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A design science approach to semantic alignment: quantifying the curriculum–market gap using NLP-driven vectorization

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ABSTRACT

The demands of modern society have increased expectations about the quality of university graduates, especially in technology-driven disciplines. Nigerian graduates appear to be struggling to meet labour-market expectations as emerging technologies continue to evolve. Graduates of Information and Communications Technology (ICT) programmes are expected to acquire employable digital skills, yet curriculum reform has not always kept pace with industry requirements. The National Universities Commission (NUC) introduced the Core Curriculum and Minimum Academic Standards (CCMAS) 70:30 policy, which permits universities to use a 30% institutional window to introduce innovative and market-responsive content. Since the policy was unveiled in 2023, however, limited use has been made of this provision. This study found that market-validated innovation was approximately 1%, far below the 30% allowance. The researchers developed a diagnostic artifact that processes curriculum learning outcomes and industry job postings through a four-stage natural language processing (NLP) pipeline comprising compound normalisation, whitelist filtering, rule-based semantic inference, and set-intersection scoring. The artifact computes a Programme Alignment Score (PAS) for each university. The study analysed learning outcomes from 150 university handbooks and 1,500 real-time ICT job postings. The results reveal statistically measurable misalignment, with a national average PAS of 28% and a legacy burden of 69%, indicating that most technical skills required by the modern workforce are absent from Nigeria's formal ICT curricula.

Keywords: Set-theoretic analysis, NUC 70:30 policy, Curriculum agility, Artificial intelligence, CCMAS.

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1. INTRODUCTION

Cloud computing, artificial intelligence (AI), and agile computing have defined the current era of digital transformation. Since 2021, the growth of the Education 4.0 approach has shifted attention toward integrating digital skills into existing modules rather than merely expanding programme content. The National Universities Commission (NUC) responded by replacing the older Benchmark Minimum Academic Standards (BMAS), under which curriculum decisions were centrally managed, with the Core Curriculum and Minimum Academic Standards (CCMAS). Under CCMAS, 70% of the curriculum remains centrally prescribed while 30% is available for university-level adaptation to institutional context and labour-market needs [1–4].

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This framework permits universities to incorporate in-demand technical skills such as cloud computing, DevOps, and data science. In practice, however, the 30% window can be underused when curriculum committees lack timely labour-market intelligence [1, 5]. Figure 1 illustrates the contrast between the old centrally controlled curriculum model and the new CCMAS autonomy window.

1.1. STATEMENT OF THE PROBLEM

Nigerian universities appear to be struggling to align teaching with industry needs. This is not only because no effort has been made to address the challenge, but also because real-time labour-market data have not consistently influenced classroom content. The curriculum review cycle can create a time lag in which students become exposed to obsolete knowledge before they graduate. Comparing job-market skill demand with curriculum learning outcomes can provide faster and more reliable evidence for reform.

Four challenges motivate this study. First, the NUC has provided the CCMAS 70:30 policy, but universities may not be using the 30% autonomy window to add high-demand digital skills [1, 5]. Second, many education administrators still rely on opinion-based assurance mechanisms even though labour-market data can be processed through dashboards and NLP pipelines to provide operational, strategic, and tactical information for decision-making [6]. Third, a theory–practice inversion persists: universities often emphasise theory and critical thinking while employers increasingly require hands-on technical skills. This curriculum–skill gap has been observed across multiple fields [7, 8]. Fourth, the slow four- to five-year curriculum review cycle is poorly matched to the speed of technological change. Continuous computational auditing is therefore needed as a data-driven complement to periodic manual review [9].

1.2. RESEARCH GAPS

Three critical gaps currently affect curriculum-performance measurement. The first is methodological. Manual peer review every four to five years may not align with dynamic labour-market conditions, and there are no widely deployed computational tools that can audit all approved universities and provide real-time decision reports. The second is semantic. Course-title keyword matching is insufficient because a course may appear compliant while teaching outdated technologies. A curriculum that mentions web development, for example, may not teach current JavaScript frameworks such as React or Angular. The third is contextual. There is limited verified evidence on whether the 30% CCMAS provision is being used for market-driven innovation or whether curricula remain dominated by theory-heavy content [9].

1.3. AIM AND OBJECTIVES

This study aimed to design and evaluate a Python-based diagnostic application, complemented by AI and NLP methods, that compares two datasets: industry data on technology job requirements and academic data on the learning outcomes taught in related programmes. The artifact uses set-theoretic metrics to calculate curriculum agility and semantic alignment between academic supply and industry demand [10].

The diagnostic core treats curriculum data as the set S_c and market demand data as the set S_m. The application assesses whether concepts match in meaning rather than merely matching surface keywords. It uses semantic inference to compare curriculum learning outcomes with job descriptions, assesses the curriculum gap, and provides evidence on whether universities are using the 30% CCMAS autonomy window [11]. A predictive stage then uses multiple linear regression to examine whether university ownership, institution type, and geopolitical region predict PAS performance. These categories help decision-makers identify universities that are critically disconnected, partially aligned, or industry aligned.

2. MATERIALS AND METHODS

2.1. DESIGN SCIENCE RESEARCH IN INFORMATION SYSTEMS

This study was guided by design science research (DSR) in information systems. DSR provides principles for developing and evaluating artifacts that solve complex organisational problems [10]. The framework supported the development of a diagnostic application intended to help administrators identify curriculum gaps and areas requiring upgrade. The methodology follows a hierarchical logic and uses an agile backward-design perspective in which curriculum planning begins with desired industry outcomes rather than only with internal academic assumptions [12, 13].

2.2. THEORETICAL FRAMEWORK AND FLAGSHIP FORMULAS

The study developed set-theoretic diagnostic metrics to identify and quantify the gap between academic learning outcomes and changing industry requirements. The Programme Alignment Score (PAS) is a percentage measure that moves curriculum review from subjective judgement to a comparable quantitative indicator. PAS is related to, but intentionally distinct from, Jaccard similarity and the overlap coefficient:

$$J = \frac{|S_c \cap S_m|}{|S_c \cup S_m|}, \tag{1}$$

$$OC = \frac{|S_c \cap S_m|}{\min(|S_c|, |S_m|)}, \tag{2}$$

$$PAS = \frac{|S_c \cap S_m|}{|S_m|}. \tag{3}$$

Jaccard similarity penalises both missing market skills and excess curriculum content, while the overlap coefficient normalises by the smaller set and may reward a small but well-targeted curriculum. PAS normalises by the market-demand set, answering the policy question: what proportion of current market demand does a curriculum address?

For a university u, PAS is defined as:

$$PAS = \frac{|S_c \cap S_m|}{|S_m|} \times 100. \tag{4}$$

Here, S_c is the set of unique curriculum skill tokens extracted from learning outcomes after whitelist filtering and semantic normalisation, S_m is the universal set of high-demand market skill tokens derived from 1,500 ICT job postings, $|S_c \cap S_m|$ is the number of skills appearing in both sets, and $|S_m|$ is the market-demand denominator. PAS ranges from 0 to 100, where 100 indicates full alignment.

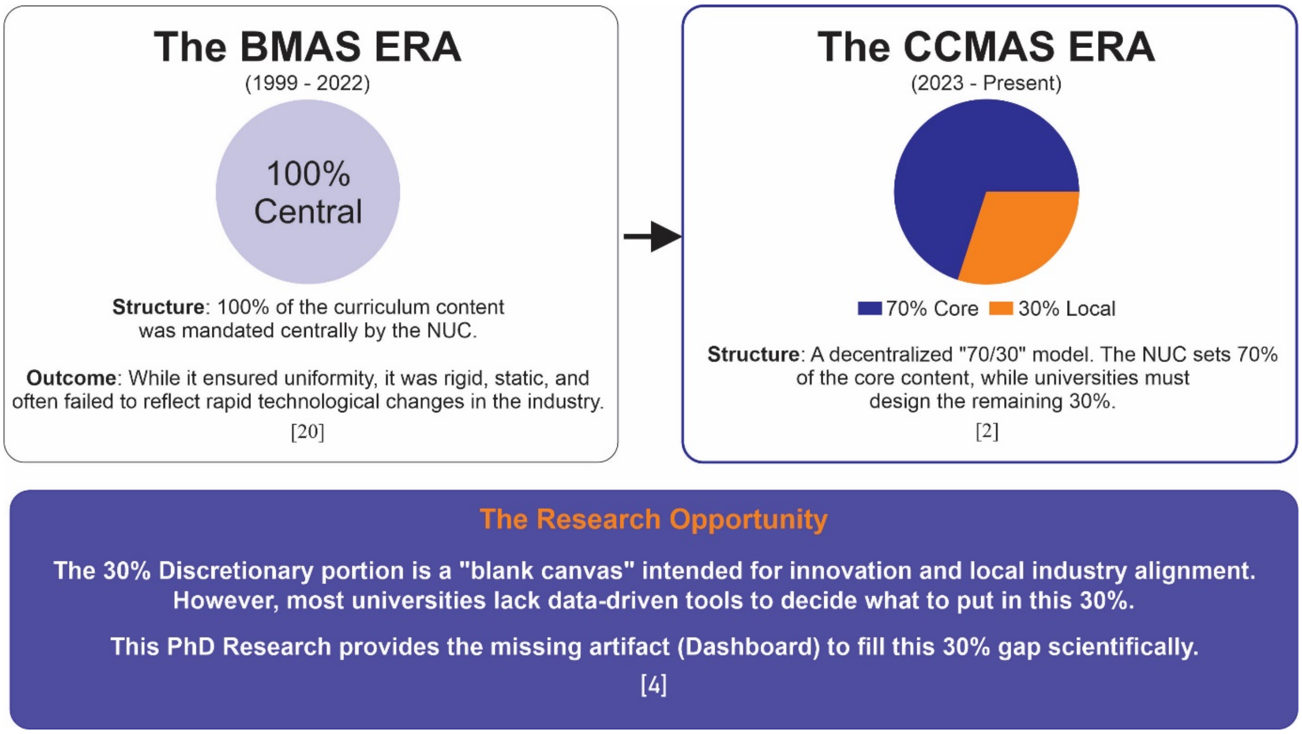

Figure 1. Old policy versus new policy: the NUC CCMAS 30% window.

Table 1. Seven ICT programmes mandated by the NUC's new CCMAS policy.

S/N	Programme	Degree in view
1	Computer Science	B.Sc.
2	Cybersecurity	B.Sc.
3	Data Science	B.Sc.
4	Information and Communication Technology	B.Sc.
5	Information Systems	B.Sc.
6	Information Technology	B.Sc.
7	Software Engineering	B.Sc.

Table 2. Alignment classification score for selected universities.

Classification	PAS range	Interpretation
Critical disconnect	PAS $< 40\%$	Severe misalignment; urgent reform required
Moderate alignment	$40\% \leq$ PAS $< 70\%$	Partial alignment; targeted improvement needed
Industry aligned	PAS $\geq 70\%$	Strong market alignment; maintain adaptively

Table 3. Stratified sample distribution by university ownership ($N = 301$ population; $n = 150$ sample).

Stratum	Population (N)	Sample (n)	Sampling (%)	Method
Federal	47	24	51	Proportionate stratified random
State	67	34	51	Proportionate stratified random
Private	187	92	49	Proportionate stratified random
Total	301	150	50	Stratified random

Gap analysis, also referred to as the critical deficit, is the complement of PAS. It measures skills demanded by the market but absent from the curriculum:

$$Market\ Gap = \frac{|S_m - S_c|}{|S_m|} \times 100. \tag{5}$$

By definition, PAS plus market gap equals 100%. Legacy burden is the obsolescence metric. It measures the proportion of curriculum content outside market demand:

$$Legacy = \frac{|S_c - S_m|}{|S_c|} \times 100. \tag{6}$$

This metric quantifies curriculum obsolescence as a proportion of the university's own taught content and provides an internal

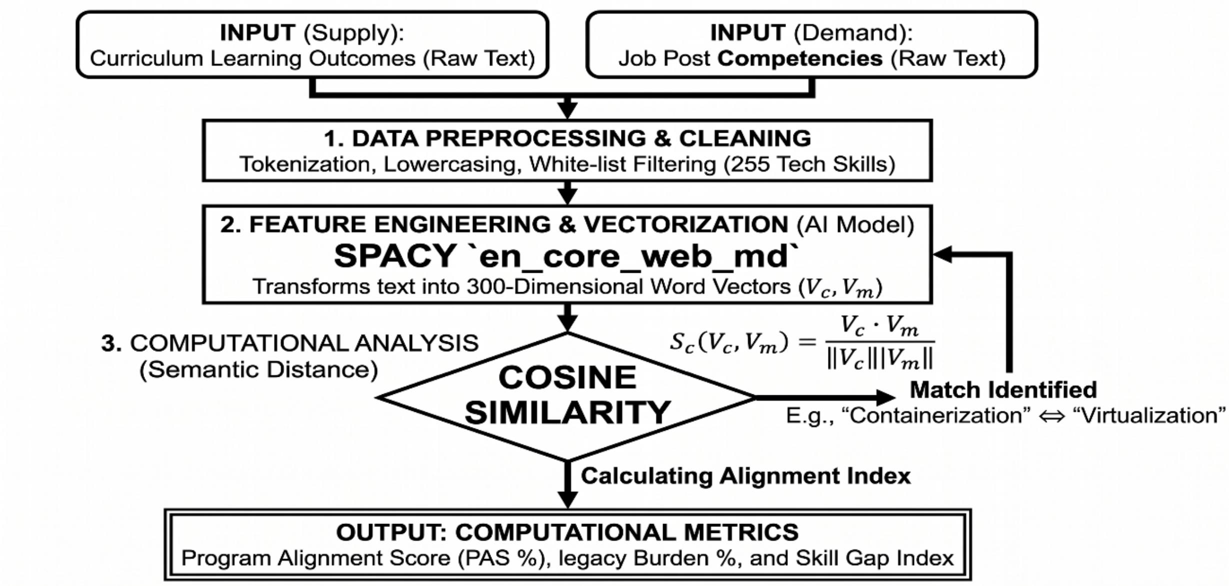

Figure 2. Semantic inference engine and similarity logic.

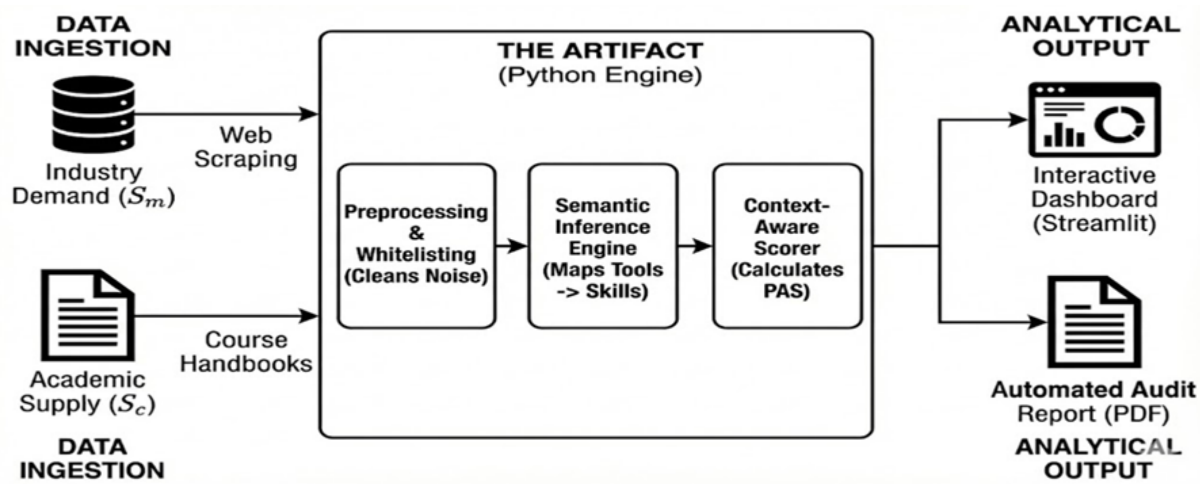

Figure 3. Logical architecture of the curriculum diagnostic artifact, showing data flow from ingestion through the semantic inference engine to diagnostic outputs.

Table 4. System health by university type.

University type	Sample size	Avg. PAS	Health status	Strategic insight
Science & Tech	35	38%	Critical	Highest technical baseline, yet struggles with cloud and DevOps gaps
Petroleum	2	34%	Critical	High alignment in legacy industrial ICT; low alignment in modern data science
Conventional	68	26%	Critical	Burdened by broad theoretical benchmarks and slow CCMAS implementation
ODL	3	24%	Critical	Scalability focus often leads to standardised and lagging curriculum content
Maritime	2	22%	Critical	Significant disconnect in maritime informatics and AI
Armed forces	2	21%	Critical	Rigid review cycles; cybersecurity modules are largely theoretical
Agriculture	15	19%	Critical	Critical lack of agri-tech and IoT data analytics in ICT modules
Medical	12	18%	Critical	ICT courses focus on basic literacy rather than health informatics
Education	11	15%	Critical	Lowest alignment; pedagogical ICT is detached from industry technology stacks

efficiency benchmark.

2.3. DATA SCIENCE, AI, AND CONTINUOUS CURRICULUM GOVERNANCE

A data-driven approach to curriculum governance can support Nigerian institutions in producing graduates who are job ready

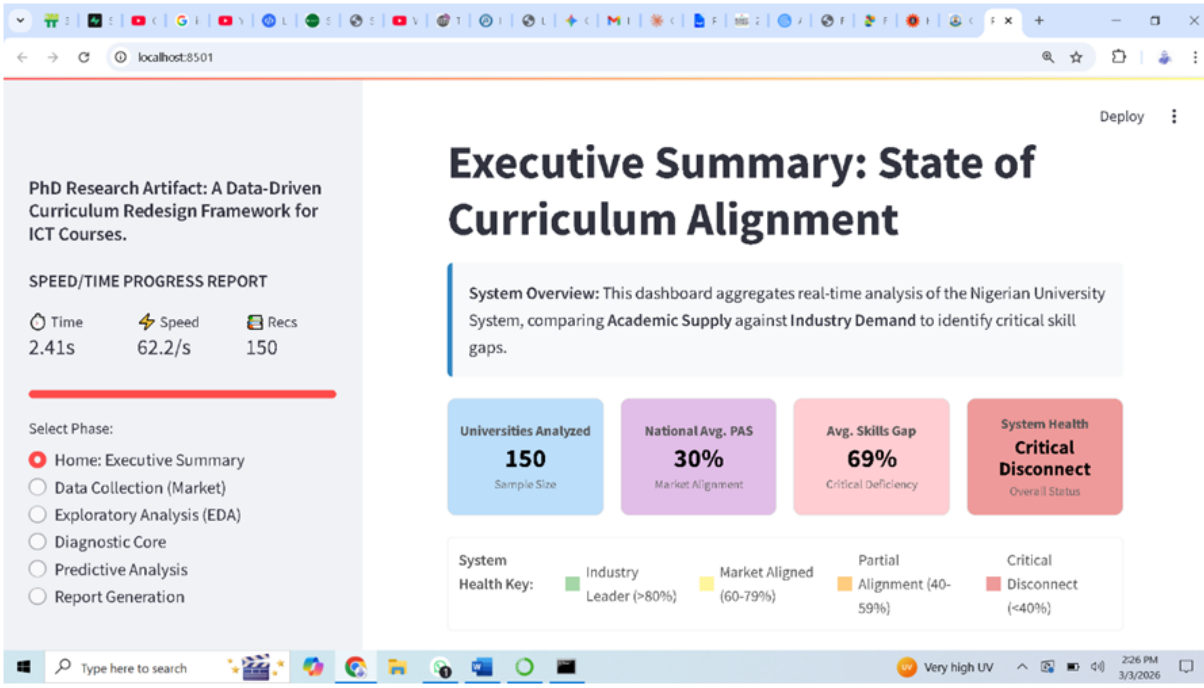

Figure 4. Decision-support system executive dashboard displaying system-wide alignment metrics and critical skill deficits for $N = 150$ universities.

Table 5. System health by university ownership.

Ownership	Avg. PAS	Correlation (r)	Health status	Key finding
Federal	18%	−0.31	Critical	Most rigid structures; highest legacy burden
State	21%	−0.28	Critical	Funding and infrastructure gaps hinder innovation
Private	43%	−0.12	At risk	More effective use of the 30% autonomy window than public peers

Table 6. System health by geopolitical zone.

Geopolitical zone	Sample size	Avg. PAS	Health status	Status narrative
South West	40	36%	Critical	Highest density of technology hubs, yet academia remains behind market demand
South South	25	29%	Critical	Disconnect in oil- and gas-related ICT competencies
North Central (FCT)	30	31%	Critical	Proximity to policy institutions has not yet yielded market agility
South East	20	27%	Critical	Strong entrepreneurial drive but low curriculum formalisation
North West	20	22%	Critical	Significant gap in emerging technology coverage
North East	15	19%	Critical	Critical infrastructure and curriculum decay observed

Table 7. Top 10 high-demand skills and academic coverage gaps.

Rank	Technical competency	Industry demand (%)	Academic coverage (%)	Coverage gap (%)	Severity level
1	Cloud computing	88	6	−82	Critical
2	DevOps and CI/CD pipelines	74	2	−72	Critical
3	AI and machine learning	71	14	−57	Significant
4	Cybersecurity operations	69	18	−51	Significant
5	Data engineering	60	12	−48	Significant
6	UI/UX design	52	8	−44	Significant
7	Agile/Scrum methodology	48	5	−43	Moderate
8	Full-stack development	65	24	−41	Moderate
9	Blockchain/Web3	35	1	−34	Emerging
10	Mobile app development	58	30	−28	Moderate

[4, 14]. Manual methods and periodic quality assurance are insufficient in a rapidly evolving technology environment. Data pipelines and AI can support data-driven decision-support systems and a continuous diagnostic lifecycle in which curriculum

Table 8. Multiple linear regression of PAS score on university ownership, type, and geopolitical zone ($N = 150$).

Predictor	B	SE	t	p	95% CI
Intercept	+17.717	1.693	+10.467	$< .001^{***}$	[14.37, 21.06]
State (vs Federal)	+4.176	1.514	+2.758	$.007^{**}$	[+1.18, +7.17]
Private (vs Federal)	+9.506	1.359	+6.997	$< .001^{***}$	[+6.82, +12.19]
North West (vs NE)	+1.717	1.921	+0.894	.373	[−2.08, +5.52]
North Central (vs NE)	+0.438	1.845	+0.238	.813	[−3.21, +4.09]
South South (vs NE)	+2.982	1.801	+1.656	.100	[−0.58, +6.54]
South East (vs NE)	+2.488	1.914	+1.299	.196	[−1.30, +6.27]
South West (vs NE)	+4.963	1.924	+2.580	$.011^{*}$	[+1.16, +8.77]
Science & Technology (vs Conventional)	+6.152	1.467	+4.193	$< .001^{***}$	[+3.25, +9.05]

Table 9. Aggregate alignment metrics.

Metric	Measured value	Interpretation
National average PAS	28%	Severe misalignment
Market-validated innovation	1%	Underused curriculum autonomy
Legacy content proportion	69%	High curriculum obsolescence
Alignment correlation (r)	−0.26	Inverse alignment trend

governance is informed by labour-market intelligence rather than subjective or delayed evidence [15–17].

2.4. CONCEPTUAL FRAMEWORK

The study extends external alignment by beginning from industry demand data and using that external dataset to evaluate what should be taught within universities. This approach avoids solving the problem only from within academia and allows the NUC and universities to assess both CCMAS compliance and the degree to which the 30% window is being used for market-responsive curriculum additions [11, 18].

2.5. DATA COLLECTION

The study used a hybrid intelligence acquisition approach. Academic supply data consisted of learning outcomes extracted from handbooks for ICT-related programmes. From 301 accredited and operational Nigerian universities, 150 were selected using proportionate stratified random sampling across ownership categories, institution types, and geopolitical zones. The sample represented approximately 50% of the university population. Academic handbook data were collected between January and December 2025 through official institutional websites and the NUC accreditation database. Handbooks unavailable online were excluded ($n = 12$) and replaced by randomly selected universities from the same ownership–zone stratum.

Industry demand data consisted of 1,500 high-demand ICT job postings collected between February and December 2025 from LinkedIn, JobberMan, MyJobMag, and Job Mag. The postings covered the seven NUC-approved ICT programme areas. Duplicate postings with the same employer, title, and collection week were removed before loading, and the artifact enforced a 1,500-record cap for reproducibility. All academic data were drawn from publicly available university handbooks, and job postings were collected from publicly accessible recruitment platforms. No personal student or staff data were processed, and the study did not involve human participants.

2.6. THE THREE-PHASE DATA-DRIVEN PIPELINE

The software artifact was designed to collect curriculum learning outcomes as academic supply data and ICT job postings as industry demand data. The diagnostic core uses an NLP semantic inference engine to compare both datasets and measure alignment.

The exploratory data analysis phase cleaned the data before counting. Skills were scored based on their frequency and relevance in the job market. Disorganised text was structured and tokenised before further analysis. The diagnostic core then processed curriculum and market text through a four-stage NLP pipeline. Stage 1 applied compound-term normalisation using a 70-entry dictionary that converts multi-word technical expressions into atomic tokens. Stage 2 applied whitelist filtering using a curated 255-term ICT skills whitelist based on WEF Future of Jobs seed terms, high-frequency job-posting terms, and current industry certification frameworks. Stage 3 applied semantic inference and ontology mapping using 15 vendor-to-parent competency mappings and a second taxonomy layer of 12 parent categories and 87 child terms. Stage 4 computed PAS as the set-intersection ratio between the semantically expanded curriculum token set $\widetilde{S}_c$ and the market-demand set S_m.

The predictive phase implemented multiple linear regression. Ownership, institution type, and geopolitical region were used as independent variables, while PAS was the dependent variable. This model was used to explore whether structural university characteristics affected market-alignment performance.

3. RESULTS AND DISCUSSION

3.1. APPLICATION SOFTWARE ARTIFACT

The artifact was developed in Python using the Anaconda environment and open-source libraries including Streamlit, Pandas, NumPy, and spaCy. The architecture is a modular data pipeline with three layers: data ingestion, computational logic, and analytical output [6, 14]. At the data-ingestion layer, labour-market data and academic data were collected in CSV format. The academic dataset also included a dedicated NUC_CCMAS_CORE baseline record encoding the skill vocabulary of the seven mandated CCMAS programme areas. Each university's unique curriculum content was defined as $\widetilde{S}_c(u) - S_{NUC}$, enabling the innovation index to isolate autonomous curriculum additions beyond compliance with the central NUC baseline.

The computational logic layer consisted of a curated whitelist filter, a semantic inference engine, and a context-aware scorer. The semantic inference engine reconciled vendor-specific technologies such as TensorFlow to parent competencies such as artificial intelligence and data science. It also mapped terms such as Docker and Kubernetes to cloud-computing and DevOps competencies. Validation against a keyword-exact baseline used a random subsample of 30 universities and 49 market-skill categories, yielding 1,470 skill–university pairs. The keyword baseline achieved a precision of 1.000, recall of 0.938, and F1-score of 0.968 against the semantic inference output. The semantic inference engine identified 22 additional alignment cases, representing a +6.6% improvement in skill detection. This confirmed that semantic expansion reduced false negatives that would otherwise suppress PAS scores.

The analytical-output layer used Streamlit to produce an executive dashboard where PAS, national average PAS, legacy burden, and critical deficits can be viewed and downloaded for administrative decision-making.

3.2. SYSTEM-WIDE ALIGNMENT ANALYSIS

The study assessed 150 universities from the 301 universities approved by the NUC, representing approximately 50% of operational universities in Nigeria. The universities were categorised by ownership, type, and geopolitical region. The national average PAS was 28%, which falls within the critical-disconnect range. Tables 4–6 show that critical alignment challenges occur across ownership models, institution types, and regions.

Private universities scored higher than federal and state universities, with an average PAS of 43% compared with 18% for federal universities and 21% for state universities. Science and technology universities performed best among institution types, although their average PAS of 38% remained within the critical category. By region, the South West had the highest average PAS at 36%, but this still indicated substantial misalignment.

3.3. EXPLORATORY DATA ANALYSIS OF THE LABOUR MARKET

The analysis of handbooks and ICT course outlines showed that the academic sector continues to emphasise legacy programming courses and theoretical frameworks focused on computer fundamentals and hardware. The diagnostic core indicates the need to move from theory-heavy curricula toward applied technical skill sets. Labour-market demand has shifted toward cloud computing, DevOps, cybersecurity operations, full-stack development, data engineering, UI/UX design, mobile development, and AI-enabled workflows.

3.4. QUANTITATIVE GAP ANALYSIS

Pearson's product–moment correlation coefficient was used to measure the relationship between market-demand frequency and academic-supply frequency across the top 10 demanded ICT skill categories. The result was $r(8) = -0.26$, $p = 0.468$, 95% CI $[-0.76, +0.44]$, indicating a weak, non-significant negative association at the skill-category level. Given the small number of skill pairs, this result is exploratory and directional; the primary evidence of misalignment is the set-intersection PAS result.

Multiple linear regression with PAS as the dependent variable and university ownership, geopolitical zone, and institution type as predictors was statistically significant: $F(8, 141) = 17.378$, $p < 0.001$, $R^2 = 0.497$, adjusted $R^2 = 0.468$, $N = 150$. Private universities scored 9.5 percentage points higher than federal universities ($B = +9.506$, $p < 0.001$), which was the strongest ownership effect. Science and technology universities outperformed conventional universities by 6.2 points ($B = +6.152$, $p < 0.001$). Geographically, only South West universities showed a statistically significant advantage over the North East ($B = +4.963$, $p = 0.011$).

3.5. INTERPRETING THE NATIONAL ALIGNMENT AVERAGE

The national average PAS of 28% indicates that approximately three-quarters of the technical skills required by the modern workforce are absent from formal ICT curricula. The national legacy burden of 69% and market-validated innovation of approximately 1% suggest substantial curriculum stagnation. Although the NUC created policy space for market-responsive innovation through the CCMAS 30% autonomy window, sampled universities have not yet used it meaningfully.

3.6. ADDRESSING LEGACY BURDEN AND THE 30% AUTONOMY STRATEGY

The results suggest that many ICT curricula retain outdated content instead of using labour-market intelligence to decide what should be taught. If Nigeria is to support Sustainable Development Goals 4, 8, and 9, curriculum design needs to shift from forward design, where learning outcomes are defined independently of labour-market demand, to agile backward design, where labour-market intelligence informs classroom content. Table 9 shows that only about 1% of sampled universities had introduced market-validated innovative modules beyond the NUC baseline.

3.7. LIMITATIONS

This study has five limitations. First, the sample covered 150 of 301 Nigerian universities, which is substantial but may under-represent recently established institutions. Second, job-posting data from online recruitment platforms may over-represent formal-sector and urban employment and under-represent informal ICT roles in northern Nigeria. Third, the rule-based semantic inference engine used 15 fixed vendor-to-parent mappings and 12 taxonomy categories; skills outside this coverage were scored only through exact whitelist matching. Fourth, PAS measures semantic overlap between curriculum learning outcomes and job descriptions but does not directly measure graduate employment outcomes. Fifth, the cross-sectional design limits causal inference. Longitudinal studies that track PAS scores against graduate employment outcomes would strengthen the policy implications.

4. CONCLUSION

This study demonstrates that computational logic and algorithms can automate large-scale curriculum diagnostic profiling. The artifact provides a scalable method for integrating labour-market intelligence into curriculum reform. It also supports Sustainable

Development Goals 4, 8, and 9 by encouraging universities to develop human capital aligned with digital infrastructure and economic growth.

The temporal misalignment between curriculum review cycles and technological change can be addressed by aggregating and processing two real-time data sources: academic supply data and industry demand data. Three recommendations follow. First, regulatory agencies such as the NUC should use real-time dashboards rather than waiting for five-year curriculum cycles. Such dashboards can monitor both the 70% CCMAS baseline and the 30% innovation window. Second, faculty upskilling and retooling should be prioritised so staff can teach high-demand competencies such as DevOps, cloud computing, data engineering, AI, and cybersecurity operations. Third, predictive simulators should be integrated into executive dashboards to help university senates model the likely effects of adding specific modules, such as UI/UX design or cloud computing, on graduate employability.

DATA AVAILABILITY

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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