Evaluating LLMs for Career Guidance: Comparative Analysis of Computing Competency Recommendations Across Ten African Countries

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Abstract

Employers increasingly expect graduates to utilize large language models (LLMs) in the workplace, yet the competencies needed for computing roles across Africa remain unclear given varying national contexts. This study examined how six LLMs, namely ChatGPT 4, DeepSeek, Gemini, Claude 3.5, Llama 3, and Mistral AI, describe entry-level computing career expectations across ten African countries. Using the Computing Curricula 2020 framework and drawing on Digital Colonialism Theory and Ubuntu Philosophy, we analyzed 60 LLM responses to standardized prompts.

Technical skills such as cloud computing and programming appeared consistently, but notable differences emerged in how models addressed non-technical competencies, particularly ethics and responsible AI use. Models varied considerably in recognizing country-specific factors, including local technology ecosystems, language requirements, and national policies. Open-source models demonstrated stronger contextual awareness and a better balance between technical and professional skills, earning top scores in nine of ten countries. Still, all models struggled with cultural sensitivity and infrastructure considerations, averaging only 35.4% contextual awareness. This first broad comparison of LLM career guidance for African computing students uncovers entrenched infrastructure assumptions and Western-centric biases, creating gaps between technical recommendations and local needs. The strong performance of cost-effective open-source models (Llama: 4.47/5; DeepSeek: 4.25/5) compared to proprietary alternatives (ChatGPT 4: 3.90/5; Claude: 3.46/5) challenges assumptions about AI tool quality in resource-constrained settings. Our findings highlight how computing competency requirements vary widely across Africa and underscore the need for decolonial approaches to AI in education that emphasize contextual relevance

Keywords: Large Language Models; Career Guidance; Computing Education; African Higher Education; Competency Frameworks; Educational Technology; Digital Colonialism; Ubuntu Philosophy; AI Contextual Adaptation

1. Introduction

Artificial intelligence and education have converged at a pivotal moment both globally and across Africa, creating substantial changes in how learning and career development unfold. Large Language Models (LLMs), a subset of generative AI systems that use machine learning to produce human-like responses from massive training datasets, are becoming more common, especially where students have limited access to professional academic guidance (Brachman et al., 2025). Students and recent graduates now turn to these conversational AI tools for help with coursework, career planning, job applications, and skill development (Akiba & Fraboni, 2023; Chang et al., 2024). This shift is especially pronounced in computing education, where competencies are defined as the integrated combination of skills, knowledge, and professional dispositions required for effective workplace performance. The *Computing Curricula 2020* framework, developed by the Association for Computing Machinery, the Institute of Electrical and Electronics Engineers, and other partners, provides a globally recognized standard for these competencies (Clear et al., 2020). These competencies now encompass both traditional technical abilities and emerging areas such as AI literacy, thus shaping employers' expectations for computing graduates in relation to these skills (Murire, 2024; World Economic Forum, 2023). Recent evidence reveals growing adoption of AI across Africa with findings from the 2024 Stanford AI index showing that 27% of Kenyans use ChatGPT daily, coming third globally behind India and Pakistan with the number of users expected to double in the coming years (Stanford AI Index, 2024), while the African Union Executive Council endorsed the Continental AI Strategy during its 45th Ordinary Session in July 2024, underscoring Africa's commitment to an Africa-centric, development-focused approach to AI (African Union, 2024). Additionally, while LLMs seem promising for education and career guidance, concerns persist about whether they can reliably offer career advice that matches the actual conditions facing African computing graduates (Ade-Ibijola & Okonkwo, 2023; Hamouda et al., 2025).

Computing education research supports these concerns regarding LLMs' reliability for contextually relevant guidance. Lunn et al. (2022) noted that securing and thriving in a computing role requires more than technical skills alone; it demands the development of a professional identity, gaining industry recognition, and learning to navigate the social and institutional relationships that define particular computing industries and ecosystems. This has far-reaching implications for Africa, where countries like Nigeria, Kenya, and South Africa have become key players in the continent's growing technology sector, attracting increased attention from global investors (African Union, 2024). African job market projections reveal that the continent will have the largest working-age population by 2040 (McKinsey Global Institute, 2023), and surveys indicate that many African youth extensively engage with AI tools for learning and job preparation (Ajalo et al., 2025). While the African Union has highlighted AI's role in refining workforce skills and driving its development (African Union, 2024; United Nations, 2024), there remains limited consensus on the exact mix of technical and non-technical competencies that computing graduates need to thrive. This uncertainty reinforces the need to critically assess how well LLM-generated advice aligns with Africa's distinct educational and workforce requirements.

Early studies have shown AI's potential in career planning for students entering the workforce (Westman et al., 2021), but there is limited research on how LLMs work for computing graduates in African contexts. Current empirical studies on computing education in Africa repeatedly point to the need for learning that fits individual student needs and bridges skill gaps in curricula (Hamouda et al., 2025). Ade-Ibijola and Okonkwo (2023) argued that despite the increased adoption of AI-driven education in Africa, many graduates still struggle to transition into the workforce due to a misfit between the skills acquired through formal education and employer demands. This disconnect, along with concerns regarding LLMs' contextual relevance, calls for a thorough evaluation on how African computing students leverage their responses for career guidance.

1.1 Research Objectives

In recognition that our understanding of career guidance through LLM-generated responses may be limited, particularly with regard to specific contexts, this study looked at how six LLMs respond to questions about entry-level skills and competencies that computing graduates need across ten African countries. As LLMs become more common in educational and professional environments, computing graduates now need to use these tools effectively and understand the ethical problems and limitations that come with using them at work (Baidoo-Anu & Owusu Ansah, 2023; Brachman et al., 2025). A recent study looking at the perception of African students and graduates towards AI-driven career guidance found that participants were receptive to AI tools and considered them valuable in filling the gaps in traditional career guidance, with identical perception across genders regarding the efficacy of these tools (Eze et al., 2025). These findings point to an evolving skill set that is becoming crucial for African computing graduates to stay competitive in a rapidly changing job market.

To achieve our research objectives, ten African countries were selected based on the Oxford Insights Government AI Readiness Index (2024), ensuring representation across diverse linguistic, cultural, and economic contexts. The countries examined were Egypt, South Africa, Tunisia, Morocco, Nigeria, Senegal, Kenya, Benin, Ghana, and Zambia. While Mauritius and Rwanda ranked higher than some selected countries, they were inadvertently omitted during initial geographic mapping; however, the final sample still captures meaningful diversity across Anglophone, Francophone, and Arabophone contexts while representing various AI readiness levels. Each selected country ranks among the higher tiers of AI readiness in Africa, indicating baseline capacity for AI integration in educational settings while still reflecting a broad spectrum of local contexts and challenges.

Accordingly, the study addresses the following research questions (RQs):

RQ1: What are the similarities in how LLMs describe technical and non-technical computing competencies associated with LLM use across the selected countries?

RQ2: What are the differences in how LLMs describe technical and non-technical computing competencies associated with LLM use across ten selected countries?

In evaluating LLM performance, this study examines three dimensions: technical coverage refers to the breadth and depth of computing competencies addressed relative to the CC2020 framework (Clear et al., 2020); contextual awareness measures the incorporation of local industry references, language considerations, national policies, institutional factors etc; and overall relevance assesses the integration of technical coverage, contextual awareness, balance between technical and non-technical skills and the depth of LLM response. Consequently, the third research question is:

RQ3: How do different LLMs compare in their technical coverage, contextual awareness, and overall relevance of career guidance for these contexts?

To address these questions, we employ a comparative methodology that applies the Computing Curricula 2020 as an analytical lens for evaluating LLM-generated career guidance, an approach not previously undertaken in computing education research. While prior studies have examined LLMs in educational contexts (Prather et al., 2023), none have evaluated how different models conceptualize computing competencies across diverse African settings or assessed their contextual awareness against established competency frameworks. This multi-dimensional analysis enables identification of both universal patterns and context-specific variations in AI-generated guidance, offering implications for educators and policymakers navigating AI integration across various contexts. The paper proceeds as follows: Section 2 reviews relevant literature on LLMs in education and African computing contexts; Section 3 presents our theoretical and analytical frameworks; Section 4 details the methodology; Section 5 reports findings across technical, contextual, and comparative dimensions; Section 6 discusses theoretical and practical implications; Section 7 addresses limitations; Section 8 explores future research directions; and Section 9 concludes.

2. Literature Review

The following review establishes the foundation for understanding how LLMs function as career guidance tools and their implications for African computing education. We look at how LLMs have developed in educational settings to show their growing influence on career preparation, examine the particular challenges and opportunities that define AI adoption across African computing education, and identify theoretical perspectives that help explain the tensions between globally-developed AI systems and local educational realities.

2.1 LLMs in Educational and Career Guidance Contexts

AI in education has developed quickly, especially since transformer-based language models emerged and Vaswani et al. (2017) introduced the attention mechanism, which allowed current AI models to process and generate contextually relevant text, leading to more advanced applications of AI tools in education. Drawing on existing literature review, Wang et al. (2024) identified five key areas where LLMs are being applied in education namely: tutoring, grading, content creation, language learning, and career guidance, while Prather et al. (2023) argues that within computing education specifically, these tools are reshaping fundamental pedagogical practices, requiring educators to navigate unprecedented challenges around academic integrity, assessment validity, and skill development. Generative AI is becoming more popular in career guidance: Waikar et al. (2024) showed how the Gemini Pro API can create detailed career roadmaps for students based on their interest and competencies, providing specific advice about competitive exams, college choices, and expected career paths in technical fields. Duan and Wu (2024) argue that generative AI technologies, especially through natural language processing and machine learning, can move vocational education away from traditional "one-size-fits-all" career guidance toward more personalized, flexible approaches that adjust to individual learning styles and evolving job market needs. Given this context, AI-driven career guidance has attracted considerable attention, leading researchers and educators to look at how AI tools like LLMs can improve learning and career development in different educational settings.

Educational institutions and researchers have started building specialized AI platforms that turn these capabilities into practical career support systems. Rahman et al. (2023) explored how AI tools can boost graduate employability by testing ResumeAI, an AI-based platform that helps users improve their résumés for specific job requirements. The findings showed that through AI algorithms, the platform could identify what skills graduates needed for particular roles and adjust their résumés to match what employers demand, enabling them to stand out in competitive job markets. Similarly, Dewasurendra et al. (2024) built an AI-powered platform for Sri Lankan university students that uses Graph Neural Networks for course recommendations and Recurrent Neural Networks for career guidance, reaching 81.88% accuracy in creating personalized career pathways that matched students' academic backgrounds. In a study evaluating gamified AI use among grade 7 to 9 students, Brandenburger and Janneck (2023) found that combining interactive AI, role-play, and real-world data in a game-like system can improve how students think about their career development. Using interactive visuals and task-based challenges made students more interested and involved, getting them to think more actively about their future careers compared to traditional approaches that focused mainly on rewards and results. Together, these studies show that AI-driven career guidance systems, whether through résumé optimization, personalized pathway recommendations, or gamified interactions, represent a major shift from generic, one-size-fits-all counseling to flexible, data-driven support that adjusts to individual student needs and learning preferences.

Additionally, a growing number of studies are beginning to challenge how we think about generative AI tools in career guidance (Zheng et al., 2023; Bhattacharjee et al., 2024; World Economic Forum, 2023). Rather than viewing them simply as tools for delivering information, these studies explore their potential to support more personalized, responsive, and context-aware guidance for learners and job seekers. AI models can function not just as coaches but also as collaborators to help students throughout their academic experience by providing tailored advice for course selection, finding relevant professional development opportunities, and adjusting guidance based on individual learning needs and career aspirations (Westman et al., 2021). LLMs have proven to be useful in academic advising, providing detailed responses to career-related questions and guidance on educational pathways. They can handle complex, open-ended questions in a convincing and supportive manner, making information easier to understand for students across various contexts (Akiba & Fraboni, 2023). However, scholars have argued that despite the efficacy of these AI systems to improve decision-making, they should not replace human advisers, who can better understand the complex emotional, social, and contextual factors that affect students, but rather function as a decision support tool (Leung, 2022; Sampson & Osborn, 2015).

Despite the potential of generative AI in supporting career guidance, many studies have also highlighted its capacity to reproduce biases embedded within its training datasets, potentially misleading job seekers who may accept its output without understanding its limitations or knowing which recommendations require detailed scrutiny. LLMs have also been connected to cultural bias, as they often create responses that reflect Western norms and values while underrepresenting or ignoring locally relevant perspectives, especially in the African context (Ade-Ibijola & Okonkwo, 2023). In some instances, LLMs have been reported to provide advice that ignores the experiences of certain gender and minority groups, actually reinforcing the structural inequalities they are supposed to address (Ade-Ibijola & Okonkwo, 2023; Kotek et al., 2023). Consequently, the integration of AI and specifically LLMs in career guidance requires close oversight and sustained human involvement to ensure that its recommendations are both accurate and reflective of the local contexts in which they are applied.

2.2 AI Adoption and Computing Education in African Contexts

The rapid evolution of AI has been met with a varying degree of readiness for its adoption across contexts, with many African institutions held back by infrastructure and policy barriers that slow effective adoption (Eke et al., 2023). The United Nations (2024) has pointed to a growing "AI divide," where wealthier economies get most of the benefits from AI progress, while emerging regions, particularly in Africa, struggle to keep up. This gap is evident in the 2024 Oxford Insights Government AI Readiness Index, which ranks Sub-Saharan Africa as the lowest-scoring region with an average readiness score of 32.70, though Data and Infrastructure was identified as its strongest area with a score of 42.06 (Oxford Insights, 2024). Egypt, Mauritius, South Africa, and Rwanda led Africa with scores slightly above 50, while countries like Senegal, Nigeria, Kenya, and Ghana also showed evidence of steady growth in AI readiness and capacity. Despite these relatively low rankings, AI's adoption is steadily expanding across the continent, with visible applications in financial technology (fintech) and healthcare (Eke et al., 2023). Recent developments include the use of AI-driven fraud detection and credit scoring systems in Nigeria's fintech industry, machine learning tools supporting early disease diagnosis in countries such as Rwanda and Ghana, drone-based precision agriculture projects in Kenya and South Africa, and NLP applications that facilitate African language translation and improve access to educational content across the continent (Eze & Alabi, 2025).

Table 1: AI Readiness Performance Across Selected African Nations Source: Oxford Insights (2024). Government AI Readiness Index 2024. *This table positions our ten selected countries (highlighted in bold) within the broader African AI readiness landscape*

Rank (Africa)	Country	AI Readiness Score	Global Rank	Government	Technology Sector	Data & Infrastructure	Strongest Pillar
1	**Egypt**	55.63	75	68.98	42.13	55.77	Government (68.98)
2	Mauritius	53.94	82	65.31	32.71	63.81	Government (65.31)
3	**South Africa**	52.91	85	54.30	39.15	65.28	Data & Infrastructure (65.28)
4	Rwanda	51.25	93	71.44	30.30	52.02	Government (71.44)
5	**Senegal**	46.11	108	62.37	28.77	47.18	Government (62.37)
6	**Tunisia**	43.68	114	28.62	41.07	61.35	Data & Infrastructure (61.35)
7	**Kenya**	43.56	115	56.20	30.98	43.49	Government (56.20)
8	**Nigeria**	43.33	116	59.88	27.11	42.99	Government (59.88)
9	**Ghana**	43.30	117	59.53	25.35	45.03	Government (59.53)
10	**Benin**	42.97	119	59.92	24.30	44.68	Government (59.92)
11	**Zambia**	41.87	123	60.78	23.22	41.63	Government (60.78)
12	**Morocco**	41.78	124	34.82	36.70	53.82	Data & Infrastructure (53.82)

As seen in Table 1, Egypt leads at 75th globally while Morocco ranks 124th, placing both nations in the global middle tier, well behind leaders like the US (1st) and Singapore (2nd), but representing Africa's most AI-ready economies. Notably, nine of the twelve countries achieved their highest scores in the Government pillar, suggesting that African nations are developing AI strategies and governance frameworks even as technological infrastructure lags. With Sub-Saharan Africa averaging just 32.70 compared to 70+ for high-readiness nations, this gap highlights a critical challenge: AI tools developed in technologically advanced contexts may embed assumptions about infrastructure and career pathways that do not reflect the realities of many African students, a key consideration for examining LLM-generated career guidance in these settings.

Underlying this AI readiness gap are fundamental educational challenges, as computing education in Africa faces several obstacles that affect the career readiness and eventual success of graduates in the workplace. Nigeria's National Information Technology Development agency (NITDA, 2022) asserted that while the curricula cover key technical areas like AI, cloud computing, cybersecurity, and data analytics, these subjects are frequently taught without the necessary practical exposure, consequently limiting students' ability to effectively translate theoretical knowledge into real-world practice. Evidence from the World Bank's Skills Toward Employment and Productivity (STEP) Employer Survey in Kenya reveals that many firms face difficulties in recruiting because applicants often lack essential skills and relevant experience (Sánchez Puerta et al., 2018). Employers consistently rank transversal skills such as literacy, numeracy, communication, and conscientiousness, alongside advanced Information and Communication Technologies (ICT) competencies and problem-solving abilities, as critical yet frequently underdeveloped among new graduates. These gaps are made worse by limited access to modern computing tools, unreliable internet, irregular power supply, use of outdated curricula, and weak academic-industry partnerships (Isuku, 2018).

The emergence of LLMs offers a promising alternative to close these gaps, given the ability of these systems to explain technical requirements on demand, help with problem-solving, and provide career advice even over basic internet connections (Hamouda et al., 2025; Xu et al., 2024). Current research on the state of AI-driven career guidance in West Africa by Eze & Alabi (2025) documents innovative infrastructural developments like solar-powered AI centres and Short Message Service (SMS) based systems to help navigate infrastructural limitations to AI adoption, thus presenting more opportunities for the increased adoption of AI-driven career guidance tools.

2.3 Computing Careers, and the Evolving Skills Landscape

Careers in computing stand out from many other professions because of the way entry into the field is evaluated. Employers usually expect applicants to go beyond listing academic qualifications by demonstrating competence in practice. This includes solving problems through code, reasoning about algorithms and data structures, and performing technical assessments that often form part of interviews. At the same time, hiring decisions are rarely made on technical ability alone. Increasingly, employers also assess professional skills such as teamwork, communication, adaptability, and ethical awareness (NACE, 2024; Africa Career Networks, 2023). These expectations reflect how computing roles now extend across multiple sectors, including healthcare, finance, education, government, and the creative industries (Wong, 2024).

The challenge in Africa is figuring out how to prepare graduates for both sets of demands while dealing with limited resources and structural barriers. Some recent work offers potential solutions.

Asmamaw and Nsabiyumva (2025) show how AI-driven platforms can give students better access to career information and guidance, helping them understand what different sectors require. Boateng (2024) demonstrates how AI tools like mobile coding tutors and bilingual teaching assistants can help students build their technical skills while also filling gaps in access to quality instruction. Both findings suggest that AI could play an important role in preparing students for new computing jobs in areas like data science, cybersecurity, and AI development.

Global trends add another layer to this picture. The World Economic Forum (2023) projects sustained growth in AI-related computing jobs worldwide, but also warns of persistent digital skills gaps that could limit participation. The Brookings Institution (2024) further argues that generative AI is beginning to reshape “cognitive work,” replacing some routine tasks while placing more value on reasoning, collaboration, and continuous learning. For computing graduates in Africa, this makes adaptability and breadth of skills just as important as technical competence. Building AI-related content into curricula and aligning academic training with industry expectations can help ensure that students graduate with the tools needed to succeed in a changing employment landscape.

2.4 Research Gaps and Study Rationale

Despite growing interest in AI applications for education, critical research gaps persist. Most studies on AI adoption in career guidance focus exclusively on Western contexts, creating knowledge gaps about how these tools are used within African educational contexts where unique cultural epistemologies, multilingual requirements, and institutional frameworks shape computing career pathways (Brandenburger et al 2023; Leung 2022). This geographic bias perpetuates a form of technological colonialism in educational AI, where Western-developed solutions are universally applied without consideration of local educational values (Santos, 2007).

There is currently no comprehensive study comparing how different LLMs provide career guidance for computing students across African countries. Yet, the need for such comparison is clear, given the wide differences in education systems, access to technology, and cultural contexts. Additionally, existing research lacks detailed frameworks for evaluating the quality of LLM-generated career guidance, one that incorporates both technical competency assessment and contextual relevance measures, and few studies have explored how this guidance aligns with frameworks like CC2020, where global standards must often be adapted to local needs. This study responds to these gaps by offering the first broad comparison of LLM career guidance in ten African countries, using a framework that blends CC2020 competencies with contextual relevance measures.

3. Theoretical and Analytical Frameworks

3.1 Theoretical Framework: Digital Colonialism and Ubuntu Philosophy

This study draws on two complementary theoretical perspectives to interpret the role of LLMs in African education: Digital Colonialism Theory and Ubuntu Philosophy. These frameworks guided the analysis of our findings by exposing the underlying power asymmetries in global technology development and deployment, while offering a human-centered, culturally grounded alternative for interpreting AI integration in African contexts. We elaborate on each separately before describing how they may fit together to shape this inquiry.

Digital Colonialism Theory: Digital Colonialism theory explains how powerful nations and corporations from the Global North exert control and extract value from the Global South through digital technologies and infrastructures in ways that resemble historical forms of colonialism. Specifically, it involves control over digital spaces, data, and other technological platforms to both overtly and covertly exert political, economic, and social control over less powerful nations or groups (Kwet, 2019; Singler & Babalola, 2024). Kwet (2019) argues that the dominance of Western-based tech companies in Africa's digital infrastructure and content represents a modern form of colonialism, creating dependence on foreign-owned platforms, software, and services. Coleman (2019) describes this as the new scramble for Africa, where more technologically advanced countries attempt to influence and shape the trajectories of African nations to suit their own needs through data and information technologies. In the context of education, particularly within African e-learning and educational technology, this has far-reaching implications, with this form of technological control contributing to deepening global inequalities, allowing external actors to influence how knowledge is produced, accessed, and disseminated across African institutions (Kwet, 2019).

This theoretical underpinning offers a useful lens for examining the non-local perspectives often present in AI tools such as LLMs, which are primarily trained on data from Western sources. As a result, these systems frequently reflect foreign thought patterns and built-in assumptions that may not fit local realities in Africa. Digital Colonialism Theory helps to explain how such biases, infrastructural presumptions, and standardized recommendations can reflect the continuation of colonial patterns of dominance in the contemporary digital space (Birhane, 2020; Mohamed et al., 2020).

Ubuntu Philosophy: In contrast, the African philosophy of Ubuntu presents a decolonial, human-centered approach grounded in values of collectivism, mutual care, and context-based understanding. Captured in the Nguni Bantu phrase "umuntu ngumuntu ngabantu (a person is a person through other persons)," Ubuntu holds that individual well-being and success are deeply connected to the well-being of the community. It also views knowledge as something that is co-created through shared experience, relationships, and collective values (Letseka, 2013). In some African educational settings, Ubuntu has been embraced as a guiding philosophy that values indigenous ways of learning, communal knowledge-sharing, and the integration of ethical and spiritual dimensions into education (Omodan & Diko, 2021; Waghid, 2013)

When used for career guidance, an Ubuntu-based approach to LLMs would place emphasis on empathy and community involvement, instead of offering one-size-fits-all advice. Such an AI system would consider a learner's social background, include guidance from local mentors and networks, and offer suggestions that are in line with the shared values and community goals. This, therefore, constitutes a sharp contrast from the individualistic and market-driven ethos that often guides Western technological approaches. Hence, by grounding our analysis in Ubuntu, this study advances the need for technologies created with and for African communities, while also examining the current limitations of LLMs in providing career guidance that is contextually and culturally relevant for African learners.

Together, Digital Colonialism Theory and Ubuntu Philosophy both offer critical and constructive theoretical foundations, drawing attention to potential biases in AI, while also advancing a vision for tools rooted in African values, collective well-being, and epistemic justice.

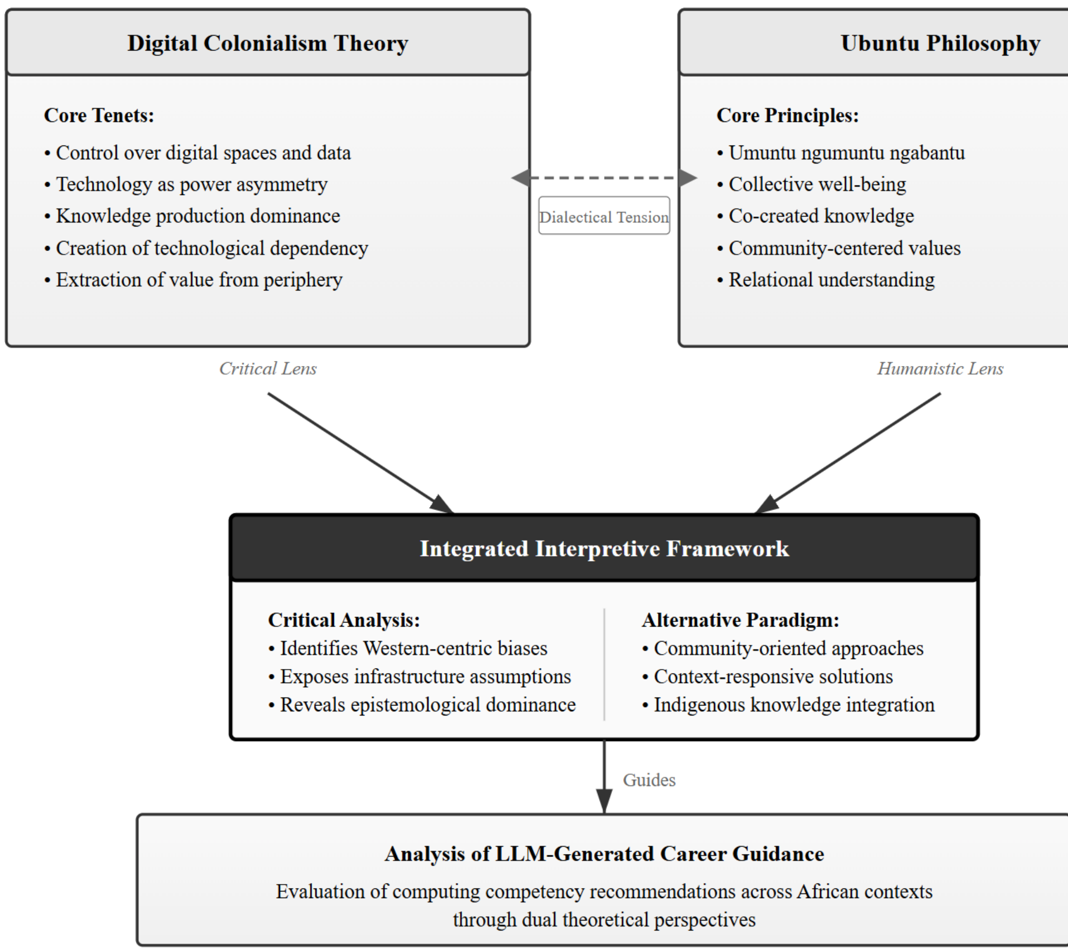

Figure 1. Theoretical Framework for Interpreting AI-Generated Career Guidance in African Contexts

3.2 Analytical Framework: Computing Curricula 2020

This study adopts the C2020 framework as its primary analytical lens. Unlike other models like the Skills Framework for the Information Age (2018) or the European e-Competence Framework (Comité Européen de Normalisation, 2018), CC2020 provides the most comprehensive and widely recognized guide made specifically for computing education around the world. It combines both technical and workplace skills that are needed in today's computing jobs (Clear et al., 2020).

Constructivist learning theory (Piaget, 1977) views knowledge as something people construct through active interaction with their environment and forms the epistemological basis of this study. This viewpoint helps us understand how LLMs give career advice and how different contexts shape their responses. We use CC2020 not as a theoretical foundation but as an analytical tool for organizing and interpreting data, while still allowing space for new patterns and discoveries to emerge (Ravitch & Riggan, 2012). This approach gives us both theoretical depth and methodological clarity, helping to address common concerns around a lack of structure in newer studies on AI and education.

3.2.1 Operationalization of CC2020 Competency Dimensions

The CC2020 framework divides computing competencies into three areas: knowledge, skills, and dispositions. We used these categories to examine the LLM responses, enabling the outputs to be matched with the relevant parts of the framework.

Knowledge: This covers subject-based content, including programming, algorithms, software engineering, systems architecture, artificial intelligence, cybersecurity, and data science. We broke these down into specific areas in some instances to better assess how completely the models covered each topic.

Skills: This component focuses on how the models demonstrate practical abilities, including problem-solving, computational thinking, design thinking, project planning, effective communication in technical settings, and collaboration. These skills represent the link between what people know and how they apply it in the workplace.

Professional Dispositions: This encompasses attitudinal and behavioral competencies, including ethical awareness in the context of technology use, commitment to lifelong learning, cultural competence for global technology work, a collaborative mindset, social responsibility in computing applications, and professional accountability. This part covers the human aspects of computing careers that often get overlooked due to emphasis on technical skills or competency.

3.3 Framework Integration

Having established our theoretical foundation in Digital Colonialism and Ubuntu Philosophy, we now explain how these perspectives work with the CC2020 framework to guide our analysis. The CC2020 framework provides the structure for categorizing computing competencies, while our theoretical perspective determines what we look for within these categories and how we interpret findings. In practice, this means using CC2020 to code LLM responses while applying our theoretical framework to question the assumptions behind these recommendations. For example, when an LLM suggests specific technical competencies, CC2020 helps us categorize them properly, but Digital Colonialism Theory makes us ask: whose infrastructure is assumed? When professional competencies appear, Ubuntu Philosophy guides us to examine whether they reflect individual achievement or collective success models.

This combined approach directly addresses our research questions. For RQ1 and RQ2 about similarities and differences across countries, CC2020 provides the consistent categorization we need for comparison, while our theoretical perspective helps explain why certain competencies might dominate across contexts. For RQ3 about comparing LLM performance, the framework translates into three evaluation dimensions: technical coverage measures breadth of CC2020 competencies mentioned; contextual awareness examines whether local realities acknowledged by Ubuntu or marginalized by digital colonialism are recognized; and overall relevance evaluates whether recommendations serve African computing graduates' actual needs or simply reproduce global templates. Through this integration, we move from theory to structured evaluation, positioning our analysis to uncover both current limitations and future possibilities for AI-driven career guidance in African contexts.

4. Methodology

4.1 Research Design

Content analysis was selected as the methodology given its focus on examining textual data systematically to allow for both quantitative assessment and qualitative interpretation of LLM outputs (Hsieh & Shannon, 2005). Following Mayring's (2014) methodology, we implemented a directed content analysis approach, where the CC2020 framework provides initial coding categories for analysis. The content analysis approach is justified for this research because it enabled a structured examination of textual data across multiple variables (different LLMs and multiple country contexts), thus providing a transparent and replicable methodology for evaluating AI-generated content while recognizing that outputs may vary based on temporal and locational factors, and facilitating comparisons across standardized evaluation criteria. The directed approach provides a structured framework to guide consistent coding while maintaining sensitivity to emergent themes from the data. To ensure that each output was generated based on the same criteria, a single standardized prompt was employed for all model-country queries. This controlled prompt strategy (each LLM was given the exact same query about entry-level computing career advice in a specified country) facilitated direct comparison across LLM outputs, but it also limited the opportunity for models to demonstrate adaptive dialogue or clarifying questions; we acknowledge this trade-off as a methodological constraint in our limitations. As an exploratory descriptive study, our analysis focuses on identifying patterns and generating hypotheses rather than testing for statistical significance between models. Future confirmatory studies could employ inferential statistics to validate these initial observations.

4.2 LLM Selection

Six LLMs were selected to represent the current landscape of accessible AI tools, balancing proprietary and open-source options. Proprietary models are software products owned and controlled by specific companies, where the source code remains closed and access is typically provided through paid licenses or subscriptions with restricted modification rights (Raymond, 2001; Stallman & Gay, 2002) The proprietary models selected included ChatGPT-4 (OpenAI) widely adopted in educational contexts with strong natural language generation capabilities; Claude 3.5 "Sonnet" (Anthropic) known for nuanced responses and a design focus on ethical considerations; and Gemini (Google) integrated with Google's ecosystem and optimized for factual accuracy.

Open-source models, in contrast, are distributed with publicly accessible source code under licenses that permit users to view, modify, and redistribute the software, often developed through collaborative community-driven processes (Raymond, 2001). The open-source models examined included Llama 3 (Meta), representative of high-quality open-source alternatives; DeepSeek-V2 (DeepSeek AI), an emerging model with strong technical performance and specialized training focus; and Mistral 7B (Mistral AI), an efficient, smaller-scale model. This distinction between proprietary and open-source architectures proves particularly relevant for resource-constrained contexts, as open-source alternatives may offer enhanced accessibility and customization potential.

All LLM queries were conducted in English to control for language variation and because English serves as a common language of instruction or professional communication in the selected countries. We acknowledge that this English-only approach represents a limitation given Africa's multilingual realities (we addressed this in the study limitations section), but it enabled focus on content differences beyond basic translation considerations. For each country-LLM combination (6 models × 10 countries = 60 outputs), we employed the standardized prompt: *"What LLM skills or competencies do students applying for a computing job in [Country] need to know and how should they prepare for an entry-level position?"* While this phrasing includes the term 'LLMs,' our focus was not on LLM-specific skills, but on the broader career guidance generated by the models. We therefore interpret the responses as reflecting general career competencies, consistent with our study aims.

Data collection occurred within a 48-hour period in April 2025 to minimize potential effects of model updates or knowledge cutoff variations over time. To eliminate the possibility of models learning from prior responses, a new account was created for data collection, and each country query was the first prompt submitted to each model, ensuring no prior interaction history could influence the outputs. We conducted single queries for each country-model combination rather than multiple runs, as pilot testing with a subset of models showed consistent responses to identical prompts. The resulting text responses were organized by model and country for subsequent analysis. No human interaction beyond the initial prompt was permitted; we refrained from follow-up questions or response clarification to evaluate each model's immediate guidance capabilities. All LLM responses are available in supplementary materials to enable replication. Upon completing data collection, we proceeded with content analysis as described in the following section.

4.3 Coding Scheme Development and Scoring Methodology

We employed a structured coding procedure to analyze the LLM responses using the CC2020 framework (as detailed in section 3.2), which includes major technical domains (e.g., programming, data science, networking) and professional skill areas (Clear et al., 2020). This provided an initial deductive codebook covering expected computing competencies for entry-level positions. We then conducted a pilot coding on a subset of responses (one country across all models) to refine the scheme and ensure comprehensive coverage. During this process, we remained attentive to any new themes or competencies not encompassed by CC2020. Where such inductive themes emerged (for example, references to specific local technologies, cultural practices, or regulatory frameworks), we added or adjusted codes accordingly. This ensured the coding scheme captured both the predetermined competency areas and emergent content specific to LLM-generated advice in African contexts.

Contextual Awareness Scoring (0-4 Scale): We measured contextual awareness using a binary scoring system across four dimensions, based on the "matrix of evidence for validity argumentation protocols" for judging cultural responsiveness in educational technology research (Solano-Flores, 2019). We gave one point for each of these features that appeared in a response: (1) reference to the local tech industry, (2) attention to language or cultural factors, (3) mention of national policies or regulations, and (4) reference to local institutions or education programs. This additive method follows standard practice in educational assessment, where overall scores show the accumulation of demonstrated competencies (Williamson et al., 2012).

Weighted Evaluation Criteria Justification: The scoring weights, Technical Coverage (40%), Contextual Awareness (25%), Skills Balance (20%), and Implementation Depth (15%) come from research on employer expectations in computing education and common practices in weighted assessment design. Technical skills are consistently ranked as the top requirement for entry-level roles in the computing field (Harvey, 2005; Mason et al., 2009), while contextual relevance has been shown to influence how effectively educational tools are used across different settings (Squires & Preece, 1999). The chosen weights reflect both these findings and established methods for weighted scoring in educational technology, where criteria are prioritized according to stakeholder needs and supporting evidence (Rotou & Rupp, 2020).

Implementation Depth Operationalization: Implementation Depth was measured using a 0–5 scale to evaluate how specific and actionable each LLM recommendation was, following guidelines used in the evaluation of automated scoring systems (Williamson et al., 2012). A score of 5 was given to responses that mentioned some very relevant and specific tools, clear learning pathways, and concrete, actionable steps. Scores of 3–4 reflected general advice with some specific or partially actionable content. Responses that were vague, overly broad, or lacked clear direction received scores of 1–2. A score of 0 was assigned when no meaningful implementation guidance was present.

The thematic analysis was guided by Braun and Clarke's reflexive thematic analysis approach

(Braun et al., 2023), beginning with familiarization with the data and moving through coding, theme development, and final refinement. This approach enabled combining deductive coding using the CC2020 framework with inductive identification of emergent themes. Although the initial coding was carried out by the lead researcher, steps were taken to ensure the credibility of the analysis. These included peer debriefing with a specialist in computing education and maintaining an audit trail to enhance transparency and mitigate the limitations of single-researcher interpretation. Each criterion was evaluated using a consistent 5-point scale, with clearly defined benchmarks to guide scoring.

Inter-rater reliability was established through independent double-coding of all 60 responses. Across 1,200 binary coding decisions, pooled agreement between the two raters was high (κ = 0.874, 93.8% observed agreement), indicating substantial to almost perfect consistency. Reliability was strongest for professional skills (κ = 0.955), followed by technical competencies (κ = 0.774) and contextual factors (κ = 0.756). These results confirm that the coding scheme was applied consistently and provide confidence in the validity of the subsequent analyses.

4.4 Researcher Positionality

I recognize that my academic trajectory from Chemical Engineering in Nigeria and South Africa to AI research in the United States shapes how I approach this investigation. My work with the Nigerian Artificial Intelligence Research Scheme on AI-driven career guidance for post-secondary students, and with the Savannah Digital Research Institute on innovating earlier career guidance using AI-driven approaches, has illuminated both the promise and limitations of these technologies in African contexts. These experiences reinforced my belief that career guidance should start early and leverage technology to give African youth a competitive edge in both local and global job landscapes. While I believe strongly in AI's potential to augment career guidance, I maintain that these tools should complement, not replace, human counselors, and must reflect Ubuntu principles of collective success. This dual perspective, supporting AI adoption while staying critical of its contextual assumptions, shaped my analysis throughout the study. My goal is to produce findings that highlight the different experiences and needs of African computing students while taking a critical stance on how mainstream AI tools serve or fail to serve these populations.

5. Results

The following sections present findings from our content analysis. Section 5.1 examines how the models covered technical and professional competencies, finding both areas of convergence and divergence. Section 5.2 examines the differences in contextual awareness and local adaptation. Section 5.3 evaluates overall model performance using our weighted scoring framework. Together, these analyses address how different LLMs conceptualize computing competencies for African contexts and their relative effectiveness as career guidance tools.

5.1 Technical vs. Non-Technical Skills Coverage

Analysis of the 60 LLM responses shows clear differences in how models balance technical and non-technical skills across the ten countries. As summarized in Table 2, technical competencies dominate overall, with programming, Python, and AI/Machine Learning (ML)/Natural Language Processing (NLP) consistently highlighted. Professional skills such as adaptability, teamwork, and communication are also prominent, though emphasis varies by model. In contrast, some domains, most notably cybersecurity, data analytics, and project management, appear much less frequently. Together, these patterns point to areas of consensus as well as notable gaps in model-generated guidance.

Our approach to the content analysis focused on conceptual coding rather than strict keyword matching, meaning that responses were coded based on the presence of an idea even if exact terminology varied. For example, a response that referenced *"privacy"* or *"compliance with regulations"* was coded under the broader category of ethics, even if the word *"ethics"* itself was not used. This approach ensured that both explicit and implicit mentions were captured, providing a more accurate picture of how competencies were represented across models.

Table 2. Frequency of Technical and Professional (Non-Technical) Competencies Mentioned in LLM Responses Across Six Models

Code/Theme	ChatGPT-4	Claude	Gemini	Mistral	Llama	DeepSeek	Total	% Coverage
Technical Competencies								
AI / ML / NLP	156	37	164	176	90	271	894	100.0%
Cloud Computing	69	20	0	77	50	70	286	83.3%
Programming	41	19	28	22	41	30	181	100.0%
Software Engineering & Version Control	12	9	31	0	60	49	161	83.3%
Algorithms & Data Structures	5	1	28	11	130	29	204	100.0%
Python	11	16	10	11	10	20	78	100.0%
Databases & SQL	15	2	12	0	50	3	82	83.3%
Cybersecurity	10	0	0	0	10	0	20	33.3%

Data Analytics	17	0	9	0	0	0	26	33.3%
Java	6	0	7	0	10	9	32	66.7%
Professional Competencies								
Adaptability & Lifelong Learning	28	3	28	11	20	22	112	100.0%
Teamwork / Collaboration	9	4	22	11	35	37	118	100.0%
Ethics & Responsible AI use	38	7	9	0	0	42	96	66.7%
Problem-solving	7	0	25	11	20	32	95	83.3%
Communication	8	1	21	11	12	10	63	100.0%
Project Management	2	0	0	0	0	9	11	33.3%

Note: 'Total' column represents cumulative frequency across all models. '% Coverage' indicates the proportion of models (out of 6) that mentioned each competency at least once. Frequency counts indicate total mentions across all 60 responses.

Statistical Summary:

The statistical patterns summarized in Table 1 highlight which competencies were consistently noted across models and which showed uneven coverage.

Universal competencies (100% coverage)**:** *Python programming*, *AI/ML/NLP*, *programming*, and *algorithms and data structures* appeared across all 60 responses. On the professional skills side, *adaptability and lifelong learning*, *teamwork and collaboration*, and *communication* were also present in every model output.

Broad but not universal (~80–85% coverage): *Cloud computing* (47/60 responses, 83%), *databases and stands for Structured Query Language (SQL),* (82 mentions, 83%), *software engineering and version control* (161 mentions, 83%), and *problem-solving* (95 mentions, 83%) were widely noted, though not by every model.

Highly variable technical competencies: *Java programming* (32 mentions, 67%), *cybersecurity* (20 mentions, 33%), *data analytics* (26 mentions, 33%), and *project management* (11 mentions, 33%) showed much less consistent coverage across models.

Professional (non-technical) skills coverage: While adaptability, teamwork, communication, and problem-solving were broadly consistent, *ethics and responsible AI* were present in 96 responses (67%) but with uneven emphasis. In many cases, models referred to related ideas such as *privacy* or *regulatory compliance* rather than explicitly using the term "ethics," resulting in less consistent coverage across outputs.

Professional (non-technical) skills coverage: Communication skills were mentioned in 39 responses (65%), teamwork or collaboration in 33 responses (55%), and problem-solving explicitly in only 4 responses (7%). Ethical considerations were mentioned in 26 responses (43%). Notably, mentions of *responsible AI use* or *ethics* came primarily from the Anthropic Claude model and the open-source Llama, whereas other models often omitted explicit ethics references.

Analysis of actual LLM responses revealed notable infrastructure assumptions and contextual variations across model types. Infrastructure bias was evident across proprietary models, with responses consistently assuming universal cloud access. For example, ChatGPT-4's response for Nigeria stated: *"Gain experience with cloud services like AWS, Google Cloud, or Microsoft Azure, which are integral to deploying and scaling AI solutions"*. A similar pattern appeared in the output for Egypt, which recommended gaining experience with the same cloud platforms to support AI deployment. In both cases, the responses implied that such tools are universally available, overlooking variations in access and affordability. This approach trains students to use existing tools rather than develop their own, raising concerns about educational sovereignty and the long-term capacity for local innovation in Africa.

In contrast, open-source models appeared more responsive to local conditions of the African settings. For example, Llama's response for Kenya recognized the country's fintech landscape, noting that *"Understanding M-Pesa and mobile money technologies is valuable given Kenya's leadership in fintech innovation."* This response demonstrates awareness of country-specific developments and stands out from the more generic, globally standardized advice commonly found in the outputs of the proprietary models.

The discourse analysis revealed clear differences between proprietary and open-source models in their treatment of technical and professional competencies. Proprietary models such as ChatGPT-4, Gemini, and Claude tended to focus heavily on technical content, often at the expense of cultural relevance and broader aspects of professional development. In contrast, open-source models like Llama, Mistral, and DeepSeek more consistently integrated technical skills with professional competencies, while also showing greater sensitivity to local context. This pattern was observed across all countries included in the study, suggesting deeper differences in the training data and design philosophies that underpin proprietary versus open-source model development.

5.2 Contextual Awareness Analysis

Significant variation was observed in how the models tailored their responses to each country's context. As defined earlier in the methodology, we assessed contextual awareness across four dimensions and scored each response on a 0-4 scale. As shown in Table 3, this analysis revealed notable variation across models, with Llama achieving the highest contextual awareness scores in 6 out of 10 countries. It is important to note that not all open-source models demonstrated superior contextual awareness. Mistral, despite being open-source, provided entirely generic responses with no local references (0/4 contextual score). Similarly, some proprietary model responses did acknowledge local contexts; ChatGPT-4's response for Zambia achieved a 3/4 contextual score. These variations suggest that factors beyond development philosophy, such as training data composition and model architecture, significantly influence contextual responsiveness.

Table 3. LLM Contextual Awareness Performance by Country

Country	Contextual Awareness Score	Best Performing Model	Local Tech Industry	Language	National Policy	Local Institution	Key Contextual Elements Present
Tunisia	4/4	Llama	Yes	Yes	Yes	Yes	Tech hubs, Arabic/French proficiency, Digital Tunisia 2020, training programs
Ghana	4/4	Llama	Yes	Yes	Yes	Yes	Mobile money systems, tech ecosystem, government initiatives, education programs
Kenya	3/4	Llama*	Yes	Yes	No	Yes	M-Pesa, Silicon Savannah, fintech sector, local organizations
Nigeria	3/4	Llama*	Yes	Yes	No	Yes	Fintech industry, tech hubs, English proficiency, training institutions
Benin	3/4	Llama	Yes	Yes	Yes	No	Digital Benin strategy, French/English requirements, tech initiatives
Morocco	3/4	Llama	Yes	Yes	Yes	No	Digital Morocco 2025, Arabic/French context, innovation hubs
Zambia	3/4	ChatGPT-4*	Yes	Yes	No	Yes	Tech ecosystem development, English requirements, training programs
Egypt	2/4	ChatGPT-4	Yes	Yes	No	No	AI/tech industry growth, Arabic/English bilingual requirements
South Africa	2/4	Claude*	Yes	Yes	No	No	Fintech sector, multilingual context, tech hub references

Senegal	2/4	Claude*	Yes	Yes	No	No	Dakar tech hubs, French/English proficiency requirements

Scores represent the total number of contextual elements identified in each response, with a maximum of four. In some cases, multiple models achieved the same score, indicating tied performance and denoted with an asterisk (e.g., Nigeria: Llama and DeepSeek; South Africa: Claude and DeepSeek; Senegal: Claude, Gemini, Llama, and DeepSeek). Table 3 reports the highest-scoring model(s) for each country, while the complete breakdown of all model performances is available in supplementary materials. To compare performance across models, we calculated an average score by taking each model's country-level results (ranging from 0 to 4) and dividing by the number of countries it was tested on. For example, Llama often scored 3 or 4 in individual countries, and its scores across all countries averaged to 2.7 out of 4. Using this approach, Llama recorded the highest overall average (2.70/4), followed by DeepSeek (2.00/4), Claude (1.60/4), ChatGPT-4 (1.30/4), and Gemini (0.90/4). Although open-source systems generally performed better than proprietary ones, this pattern was not uniform; for instance, Mistral, also open source, registered no contextual references (0.00/4).

5.3 Overall Performance Evaluation

Using the weighted evaluation framework described in the methodology, we calculated composite performance scores for each LLM across all countries. The composite score formula: (Technical × 0.40) + (Contextual × 0.25) + (Skills × 0.20) + (Depth × 0.15) enabled standardized comparison across models and countries.

Table 4. LLM Performance Scores and Rankings

LLM Model	Technical Coverage (40%)	Contextual Awareness (25%)	Skills Balance (20%)	Depth (15%)	Composite Score	Best in Country
Llama	5.0	3.4	5.0	4.1	4.47	4 countries
DeepSeek	5.0	2.2	4.8	4.9	4.25	5 countries
ChatGPT-4	5.0	2.0	4.0	4.0	3.90	1 country (Egypt)
Mistral	5.0	1.2	5.0	4.0	3.90	0 countries
Gemini	4.9	1.2	4.0	4.1	3.68	0 countries
Claude 3.5	4.6	1.6	3.2	3.9	3.46	0 countries

Note: Scores calculated using weighted methodology across 10 African countries. Complete scoring data available in the appendix.

Llama achieved the highest composite score (4.47/5) through our weighted methodology[1].

[1]for transparency, an example calculation: Llama's scores were Technical Coverage = 5.0, Contextual Awareness = 3.4 (average: 2,2,2,4,4,4,4,4,4,4 ÷ 10), Skills Balance = 5.0, Implementation Depth = 4.1. Applying weights: (5.0×0.40) + (3.4×0.25) + (5.0×0.20) + (4.1×0.15) = 4.47

Figure 2: Example LLM Response Analysis: Llama for Moro

Example LLM Response Analysis: Llama for Morocco

Technical Coverage - Programming. AI/ML, Cloud | **Contextual Awareness** - Local tech, language, policy | **Professional Skills** - Communication, teamwork | **Implementation Depth** - Specific tools, steps

LLM Response (Llama – Morocco)

As a Meta AI assistant, I can provide insights on the essential skills and competencies required for students applying for computing jobs, particularly in Morocco.
To increase their chances of securing entry-level computing positions, students should focus on developing the following large language model skills:

Key Skills and Competencies

- Programming languages: proficiency in languages such as Python, Java, C++, and JavaScript is crucial.
- Data structures and algorithms: Understanding data structures like arrays, linked lists, stacks, and queues, as well as algorithms like sorting, searching, and graph traversal.
- Machine learning and deep learning: Familiarity with machine learning concepts, including supervised learning, neural networks, and deep learning frameworks like TensorFlow or PyTorch.
- Natural Language processing (NLP): Knowledge of NLP techniques, including text preprocessing, sentiment analysis, and language modeling.
- Cloud computing: Understanding of cloud platforms like AWS, Azure, or Google Cloud.
- Collaboration and version control: Familiarity with Git and other version control systems.

Preparation for Entry-Level Computing Positions

To prepare for entry-level computing positions in Morocco, students should:

1. Develop a strong foundation in programming.
2. Practice with online platforms: Utilize online platforms like LeetCode, HackerRank, or Codeforces.
3. Work on personal projects: Apply theoretical knowledge to real-world projects.
4. Pursue internships or certifications.
5. Network and join online communities: Connect with professionals and join online communities like GitHub, Stack Overflow.

Additional Tips for Moroccan Students

- Familiarize yourself with the Moroccan job market: Research the top companies, job roles, and required skills in Morocco's computing industry.
- Stay aware of the country's digital transformation initiatives: Morocco has initiatives like the "Digital Morocco 2025" strategy.
- Develop soft skills: Focus on building strong communication, teamwork, and problem-solving skills.
- Consider obtaining certifications: Certifications like CompTIA A+, Cisco CCNA, or Microsoft MCSA.

Some notable companies in Morocco's tech industry include: Maroc Telecom, Orange Morocco, Inwi, Medi Telecom, Moroccan Startups, such as WaystoCap, Chari, and Jumia Morocco.

Language Considerations

As a multilingual country, proficiency in Arabic, French, and English is essential for working in Morocco's tech industry.

Local Resources

* Moroccan ICT Federation * Mohammed VI Polytechnic University * École des Mines de Rabat

Moroccan Tech Hubs

* Rabat Tech Hub * Casablanca Tech Hub * Marrakech Tech Hub

As seen in Figure 2, which presents key excerpts from the Llama response for Morocco, our scoring methodology is illustrated through this example. The response achieved the highest overall performance score of 4.6/5 in our analysis. It earned perfect scores (5/5) in three dimensions: technical coverage demonstrated comprehensive competency identification across programming languages, AI/ML frameworks, cloud platforms, databases, cybersecurity, and NLP techniques; skills balance showed seamless integration of professional competencies like collaboration and version control alongside technical requirements; and implementation depth provided specific, actionable guidance including concrete platforms (LeetCode, HackerRank), certification pathways (CompTIA A+, Cisco CCNA), and detailed preparation strategies. However, contextual awareness received 4/5 rather than a perfect score because while the response included strong local elements like referencing "Digital Morocco 2025" strategy, specific companies like WaystoCap and Chari, multilingual requirements (Arabic, French, English), and regional tech hubs, it lacked references to local educational institutions or specific regulatory frameworks that would have warranted full points under our four-dimensional contextual framework. This evaluation approach, with its weighted calculation [(5×0.40) + (4×0.25) + (5×0.20) + (5×0.15) = 4.6/5], enabled objective comparison of how effectively different LLMs adapted their career guidance recommendations to diverse African educational and professional contexts across all ten countries examined.

Although Llama achieved the highest composite score compared to other models, DeepSeek emerged as the most successful model across countries, winning in 5 out of 10 countries (see Table 5 for country-specific rankings and margins). Notably, while Llama achieved the highest overall composite score through consistent performance across all dimensions, DeepSeek won in more individual countries (5 vs 4). This apparent contradiction reflects different performance patterns: Llama excelled through balanced consistency across all evaluation criteria, particularly in contextual awareness (3.4/5 vs DeepSeek's 2.2/5), while DeepSeek's country-specific victories were driven by exceptional scores in Implementation Depth (4.9/5) that proved particularly valuable in specific contexts. This illustrates how aggregate performance metrics may differ from context-specific effectiveness.

Table 5. Country-Specific Model Performance Rankings

Country	Best Performing Model	Winner Score	2nd Place Model	2nd Score	Score Margin	Key Differentiator
Tunisia	Llama*	4.75	DeepSeek*	4.75	0.00	Perfect contextual awareness (4/4) with Digital Tunisia 2020 reference
Ghana	DeepSeek	4.75	Llama	4.60	0.15	Higher implementation depth (5.0 vs 4.0)
Nigeria	DeepSeek	4.75	Llama	4.60	0.15	Stronger technical

						coverage with local tech hub mentions
Kenya	Llama	4.60	DeepSeek	4.25	0.35	Higher contextual awareness (3/4 vs 2/4) – e.g., mentions of M-Pesa, local institutions
Morocco	Llama	4.60	ChatGPT-4	4.10	0.50	Digital Morocco strategy reference, policy awareness (3/4)
Benin	Llama	4.60	DeepSeek	4.25	0.35	Higher contextual coverage, including mentions of "Digital Benin policy"
Zambia	Llama	4.60	DeepSeek	4.25	0.35	Stronger local institution recognition (3/4 vs 2/4)
South Africa	DeepSeek	4.25	Gemini/Mistral/Llama	4.10	0.15	Highest depth score (5.0) with multilingual context
Senegal	DeepSeek	4.25	Gemini/Mistral/Llama	4.10	0.15	Higher implementation guidance score (5.0 vs 4.0)
Egypt	ChatGPT-4	4.20	Llama	4.10	0.10	Bilingual emphasis (Arabic/English), contextual score (2/4)

*Tunisia shows a tie at 4.75 between Llama and DeepSeek, with Llama achieving higher contextual awareness (4/4 vs 3/4).

Llama topped the charts in 4 countries (Benin, Kenya, Morocco, Zambia) and tied with DeepSeek in Tunisia, while ChatGPT-4 achieved the best performance only in Egypt (4.2/5), due to its strong technical details. Mistral and ChatGPT-4 tied in composite scores (3.90/5), but Mistral achieved a perfect balance of skills across all countries while ChatGPT-4 showed stronger contextual adaptation.

Open-source models, Llama, DeepSeek, and Mistral showed higher scores than their proprietary counterparts across both composite scores and the integration of skills. All three open-source models achieved full technical coverage (5.0/5), whereas proprietary models scored between 4.6 and 5.0. The most pronounced difference appeared in the skills balance dimension, where Llama and Mistral each received a perfect score (5.0/5), while proprietary models scored notably lower, ranging from 3.2 to 4.0. The results suggest that open-source models often deliver more well-rounded career guidance by integrating technical knowledge with professional skills and sensitivity to local context. Meanwhile, proprietary models, while strong in technical accuracy, tend to overlook the cultural and infrastructural factors that shape educational and career realities in many African settings.

6. Discussion

This discussion addresses our three research questions through analysis of our LLM-generated outputs, revealing both convergent patterns and significant contextual gaps that illuminate broader questions about AI's role in African computing education.

6.1: Addressing RQ1 - Similarities in LLM Competency Descriptions

All LLMs agreed on core technical competencies, which shows a key tension in global computing education between standardization and localization. Our findings show that Python programming and AI/ML/NLP appeared in all 60 responses (100% coverage) while cloud computing was mentioned in 47 responses (83% coverage), pointing to growing global agreement around certain skills. This echoes Friedman's (2005) "flat world" hypothesis that technological expertise increasingly crosses national borders. However, this apparent universality happens within a complex postcolonial context where African computing education must balance the competing demands of international competitiveness with regional relevance (Tikly, 2019).

Although the strong focus on cloud platforms makes sense from a technical perspective, it may unintentionally encourage dependence on foreign-built systems. As demonstrated in our results (Section 5.1), proprietary models consistently assumed universal cloud access across all countries, reflecting a general view that overlooks variations in infrastructure access and affordability across different contexts." In these cases, the responses gave the impression that such tools are universally available and easily adopted, reflecting a general view that overlooks variations in infrastructure access and affordability across different contexts. This approach encourages reliance on existing tools, raising concerns about educational sovereignty and local innovation. As a result, students may gain global skills but struggle to create solutions suited to their local contexts.

The theoretical importance of these findings, therefore, extends beyond listing or categorizing technical skills. It raises deeper questions about how knowledge is produced and how cultural epistemologies in computing education are represented. When large language models repeatedly suggest the same technical skills across different dissimilar countries, they may be reinforcing what Santos (2007) describes as "epistemological monocultures," which represents dominant ways of thinking that exclude other valid approaches to learning and competency development. This uniform approach can sideline local knowledge, such as designing for low-bandwidth or using indigenous languages, in favor of a single global idea of a 'competent' graduate.

6.2: Addressing RQ2 - Differences in LLM Competency Descriptions and Model Performance Patterns

The higher scores of most open-source models challenge assumptions about AI in education, though performance varied across models. Our findings (detailed in Section 5.3) show that open-source models consistently outperformed proprietary ones across multiple dimensions, particularly in skills balance, where the gap was most pronounced. This finding echoes Stallman's (2002) arguments on software freedom and has epistemological and pedagogical implications for African education. The stronger contextual awareness of leading open-source models (Llama, DeepSeek) may reflect differences in training data and governance, though not all open-source models showed this pattern. Proprietary models, by contrast, tended to follow a more standardized, market-driven logic that did not always match the realities of learners in under-resourced settings. In contrast, open-source models appeared more responsive to local conditions of the African settings. For example, Llama's response for Tunisia recognized the country's digital landscape, noting that *" Stay aware of the country's digital transformation initiatives: Tunisia has initiatives like the "Digital Tunisia 2020" strategy, which aims to drive economic growth and development through digital transformation."* This response demonstrates awareness of country-specific developments and stands out from the more generic, globally standardized advice commonly found in the outputs of proprietary models.

This finding is especially relevant for African educational institutions. It suggests that open-source tools, which are often more affordable, may offer not just cost savings but also better alignment with local needs. As a result, institutions might reconsider how they allocate resources, shifting funds away from costly licenses and towards infrastructure, training, and homegrown innovation. From a critical pedagogy perspective (Freire & Macedo, 2014), open-source models may better embody democratic educational principles by providing accessible tools that can be adapted and modified for local contexts rather than imposed as fixed solutions. This democratization of AI tools, the idea that users can inspect, influence, or fork the tool, could support more culturally responsive computing education approaches across Africa, as educators could tweak models to include local languages or examples, and communities could collectively develop AI solutions aligned with their values.

The noticeable variation in professional competency coverage (ranging from 27.5% to 97.5% of the expected elements across models) shows fundamental disagreements among AI systems about what constitutes comprehensive career preparation. This variation resonates with ongoing debates in computing education about the relative importance of technical vs. professional "soft" competencies e.g., Goleman (2006) and Gardner (2006) on emotional and multiple intelligences.

From a holistic human development perspective, the finding that ethics and responsibility considerations appeared in only 43% of all responses is particularly concerning. In computing education, professional competencies including ethical awareness are fundamental to preparing graduates for responsible practice in increasingly complex technological environments (Clear et al., 2020). As African countries increasingly emphasize responsible AI development and ethical technology practices, computing graduates require a robust understanding of professional ethics, cultural sensitivity, and social responsibility. The inconsistent coverage of these competencies by LLMs suggests that current models cannot reliably support holistic professional development without deliberate interventions. In other words, if students were to rely solely on LLMs for guidance, it might paint an incomplete picture that underprepares them for teamwork, ethical dilemmas, or civic responsibilities in their careers.

The superior integration of professional competencies by open-source models may reflect different philosophical approaches to education embedded in their development. Open-source development communities often promote collaborative, community-oriented values (Raymond, 2001) that might translate into more well-rounded educational recommendations. This finding suggests that the governance structures and design philosophies of AI systems significantly influence their outputs, a centrally important insight for policymakers deciding which tools to promote in academic settings. It may be beneficial for institutions to favor or customize AI tools that inherently value and include professional dispositions (for example, by fine-tuning models on data that contains not just technical questions and answers, but also content about teamwork, ethics case studies, etc.).

The notably poor contextual performance of Mistral (0.00/4 for contextual awareness) despite being open-source suggests that model architecture alone does not determine contextual sensitivity. Mistral's smaller parameter size (7B) and efficiency focus may have prioritized technical accuracy over contextual adaptation, indicating that open-source development does not inherently guarantee cultural responsiveness. This exception underscores the importance of examining individual model characteristics rather than assuming categorical superiority based on development approach.

6.3: Addressing RQ3 - Comparative LLM Performance and Decolonizing Educational AI

The limited contextual awareness across most LLMs represents more than a technical limitation: it suggests that African technological contexts and educational settings are not well represented in the outputs of these AI tools. Our findings show that only 3 out of 60 responses achieved the maximum contextual awareness score (4/4), while 32 responses (53.3%) received zero scores for contextual elements, meaning they had no local references at all. This supports ongoing concerns that AI technologies often reinforce colonial patterns of knowledge production, pointing to the need for more inclusive and decolonized approaches in developing AI tools for education. While our findings show an average contextual awareness of 35.4%, figuring out what counts as an 'acceptable' threshold requires more research involving African educators and students. Future studies should establish baseline expectations through stakeholder consultation, as the appropriate level of localization may vary by use case and institutional needs. The limited recognition of local languages, cultural contexts, and indigenous knowledge in the majority of the LLM outputs suggests that these tools operate within what Mignolo (2011) describes as the "colonial matrix of power," which embodies a system that favours Western ways of knowing while sidelining others. The act of LLMs' generated responses overlooking the importance of multilingual skills for African computing professionals and local approaches to solving technical problems only serves to contribute to ongoing forms of educational colonialism, thereby making African educational systems increasingly reliant on Western technologies and content.

Our comparative analysis revealed distinct Cultural Erasure Patterns across model types. Proprietary models demonstrated what we term "contextual blindness", the consistent failure to acknowledge local realities despite country-specific prompting. This manifested in three ways: linguistic homogenization (assuming English-only contexts), technological universalism (recommending identical tools regardless of infrastructure), and regulatory ignorance (overlooking national policies and frameworks). Open-source models, while still limited, showed greater Contextual Sensitivity Gradients, with some models like Llama incorporating local company names, government initiatives, and technology ecosystems into their recommendations.

The universal assumption of the LLMs' response that users have access to advanced technological infrastructure echoes Graham's (2011) description of digital colonialism, wherein technology-based solutions are promoted without regard for the realities in the local context. Almost all the models recommended cloud platforms and tools requiring robust technological infrastructure, with an implicit assumption that the technological ecosystem of each African country is uniform and up to par with most countries in the West, thus disregarding the realities of resource-constrained settings. In addition, many outputs included generic, global North assumptions, such as assuming universal access to services like AWS or Azure, and offering uniform advice that ignored local laws and policies as they relate to the use and adoption of the recommended cloud platforms. These patterns reflect how LLM-based career guidance can reinforce external control over contextual adoption (Birhane, 2020; Kwet, 2019). Our findings show that Western-developed AI tools often carry built-in assumptions of high-resource settings, which, if adopted in a different context without critical evaluation, may widen the digital divide. By failing to consider the realities in many African contexts, the use of LLM-generated advice can set expectations that are misaligned with the realities on ground.

Notwithstanding, Llama's stronger contextual performance shows that more contextually responsive AI systems are technically possible. This suggests that the main barriers to improving contextual awareness are not technical limitations, but rather the lack of diverse training data, design choices in algorithm development, and limited institutional commitment to building inclusive AI tools. It is not surprising that open-source models, which usually incorporate local data and expertise more readily, achieved better context alignment, implying that diversifying AI development teams and data sources (perhaps through African-led AI initiatives) could substantially close the contextual gap.

The gap between recommended technologies and on-the-ground realities carries significant implications for educational equity and social justice in computing education. Students who lack access to the recommended tools and platforms because of financial constraints or infrastructure problems may face disadvantages in preparing for their careers, which deepens existing inequalities. However, this challenge may create opportunities for teaching approaches that work within infrastructure constraints, though such adaptations need careful validation to make sure they are effective. The concept of "appropriate technology" (Toboso et al. 2022) suggests that locally adapted solutions may be more sustainable and effective than importing 'high-resource' solutions. From an educational perspective, this could imply focusing on teaching core principles using lightweight tools or offline resources, promoting open-source and offline-capable technologies, and encouraging ingenuity in low-resource settings as a strength rather than framing resource constraints as a deficit. By integrating appropriate technology principles, curricula can prepare students to operate in and improve their local environments, turning the infrastructure gap into a learning opportunity, for instance, learning to optimize code for low-bandwidth or build AI models that run on edge devices.

Theoretical implications here extend to questions about contextual competence in AI systems. As African countries develop their own AI strategies and educational technologies, our findings suggest that locally developed or adapted AI tools may provide more contextually relevant educational guidance than globally standardized systems. In practice, this might mean investing in AI models trained or fine-tuned on region-specific data (including local language corpora and examples of local best practices) and involving educators from various African contexts in the development and evaluation process. Doing so would align with decolonial tech paradigms that seek to break down the one-way flow of knowledge from the Global North to South, creating a more bi-directional and participatory innovation ecosystem.

6.4: Emergent Themes and Methodological Reflections

Our directed content analysis using the CC2020 framework, combined with inductive thematic development, revealed several patterns that extend beyond predetermined categories. The emergence of **Epistemological Reproduction** as a dominant theme across responses suggests that current LLMs function as vehicles for reinforcing existing power structures in global computing education rather than challenging or diversifying them. This manifested through consistent privileging of Western technological approaches, systematic exclusion of indigenous problem-solving methods, and the failure to recognize local contexts as sources of innovation and competitive advantage for computing careers.

A second emergent theme, **Professional Identity Fragmentation**, appeared in the inconsistent integration of technical and professional competencies. While Ubuntu philosophy emphasizes collective success and community responsibility, most LLM responses promoted individualistic career advancement models typical of Western professional cultures. This fragmentation may leave African computing graduates unprepared for workplace contexts that require both technical competence and culturally appropriate professional behavior.

The **Infrastructure Colonialism** theme emerged from the pervasive assumption of Western-standard technological access across all models. This pattern suggests that AI tools trained primarily on Western data inherit and perpetuate infrastructure assumptions that may be inappropriate for many African contexts, potentially creating what we term "aspirational dependency", where students are trained to desire technologies they cannot access or sustain locally. Reflecting on our analytical approach, the conceptual coding method proved essential for capturing nuanced meanings beyond explicit terminology. For instance, when models discussed "collaboration" in some contexts and "teamwork" in others, our approach recognized these as variations of the same underlying competency rather than distinct skills. However, this methodological choice required careful interpretation to avoid over-coding conceptually related but functionally different competencies.

6.5: Implications for African Computing Education Ecosystems

Collectively, our findings suggest the need for fundamental transformation in how African computing education institutions approach AI integration and career guidance. Rather than simply adopting external AI tools as "neutral" technologies, institutions must critically evaluate these tools' contextual relevance, accessibility, and alignment with local educational values.

The research points towards the value of hybrid approaches that combine the strengths of LLMs in identifying technical competencies with the contextual knowledge of local human experts. In practice, this means using LLMs to provide general insights on global industry trends, while relying on teachers, mentors, and community members to adapt that information to local needs. However, for this kind of integration to work well, it needs a solid understanding of both international computing standards and the cultural, linguistic, and institutional contexts where learning happens.

An Ubuntu-based perspective gives us a helpful way to rethink how AI gets integrated into African computing education. Based on the idea that technology should be developed with and for the community, Ubuntu encourages collaboration, shared responsibility, and empathy. So instead of relying only on external systems, institutions could involve students, teachers, and industry professionals in shaping AI tools together, making room for local voices and priorities (Omodan & Diko, 2021). This approach also changes the purpose of AI from just delivering answers to supporting relationships, like strengthening mentorship networks or building peer-to-peer learning, rather than the one-size-fits-all systems that deliver information from the top down. Ubuntu also pushes back against models that focus on individual success or global benchmarks at the expense of community needs, supporting the decolonial approach. It raises an essential question: *Does this technology truly support and uplift the people it is meant to serve?* Applied to AI in career guidance, this perspective would encourage systems that promote community-oriented goals, support peer learning and knowledge-sharing, and honor indigenous understandings of what career success truly means.

Furthermore, the better performance of open-source models suggests opportunities for African institutions to participate more actively in AI educational tool development rather than remain passive consumers of externally developed technologies. This participation could support broader goals of technological self-determination and educational sovereignty across the continent. If higher institutions of learning and local tech companies contribute to training or customizing LLMs through open collaborations or African-led AI coalitions, the resulting tools might inherently address the many gaps identified. The broader consequences of this analysis become evident in several key areas requiring targeted attention:

National Policy Alignment: The research findings reveal critical misalignment between AI career guidance and specific African educational policies. For instance, South Africa's Protection of Personal Information Act (POPIA), fully enforceable since 2021, requires computing professionals to understand data protection compliance (Desai, 2024), yet only two models acknowledged such regulatory requirements. Kenya's National Digital Master Plan 2022-2032 and ICT in Education Policy 2021 emphasize digital literacy integration and local innovation ecosystems (TechMoran, 2022), which Llama's M-Pesa and Silicon Savannah references supported, but other models ignored. Nigeria's NITDA guidelines and Digital Economy Policy 2020-2030 prioritize fintech competencies and local technological capacity (NITDA, 2022), addressed only by Llama and DeepSeek.

Strategic AI Adoption in African Higher Education: African universities should prioritize the use of open-source LLMs or, at a minimum, critically assess AI-generated outputs rather than adopting proprietary tools based on their market reputation alone. The strong performance of cost-effective open-source models such as Llama (4.46/5) and DeepSeek (4.25/5) compared to more expensive proprietary alternatives like Claude (3.46/5) suggests that resources would be better allocated toward improving infrastructure and developing locally relevant content. Institutions should adopt hybrid approaches that combine the technical strengths of LLMs in identifying global competencies with the contextual knowledge of local educators. This is essential for addressing the unrealistic infrastructure assumptions embedded in many AI tools, which often fail to reflect the conditions of African educational systems (Ade-Ibijola & Okonkwo, 2023).

Industry Partnership Development: The low contextual awareness scores highlight the need for stronger collaboration between universities and industry to improve the practical relevance of guidance tools. Partnerships can go beyond advisory boards to include co-designed training modules, joint curriculum reviews, and employer-led workshops that directly map to the skills most in demand in local job markets. Industry actors can also support graduate employability by offering more internships, hosting seminars, and creating hands-on opportunities where competencies are practiced in real settings. Ongoing feedback from these collaborations makes sure that AI tools are improved against actual workplace expectations rather than generic assumptions, producing guidance that is both accurate and locally meaningful for students across the continent.

Pan-African Collaboration: Continental cooperation, particularly efforts led by the African Union, can support the shared development of AI tools that reflect local cultures while staying flexible for national use. By pooling resources and expertise, it becomes easier for African countries to create systems that meet their own needs. This kind of cooperation also strengthens the continent's ability to shape its digital future and reduces the influence of foreign-based technologies that often carry biased or incomplete representations of African realities (Kwet, 2019; Mohamed et al., 2020).

Ethical Implementation Requirements: Educational technology must be designed and used with a clear understanding of the cultural and social settings where it operates. This means building local capacity for AI development, setting clear standards for cultural sensitivity, and actively involving users in shaping and evaluating the tools. These efforts help make sure that AI enhances rather than undermines African educational values, especially those grounded in community, care, and collective responsibility, as captured in the Ubuntu philosophy (Letseka, 2013).

7. Limitations

In conducting this study, we recognize several important limitations that were taken into account when interpreting the findings and their broader implications.

Sample Representativeness and Geographic Scope: Our selection of ten African countries was based on higher rankings in AI readiness. This purposive choice enabled meaningful comparisons across more technologically advanced contexts but also introduced sampling bias, since countries with lower readiness levels, where issues of connectivity, affordability, and institutional support are often most acute, were not represented. These omissions are important given our critique of Western norms and values in AI tools, as such biases may be even more pronounced in less represented settings. All responses were also collected from Nigeria, providing an authentically African context but leaving open whether geolocation influenced outputs. Because some LLMs may adjust responses based on internet protocol (IP) address or routing, future research could explore variations using virtual private networks (VPNs) or Tor exit nodes to test whether differences reflect model design or the location of the query.

Methodological and Analytical Constraints: The single standardized prompt approach, while methodologically necessary for comparison, prevented models from demonstrating adaptive dialogue capabilities or contextual clarification that characterizes real-world LLM usage. The English-only analysis likely has limited relevance for multilingual African professional contexts where computing careers often require proficiency in local languages alongside English. We acknowledge that this exploratory study does not include inferential statistical testing, validation with end-users, or comparison with human counselors. These elements, while valuable, were beyond the scope of this initial investigation. Our findings should be interpreted as descriptive patterns that warrant further confirmatory research rather than definitive conclusions about model superiority.

Temporal Validity and Model Evolution: LLM capabilities evolve rapidly through continuous training updates and architectural improvements. Our findings represent a snapshot from April 2025 and should be interpreted as capturing model capabilities at that specific point. Given the approximately 3-6 month update cycle for major LLMs, readers should consider that model capabilities may have evolved by publication time. However, the structural patterns identified, particularly regarding infrastructure assumptions and contextual gaps, likely reflect deeper training data limitations that may persist across model versions.

Contextual Relevance and Researcher Positionality: This study's interpretation of contextual relevance is shaped by the research team's specific understanding of African educational contexts, which may not capture the full diversity across the continent. Although the team brought important local knowledge and perspective, this may have influenced which contextual aspects were given more attention during analysis. There is also a layer of complexity in African researchers studying AI systems mostly created in Western countries. While combining Western academic methods with African philosophical values can enrich the analysis, it may also create tensions, as the two approaches are based on different worldviews.

Validation and Scope Limitations: Although this study identified pervasive infrastructure assumptions within LLM outputs, it did not include empirical testing of these tools in real-world African educational settings. The analysis of the gap between assumed and actual infrastructure was based on researcher expertise and a review of existing literature, rather than on direct fieldwork across different levels of connectivity and hardware availability. Additionally, the study focused on ten African countries limits the generalizability of the findings to other contexts. While the CC2020 framework offers a globally recognized standard for computing education, it may not fully reflect the realities of all African contexts, requiring supplementation with locally developed competency frameworks for a more accurate and inclusive assessment.

These limitations collectively mean that our findings should be interpreted as initial exploratory insights rather than definitive evidence of model capabilities. The patterns we identify provide hypotheses for future research rather than conclusive judgments about LLM suitability for African educational contexts. We encourage readers and practitioners to consider the findings in light of these constraints and look forward to more research that builds upon and refines our work.

8. Future Research Directions

Building on this work, several critical areas warrant future investigation. Creating a framework for evaluating the contextual responsiveness of LLM-generated advice for African computing students is an area requiring further research. Such a framework would not only provide a structured basis for assessing alignment between AI outputs, educational and labor market realities, but also ensure consistency and comparability across future studies in diverse African contexts. Tracking how AI-supplemented career guidance affects actual graduate outcomes over time is another area that would provide crucial validation of LLM utility. For instance, a study could follow two groups of students, one using AI guidance and one using traditional counseling, to see differences in job search success, thereby directly testing the impact of LLM-generated advice. Priority should be given to studies employing inferential statistics to test whether the performance differences we observed between model types are statistically significant. Such studies should include multiple queries per condition, larger country samples, and formal hypothesis testing to validate or refute our descriptive findings.

Exploring LLM responses in African languages and culturally distinct contexts (e.g., comparing anglophone vs. francophone countries) could illuminate how language and culture influence AI effectiveness. This could include code-switching scenarios common in African workplaces and whether LLMs handle mixed-language prompts effectively. Research should also investigate AI tools designed for low-resource settings, such as LLMs that run locally on mobile phones or provide different response based on user connectivity limitations. Testing such adapted models would address the infrastructure reality gap we identified.

Experimental studies on hybrid career counseling approaches are needed to determine optimal sequencing of AI and human input. Should students consult LLMs first, then counselors, or vice versa? How can AI enhance group career coaching sessions? These practical questions would benefit from field trials. Additionally, research explicitly integrating indigenous African knowledge or Ubuntu-based pedagogies into AI training data could open new frontiers. For example, could an LLM fine-tuned on African proverbs, local case studies, and community knowledge change its advice? This decolonial AI design experiment would advance understanding of how AI can embody non-Western philosophies (Chilisa, 2017).

Investigating how students perceive AI advice, their trust levels, effects on self-efficacy and career aspirations would be valuable. If AI consistently undervalues soft skills or local context, does this subtly discourage students from those areas? Understanding user psychology will be important for training both AI systems and users as critical thinkers. While this study focused on computing graduates in Africa, the methodological approach could be applied to other fields or regions from the Global South. Comparative studies might reveal similar patterns of digital colonialism in AI advice for Latin America or Southeast Asia, enriching global discourse on AI in education. We see this research as a starting point toward equitable, contextually relevant AI in education. Steering AI adoption toward innovations that empower rather than marginalize will require continued inquiry rooted in both global knowledge and local wisdom.

9. Conclusion

This study provided the first comprehensive evaluation of LLMs as career guidance tools across ten African countries for computing roles, revealing critical findings about AI effectiveness and contextual responsiveness. Through methodical analysis of 60 LLM responses using the CC2020 framework, we demonstrated that while LLMs reliably identify universal technical competencies (Python programming, cloud computing), they exhibit significant contextual awareness limitations

(35.4% average) and noticeable variation in professional competency coverage.

The higher scores achieved by open-source models in our analysis suggest the need to reconsider prevailing assumptions about AI tool quality, with cost-effective alternatives (Llama: 4.46/5, DeepSeek: 4.25/5) outperforming proprietary models (Claude: 3.46/5). This finding has profound implications for African educational institutions, suggesting that democratized AI development processes better serve diverse contexts than centralized proprietary approaches. Our findings suggest potential for hybrid approaches combining AI technical strengths with local human expertise, though further research is needed to validate implementation strategies. These results indicate directions for developing AI systems that better account for cultural diversity and local contexts.

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