.

RESULTS

Response Rate and Respondent Profile

Of the 480 questionnaires distributed across the six universities, 441 were returned, a return rate of 91.9%. Twenty-nine returns were excluded: 19 because of missing responses and 10 because of invariant response patterns, which left 412 usable questionnaires (85.8% of those distributed). Table 3 gives the profile of these respondents. Female students formed 53.2% of the sample, and 400-level students were the largest year group (36.9%). Marketing and business students were the largest programme group (41.0%), and 53.4% of respondents came from public universities.

Table 3
Respondent Profile (N = 412)

Variable	Category	*f*	%
Gender	Female	219	53.2
	Male	193	46.8
Year of study	200 level	119	28.9
	300 level	141	34.2
	400 level	152	36.9
Programme type	Marketing and business	169	41.0

Variable	Category	*f*	%
	Computing and information systems	119	28.9
	Other programmes	124	30.1
Institution type	Public	220	53.4
	Private	192	46.6

Note. f = frequency.

Descriptive Statistics

Table 4 reports the means, standard deviations, and interpretation levels for each dimension and construct. Overall MAE had a mean of 3.17 (*SD* = 0.53) and overall DDMC had a mean of 3.42 (*SD* = 0.60), and both fell in the moderate band. Among the MAE dimensions, CC had the highest mean (3.54, *SD* = 0.64), followed by TP (2.99, *SD* = 0.83) and AL (2.97, *SD* = 0.79). Among the DDMC dimensions, AR had the highest mean (3.54), followed by IN (3.46), DL (3.35), and DA (3.32). All seven dimension means fell in the moderate band, as Figure 3 shows.

Table 4

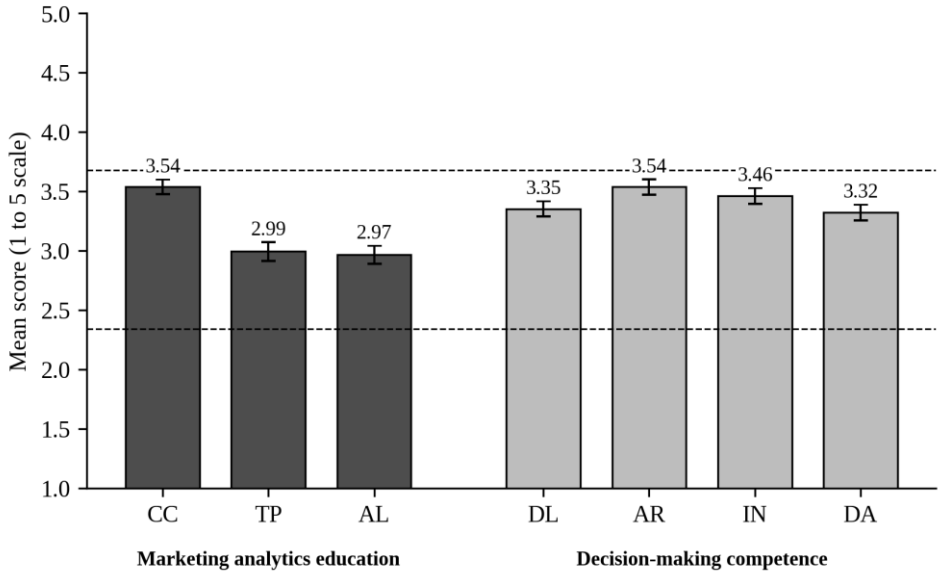
Means, Standard Deviations and Interpretation Levels for MAE and DDMC (N = 412)

Variable	*M*	*SD*	Level
Curriculum content (CC)	3.54	0.64	Moderate
Tool-based practice (TP)	2.99	0.83	Moderate
Applied learning (AL)	2.97	0.79	Moderate
Overall MAE	3.17	0.53	Moderate
Data literacy (DL)	3.35	0.66	Moderate
Analytical reasoning (AR)	3.54	0.68	Moderate
Interpretation (IN)	3.46	0.69	Moderate
Decision application (DA)	3.32	0.69	Moderate
Overall DDMC	3.42	0.60	Moderate

Note. Scores range from 1 to 5. Levels: low = 1.00 to 2.33; moderate = 2.34 to 3.67; high = 3.68 to 5.00.

Figure 3

Mean Scores on the Dimensions of Marketing Analytics Education and Decision-Making Competence



Note. Error bars show 95% confidence intervals. Dashed lines mark the boundaries of the moderate band (2.34 and 3.68). CC = curriculum content; TP = tool-based practice; AL = applied learning; DL = data literacy; AR = analytical reasoning; IN = interpretation; DA = decision application.

Reliability, Validity, and Assumption Checks

Table 5 presents the reliability and validity indices for the seven dimensions, together with the assumption checks used in the later analyses. Cronbach's alpha ranged from .84 to .91 across the seven dimensions, composite reliability from .84 to .91, and AVE from .52 to .66. Alpha for the 15 MAE items together was .86 and for the 20 DDMC items .94. For every dimension, the square root of AVE exceeded the highest correlation with a dimension of the other construct, which ranged from .23 to .47.

Table 5

Reliability, Convergent and Discriminant Validity, and Assumption Checks

Dimension or test	**Items**	**α**	**CR**	**AVE**	**√AVE**	**Highest *r* with other construct**
Curriculum content (CC)	5	.85	.85	.54	.73	.23
Tool-based practice (TP)	5	.91	.91	.66	.81	.47
Applied learning (AL)	5	.89	.89	.62	.78	.47
Data literacy (DL)	5	.84	.84	.52	.72	.47
Analytical reasoning (AR)	5	.86	.86	.55	.74	.46
Interpretation (IN)	5	.86	.86	.56	.75	.43
Decision application (DA)	5	.87	.87	.57	.75	.47
Assumption checks						
Normality of residuals (multiple regression)	Skewness = −0.05, excess kurtosis = 0.09; Shapiro-Wilk W = .997, p = .607					

Dimension or test	Items	α	CR	AVE	√AVE	Highest *r* with other construct
Multicollinearity	Variance inflation factors: CC = 1.08, TP = 1.10, AL = 1.11					
Independence of residuals	Durbin-Watson statistic = 2.02					
Equal variances, year of study	Levene's $F = 0.90$, $p = .409$					
Equal variances, programme type	Levene's $F = 0.38$, $p = .682$					
Equal variances, institution type	Levene's $F = 0.90$, $p = .342$					

Note. α = Cronbach's alpha; CR = composite reliability; AVE = average variance extracted. The highest r is the largest correlation between the dimension and any dimension of the other construct.

Hypothesis Testing

Table 6 shows the correlations among the three MAE dimensions, overall MAE, and DDMC. All correlations were positive and statistically significant at $p < .001$. DDMC correlated with overall MAE at $r = .61$, with TP at $r = .51$, with AL at $r = .49$ and with CC at $r = .24$. The correlations among CC, TP and AL ranged from .21 to .26.

Table 6

Pearson Correlations among MAE Dimensions, Overall MAE and DDMC (N = 412)

Variable	1	2	3	4	5
1. Curriculum content (CC)	1.00				
2. Tool-based practice (TP)	.21	1.00			
3. Applied learning (AL)	.23	.26	1.00		
4. Overall MAE	.63	.74	.73	1.00	
5. Overall DDMC	.24	.51	.49	.61	1.00

Note. All correlations are statistically significant at p < .001.

For H1, overall MAE significantly predicted DDMC ($B = 0.69$, $SE = 0.04$, $\beta = .61$, $t(410) = 15.43$, $p < .001$), and the model accounted for .37 of the variance in DDMC, $F(1, 410) = 238.1$, $p < .001$. For H2a to H2c, the multiple regression with CC, TP and AL was statistically significant, $F(3, 408) = 90.3$, $p < .001$, with $R^2 = .40$ and adjusted $R^2 = .39$. TP ($\beta = .39$, $p < .001$) and AL ($\beta = .37$, $p < .001$) were statistically significant predictors, whereas CC was not ($\beta = .08$, $p = .056$; 95% CI [−0.002, 0.144]). Table 7 gives the coefficients, and Figure 4 shows the standardized estimates.

Table 7

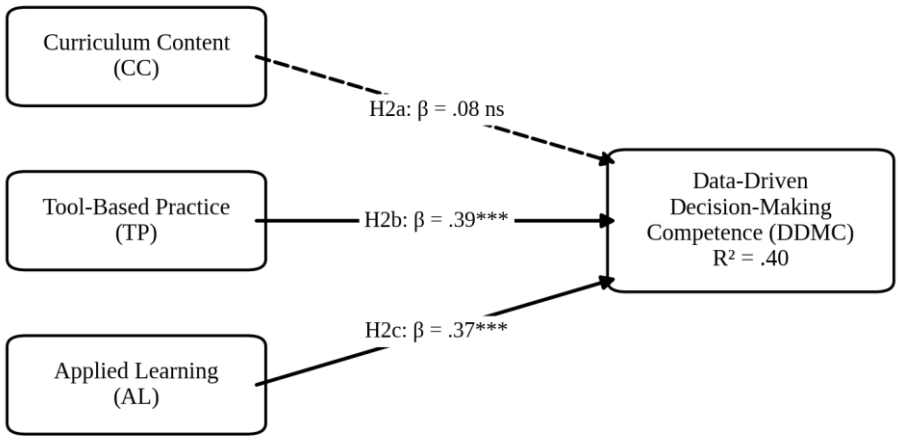
Regression Results for the Prediction of DDMC (N = 412)

Predictor	*B*	*SE*	95% CI for *B*	β	*t*	*p*
Model 1 (H1)						
Overall MAE	0.69	0.04	[0.599, 0.774]	.61	15.43	< .001
$R^2 = .37$, adjusted $R^2 = .37$, $F(1, 410) = 238.1$, $p < .001$						
Model 2 (H2a to H2c)						
Curriculum content (CC)	0.07	0.04	[−0.002, 0.144]	.08	1.91	.056
Tool-based practice (TP)	0.29	0.03	[0.228, 0.342]	.39	9.80	< .001

Predictor	*B*	*SE*	95% CI for *B*	β	*t*	*p*
Applied learning (AL)	0.28	0.03	[0.220, 0.341]	.37	9.12	< .001
R^2 = .40, adjusted R^2 = .39, $F(3, 408) = 90.3$, $p < .001$						

Note. Dependent variable: overall DDMC. B = unstandardized coefficient; β = standardized coefficient; CI = confidence interval.

Figure 4
Standardized Regression Coefficients for the Prediction of DDMC by MAE Dimensions



Note. Standardized coefficients from the multiple regression. The dashed line marks a path that was not statistically significant. *** p < .001; ns = not significant. Correlations among CC, TP, and AL ranged from r = .21 to r = .26.

For H3a, DDMC differed by year of study, $F(2, 409) = 15.03$, $p < .001$, $\eta^2 = .07$. Mean DDMC rose from 3.20 at 200 level to 3.41 at 300 level and 3.59 at 400 level, and Tukey comparisons showed statistically significant differences for 200 and 300 level ($p = .012$), 200 and 400 level ($p < .001$) and 300 and 400 level ($p = .021$). For H3b, DDMC differed by programme type, $F(2, 409) = 11.57$, $p < .001$, $\eta^2 = .05$. Students in computing and information systems (3.56) and in marketing and business (3.47) scored higher than students in other programmes (3.22), with $p < .001$ and $p < .001$, while the first two groups did not differ ($p = .423$). For H3c, DDMC did not differ between public (3.38) and private (3.47) universities, $t(410) = -1.50$, $p = .135$, $d = 0.15$. Table 8 summarises the group comparisons.

Table 8
Differences in DDMC by Year of Study, Programme Type and Institution Type

Variable	Group	*n*	*M*	*SD*	Test	*p*	Effect size
Year of study	200 level	119	3.20	0.56	$F(2, 409) = 15.03$	< .001	$\eta^2 = .07$
	300 level	141	3.41	0.61			
	400 level	152	3.59	0.56			
Programme type	Marketing and business	169	3.47	0.59	$F(2, 409) = 11.57$	< .001	$\eta^2 = .05$

Variable	Group	*n*	*M*	*SD*	Test	*p*	Effect size
Institution type	Computing and information systems	119	3.56	0.59	$t(410) = -1.50$	.135	d = 0.15
	Other programmes	124	3.22	0.56			
	Public	220	3.38	0.57			
	Private	192	3.47	0.62			

Note. Tukey post hoc comparisons: all three pairs of year groups differed ($p < .05$); computing and information systems and marketing and business students each exceeded students in other programmes ($p < .001$), and did not differ from each other.

Summary of Findings

Table 9 lists each hypothesis with the test used and the decision, and it shows that H1, H2b, H2c, H3a and H3b were supported while H2a and H3c were not.

Table 9
Summary of Hypothesis Tests

Hypothesis	Statement	Test	Key statistic	Decision
H1	Overall MAE positively predicts DDMC	Simple regression	$\beta = .61$, $p < .001$	Supported
H2a	CC positively predicts DDMC	Multiple regression	$\beta = .08$, $p = .056$	Not supported
H2b	TP positively predicts DDMC	Multiple regression	$\beta = .39$, $p < .001$	Supported
H2c	AL positively predicts DDMC	Multiple regression	$\beta = .37$, $p < .001$	Supported
H3a	DDMC differs by year of study	One-way ANOVA	$\eta^2 = .07$, $p < .001$	Supported
H3b	DDMC differs by programme type	One-way ANOVA	$\eta^2 = .05$, $p < .001$	Supported
H3c	DDMC differs between public and private universities	Independent-samples *t* test	$d = 0.15$, $p = .135$	Not supported

DISCUSSION

Principal Findings

Students in the six universities reported moderate exposure to marketing analytics education and moderate decision-making competence, with no dimension of either construct reaching the high band (Table 4, Figure 3). The two practice-oriented dimensions of MAE, TP (2.99) and AL (2.97), had the lowest means, well below CC (3.54). That pattern suggests that students meet analytics content more often than they get to use tools or work on applied projects, although the study did not measure how often each type of activity was offered.

Overall MAE was a statistically significant positive predictor of DDMC and accounted for about 37% of its variance (Table 7). The result is consistent with the expectation behind H1, but the cross-sectional design allows only an association to be claimed. When the three dimensions were entered together, TP and AL carried the association, with standardized coefficients of .39 and .37, while the coefficient for CC was small and its confidence interval included zero (Table 7, Figure 4). CC still correlated positively with DDMC on its own (.24), so its unique contribution to the model may have been absorbed by TP and AL, which share some variance with it. Because the coefficient for CC was near the conventional threshold ($p = .056$), the data do not show that content has no unique relation to competence; they show that the relation was not detectable at this sample size once practice was taken into account.

DDMC rose with year of study and was higher among computing and information systems students and marketing and business students than among students in other programmes, whereas public and private universities did not differ (Table 8). The year effect and the programme effect were small to moderate in size ($\eta^2 = .07$ and .05). The institution-type difference was small ($d = 0.15$), and with groups of 220 and 192 students the test had limited power for effects of that size, so the finding is best read as no evidence of a difference, not as evidence of equivalence.

Comparison with Prior Literature

Table 10 sets the present findings beside the studies listed in Table 1, and the agreement is closest for the group comparisons. Moderate data literacy was reported for southern Nigerian students (Oguguo et al., 2020), and the moderate DL mean here is in line with it, although the instruments differ and the comparison is one of level only. Differences in data literacy among colleges, disciplines, and study areas (Chung & You, 2022; Nath & Kirby, 2022) resemble the programme differences in DDMC found here, and the rise in DDMC across year groups echoes the advantage of higher-level students in the Nigerian survey, with the same caution that cross-sectional comparisons cannot separate exposure from selection.

Table 10
Comparison of the Present Findings with Prior Studies

Study	Earlier finding	Present finding	Relation
Oguguo et al. (2020)	Moderate data literacy among students in southern Nigerian universities	DL mean of 3.35 and moderate DDMC overall	Agrees
Chung & You (2022)	Data literacy differed among colleges and disciplines	DDMC differed by programme type ($\eta^2 = .05$)	Agrees
Nath & Kirby (2022)	Data literacy scores varied by study area	DDMC differed by programme type ($\eta^2 = .05$)	Agrees
Kosim et al. (2025)	Quantitative skills and statistical mastery influenced managerial decision-making (60.8% of variance)	Overall MAE explained 36.7% of DDMC variance	Agrees in direction; predictor is analytics education, not skills, and the sample is larger
Xu et al. (2022)	Big data analytics courses improved hard and soft skills	Overall MAE predicted DDMC ($\beta = .61$)	Agrees; extends to marketing and decision-making competence

Study	Earlier finding	Present finding	Relation
Yazici (2020)	Project-based learning improved analytical skills	AL predicted DDMC (β = .37)	Agrees
Teimourzadeh et al. (2022)	Python-based teaching improved learning experience and perceived effectiveness	TP predicted DDMC (β = .39)	Agrees in direction; outcome here is competence, not perceived teaching quality
Keiper et al. (2023)	Technical support, administrative support and time shaped use of analytics technology	TP and AL had the lowest dimension means (2.99 and 2.97)	Consistent with a resource explanation, which this study did not test
Persaud (2020)	Employers often require extra training of graduates	No dimension of DDMC reached the high band	Consistent

On the main relationships, the present results agree with studies that tie analytics courses, projects, and tools to student skills (Teimourzadeh et al., 2022; Xu et al., 2022; Yazici, 2020) and extend them in two ways. The outcome is decision-making competence in a Nigerian sample, and education is split into three dimensions, which shows that the association with competence was concentrated in TP and AL. The share of variance explained here (36.7% for overall MAE) is lower than the 60.8% reported by Kosim et al. (2025), but that study used quantitative skills as the predictor, which is closer to the outcome than education is, and a census of 67 students, so the two figures are not directly comparable. The low means for TP and AL fit the resource conditions that other studies tie to the use of analytics technology in teaching (Keiper et al., 2023; Mukred et al., 2024), but the present data contain no measure of resources, and this reading remains a hypothesis. That employers often have to train graduates further (Persaud, 2020) is consistent with the finding that no DDMC dimension reached the high band.

Theoretical Implications

The concentration of the association in TP and AL is what an experiential learning perspective would lead one to expect, since both dimensions involve doing analytics rather than hearing about it (Jaggia et al., 2020; Zhang & Scribner, 2024). The weaker unique contribution of CC does not contradict the human capital view that education raises competence, but it suggests that the form of the investment matters. Content coverage without opportunities to use tools and work on realistic problems may add little to what practice-based components already provide, and this refines the broad claim that more analytics education means more competence. The conceptual framework in Figure 1 held up in the sense that its three MAE dimensions behaved differently, which supports treating them separately in future work, though a model with mediating or moderating paths would be needed to say how they interact.

Practical and Policy Implications

For curriculum designers, the findings favour building tool use and applied projects into marketing and business courses with content. Low-cost options exist, since spreadsheet skills (Bakir et al., 2025), Python-based case work (Teimourzadeh et al., 2022), and dashboard exercises (Hoang et al., 2025) have all been used in teaching, and client-based and simulated projects offer ways to provide applied learning (Anand & Mitchell, 2022; Lim & Heinrichs, 2021; Zhang & Scribner,

2024). University managers face the resource questions that earlier studies associate with analytics adoption, namely technical support, time, and administrative backing for faculty (Keiper et al., 2023) and management and financial support for analytics tools (Mukred et al., 2024). Regulators such as the National Universities Commission could consider whether minimum standards for marketing and business programmes should specify practice-based components, and whether students in other programmes, whose competence scores were lower here, should have access to introductory analytics modules; Gerhart et al. (2024) and Dingus et al. (2024) discuss how analytics provision and interest can be extended across business majors. Employers and universities could also strengthen industry linkages for applied projects, as in the industry-enriched project-based learning described by Naseer et al. (2025), which would address the extra training that employers report having to provide (Persaud, 2020).

Limitations and Future Research

Several limitations qualify these results and should be kept in view when the associations are interpreted. The design is cross-sectional, so the direction of the association between MAE and DDMC cannot be established, and students with higher competence may also seek out more practice-based activities. Both constructs were self-reported, and DDMC is therefore perceived competence rather than performance; although self-rated skills have been related to job-related performance in at least one tool (Bakir et al., 2025), performance-based assessment would give firmer evidence. Respondents came from intact classes in six universities, which limits generalisation to all Nigerian universities, and the year-of-study distribution reflects class availability. Programme and year differences in MAE exposure were not tested, and variables such as prior statistical ability were not measured.

Future studies could use longitudinal or quasi-experimental designs that follow students through analytics courses, combine self-reports with assessed tasks, sample more institutions so that institution-level effects can be modelled, and add measures of laboratory resources and staff capacity to test the resource explanation suggested by earlier work (Keiper et al., 2023). Qualitative work could also examine how students use software tools and generative artificial intelligence in analytics tasks, a development that curriculum proposals have begun to address (Sood & Pattinson, 2023).

CONCLUSION

Students in six Nigerian universities reported moderate marketing analytics education and moderate data-driven decision-making competence (RQ1), with tool-based practice and applied learning rated lowest among the education dimensions. Overall marketing analytics education positively predicted competence (RQ2, H1), and tool-based practice and applied learning were statistically significant predictors when the three dimensions were considered together, whereas curriculum content was not (RQ3, H2a not supported, H2b and H2c supported). Competence differed by year of study and by programme type but not between public and private universities (RQ4, H3a and H3b supported, H3c not supported).

The contribution of the study is an association, within a Nigerian sample, between analytics education and decision-making competence that separates what is taught from what students practise and apply. Longitudinal and performance-based studies across more institutions are needed to test whether the associations reported here reflect effects of education.

RECOMMENDATIONS

Curriculum designers in marketing and business programmes should add tool-based practice and applied projects to every analytics course instead of expanding content coverage alone, because these two dimensions had the lowest mean scores and were the only statistically significant predictors of competence in the multiple regression. Practical options include spreadsheet exercises, Python-based case work, dashboard activities, and client-based or simulated projects that give students real data and a decision to defend.

Universities should also introduce practice-based analytics early and extend it beyond the programmes that already teach it. Competence rose from 200 to 400 level, which suggests that students gain from accumulated exposure, and students in programmes other than marketing and business or computing and information systems scored lower. An introductory analytics module with a hands-on component, open to students in those other programmes, would address this difference, and short classroom activities can be used to build interest among students who tend to avoid quantitative courses.

University managers should provide the resources that practice-based teaching needs, namely software access, computer laboratory capacity, staff training and technical support. The present study did not measure resources, so this recommendation rests on the low practice scores reported here and on the resource conditions discussed earlier in the paper. Because competence did not differ between public and private universities, the same priorities apply to both types of institution.

Regulators such as the National Universities Commission should consider requiring practice-based components in the minimum standards for marketing and business programmes, and universities and employers should build industry partnerships through which students can work on real data. Employers who currently train graduates further would also benefit from such partnerships. Finally, institutions should monitor competence with performance-based tasks as well as self-ratings, and research should follow students over time to establish whether practice-based teaching raises competence.

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