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Artificial Intelligence in Career Counseling Across Global Contexts: A Comparative Framework for Digital Transformation, Equity, and Human Capital Development

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ABSTRACT

The labor market is changing in unprecedented ways powered by the rapid pace of technological change and the disruption of occupations and career pathways. Career counselling systems are not effective at offering individualised and evidence-based advice, at scale especially within constrained environments. With its transformative potential to democratise access to career services, the AI adoption patterns are starkly different between developed and developing countries. Developed countries are striving to develop AI-powered career counseling platforms, but developing countries are facing high technology, institutional, and policy barriers for the implementation of the platforms. The study was based on a systematic integrative literature review of academic research studies, policy documents, conference papers and country case evidence. Eligibility criteria were predetermined for the selection of relevant sources and comparative thematic synthesis was used for analysing the sources. The results were leveraged in the creation of the five dimensions framework (technological readiness, institutional capacity, policy and governance, labor-market integration, and social equity). There is limited comparative research to explore the effect of the various economic contexts on the adoption of AI in educational technology. This paper aims to review evidence of uses of AI in career counseling, to synthesize that evidence and to compare and contrast adoption patterns between developed and developing countries, as well as identify contextual barriers and enablers, and to develop a comparative framework for equitable systems for career guidance based on AI that respond to local needs and constraints in developed and developing countries. The Integrative review of academic databases, policy documents and case studies of different countries, using comparative synthesis and thematic synthesis. Personalisation of career recommendations, accessibility and labour market intelligence, are areas where AI shows great potential. However, technological infrastructure, counselor capacity, ethical governance and cultural adaptation are critical factors for implementation outcomes. Developed countries are using advanced predictive analytics and custom learning trajectories while developing countries need context-based and low-cost solutions to overcome barriers of the digital divide. A five-dimensional matrix that combines technological readiness, institutional capacity, policy environment, labor market alignment with social equity, foresees implementation success in different contexts. This paper offers an original comparative conceptual framework to understand how AI is being integrated into career counseling; identifies gaps and opportunities in career counseling literature; and provides evidence-based policy implications for governments, institutes, and practitioners interested in implementing equitable and responsible AI career counseling systems to improve human capital development around the world.

Introduction

The Evolving Landscape of Career Counseling in the Digital Era

Historically, career counseling has been an important institutional role to support the educational to employment transition (Kvasková et al., 2023). But in the twenty-first century job market the counselor and the student have to face a new level of complexity. The contemporary theory of career counseling is based on the career construction model, which states that people's careers need to be constructed and adjusted to new economic demands, disruptions in technology, and new needs and skills (Šverko & Babarović, 2019). Traditional career counseling, which is typically provided in a one-to-one relationship in institutional settings, continues to be widely inaccessible, inequitable and resource-heavy, especially in developing countries where there are significant counsellor shortages.

Automation, AI and outsourcing, and the introduction of new occupations have transformed the global employment landscape (Hanson, 2023). At the same time, the skills sought by employers are also changing faster than the skills being delivered by education bodies, resulting in persistent skills gaps that have a negative impact on graduates (Sairmaly, 2023). There are several interrelated barriers for young people to make informed career decisions: poor access to reliable labor market information, lack of knowledge about the new skills required in the world of work, insufficient exposure to career pathways and psychological barriers to career decision making self-efficacy (Kvasková et al., 2023). It is difficult for educational institutions to offer the types of real-time labour market intelligence that is so much needed to ensure that students are well-prepared for jobs.

This setting has led to significant investments in technology-based career guidance systems. Artificial Intelligence, especially with machine learning algorithms, natural language processing, and predictive analytics, holds the promise of unprecedented opportunities for offering scalable, personalized, data-driven career support (Bankins et al., 2024). But the potential of AI-powered career advice is unevenly distributed around the world, mirrored by broader structural inequities in digital infrastructure, institutional capacity, and policies.

Artificial Intelligence Applications in Career Counseling: Emerging Technologies and Approaches

Career counseling systems are now increasingly incorporating AI, with various technical methods touching on different aspects of career counseling. Intelligent career recommendation systems use collaborative filtering and content-based algorithms to align each user's profile with appropriate educational programs and career paths, which include education and skills, user interests, and personality traits (Aithal et al., 2023). Analytical models powered by machine learning use huge amounts of data on the labor market to forecast skills needs, growth in jobs and employment likelihoods for various career paths. The utilization of NLP by AI chatbots and virtual counselling assistants allows for conversational interfaces that deliver preliminary career information, answer students' enquiries and offer basic guidance anytime, anywhere (Ifraheem et al., 2024).

Predictive analytics systems employ educational data mining methods to detect at-risk students and/or misaligned students in relation to selected career pathways, and allow for early intervention (Malik et al., 2025). An adaptive learning platform customizes learning materials and career skills training to match each student's learning style and gaps. Labor market intelligence systems are designed to integrate real-time information about job openings, the skills and education needed for every occupation, wages, and demand for a specific job type to provide counselors and students with evidence based information (Alabi et al., 2024). Together, these technologies provide the means to what could be called "precision career counseling"—very personalized advice based on detailed information on one's personality and educational path, skills, labor market conditions, and employment outcomes.

Theoretical bases of AI career counseling come from well-established career development theories. Self-efficacy, outcome expectations, and contextual supports are important factors that influence career interests and decisions, as per social cognitive career theory (SCCT) (Domínguez et al., 2022; Hardin & Longhurst, 2016). Career construction theory focuses on adaptiveness in navigating dynamic career transitions, the importance of career adaptability, identity clarity and proactive career behaviors (Van der Horst et al., 2021; Lu, 2020). Human capital theory suggests that spending on education and skill acquisition will yield individual and social benefits in terms of increased productivity and employability. All these aspects can be reinforced with the support of AI-enabled career systems, which can offer personalized support on the development of self-efficacy, clarify realistic expectations in the labor market according to the information present in the system, contextualise supports according to the individual and geographical situation, and make career adaptability possible through dynamic information and skill-building opportunities.

Global Inequality in AI Adoption: Divergent Pathways for Developed and Developing Countries

When it comes to career counseling, AI usage shows significant geographic variation, which mirrors broader trends of technological diffusion and digital inequality (Vesna et al., 2025). In developed countries, such as the United States, the United Kingdom, Germany, Singapore, Australia, and Nordic countries, there is institutional support for adoption of AI, including high-speed internet connectivity, a well-developed digital infrastructure, abundant investment capital to support the development and deployment of AI, established regulatory frameworks for data protection and algorithm governance, and counselor workforce capacity to embrace the use of technology in their practices.

Developing countries, however, in South Asia, Sub-Saharan Africa, Southeast Asia, and Latin America have significant structural limitations in the adoption of AI. These range from limited digital infrastructure and connectivity in rural areas, to very limited capacity for technology investment due to severe resource constraints, to the absence of skilled people in the field of AI and data science and educational technology, to fragmented and incomplete labour market information systems, to weak or non-existent regulatory frameworks for data governance and algorithmic transparency, as well as underprepared workforces of counsellors who are less than well equipped to integrate technology, and linguistic and cultural limitations of predominantly English-language systems (Ndibalema, 2025; NIRMANI, 2025). Access to and experience of technology is unequal, disproportionately impacting rural communities, women, and those with low-income and students in under-resourced schools, colleges and universities (Afzal et al., 2023; Li, 2025).

Studies of the adoption of educational technology in developing nations have shown that lack of infrastructure is not the only reason for the failure to implement it. Instead, it is important to consider institutional capacity, teacher training, policy support, culturally responsive design, and funding support for technology integration in tandem (Folorunso et al., 2024). A big challenge for developing countries is to not only use AI technologies that are developed in wealthier countries, but to also adapt or build local solutions that are local-based, local language, local workforce, and local education system.

Research Problem and Justification

AI's impact on career guidance is profound, yet there is a lack of academic research on a direct basis when compared to other countries. Much existing research is conducted in developed country contexts, such as Europe and the United States. Very few studies look into the challenges of implementation and success factors in developing country settings. A systematic understanding of how technological, institutional, policy, and cultural factors play out in national contexts to facilitate or hinder integration of AI in career guidance is still in an underdeveloped state. Moreover, there is extensive literature on digital inequality in education which has been neglected in systematic integration with the new research on career guidance using AI, hindering the understanding of how digital inequalities influence the outcomes of career guidance.

This lack of knowledge has major implications for practice. Governments and educational institutions in developing countries are increasingly looking to provide career services through technology, but lack evidence-based frameworks of contextually appropriate implementation. The lack of a blueprint for supporting AI in educational systems in various contexts is a challenge for international development organizations. Teachers are uncertain with regard to professional learning needs and barriers to implementation. There is a lack of understanding and awareness among technologists and entrepreneurs on the implementation requirements in resource-constrained environments for the development of AI career platforms.Lack of understanding and awareness in the context of implementation in resource constrained environments for the development of AI career platforms by technologists and entrepreneurs. Policy makers are currently without evidence with which to build an effective regulatory framework that will strike a balance between innovation and responsible governance of AI.

Research Objectives and Questions

This paper aims to fill these gap with the following four main objectives of the research:

Objective 1: Review evidence of the applications of AI in the field of career counseling and their benefits, challenges and effectiveness.

Objective 2: Systematically compare the pattern, extent and impacts of AI adoption in developed vs developing country contexts.

Objective 3: Assess and explain technology, institutional, policy, cultural and social factors that facilitate or hinder the successful incorporation of AI into career counseling systems.

Objective 4: Design a new comparative conceptual model that elucidates the conditions that influence the success or failure of the integration of AI and offer strategies for the equitable and responsible use of AI in various settings.

The following objectives align to four main research questions:

RQ1: What evidence is there of the effectiveness, equity, and ethical issues of AI's impact on career counselling globally?

RQ2: How do developed and developing countries vary in terms of the adoption, implementation, and reported outcomes of AI in career counseling?

RQ3: What technological, institutional, organizational, policy and contextual factors facilitate and/or impede the successful implementation of AI in career counseling systems in various economic and institutional settings?

RQ4: What are the implications for designing more equitable, responsible, and contextually appropriate career counselling frameworks that can be informed by comparative analysis across how career counselling is implemented in different parts of the world, across a diverse range of populations in different development contexts?

Methodology

The design of this study was systematic integrative literature review to investigate the application of artificial intelligence in career counseling in developed and developing countries. The most important academic databases were used to locate peer-reviewed articles, conference papers, policy papers and institutional papers relevant to the research: Scopus, Web of Science, ERIC, PsycINFO, IEEE Xplore and Google Scholar.

Research was included if it focused on one of the following topics: AI-based career guidance, career recommendation systems, predictive analytics, chatbots, labour-market intelligence, digital accessibility, institutional capacity, ethical governance, equity in career counselling. Sources that did not have some sort of connection to career guidance, were not academically supported, or apply only to general AI were not included.

The researchers applied comparative thematic synthesis on the literature selected. Findings were coded and were grouped into four broad themes: technological infrastructure, institutional readiness, policy and governance, labor-market integration and social equity. A comparison of the developed and the developing country context was then made to uncover differences in adoption, barriers to implementation, enabling factors, and outcome.

A conceptual framework was created based on the themes identified; this 5-dimensional framework includes technological readiness, institutional capacity, policy and governance environment, human-capital and labor-market integration, and social equity and accessibility.

Literature Review and Theoretical Foundation

Career Development Theories and Human Capital Foundations

Career counseling practice is supported by a number of complementary and related theories that provide a glimpse into how career decisions are made and how people manage career transitions. Social Cognitive Career Theory (SCCT) developed by Lent, Brown and Hackett suggests that career interests, career choices and career outcomes are a product of interactions between self-efficacy beliefs, outcome expectations, environments and social influences (Domínguez et al., 2022). In SCCT, self-efficacy, defined as the individuals' belief in his or her ability to perform specific career-relevant behaviors, is a key mediator of career decision making (Hardin & Longhurst, 2016). AI systems have the potential to enhance contextual support by delivering individualized information, demonstrating career pathways, and fostering self-efficacy through adaptive challenges, potentially complementing the impact of contextual support systems on career trajectories.AI systems can complement the impact of contextual support systems on career trajectories by delivering individualized information, demonstrating career pathways, and fostering self-efficacy through adaptive challenges.

Career Construction Theory (CCT) (Savickas, et al., 2019) puts forward the concept of career adaptability, which consists of a set of psychological resources that help people cope with career changes and environmental shifts. The career construction model of adaptation pinpoints four elements: concern (career planning motivation), control (career decision-making agency), curiosity (career exploration and openness to new opportunities), and confidence (self-efficacy in career management) (Lu, 2020). Career adaptability indicates successful school-to-work transitions, employment retention and overall life satisfaction at various career levels (Kvasková et al., 2023). The framework is especially relevant for career counseling using AI, where adaptive systems can offer customized feedback and guidance to bolster each adaptability dimension by presenting personalized information, exploration tools, skill-building activities, and continuous feedback and support.

The economic basis for career counseling is human capital theory. This theory is that an individual's investment in education and skill development is to increase productivity and income, which in turn will come back to them in the form of better employment and higher income throughout their life (Sairmaly, 2023). In this sense, career counseling is an investment in human capital, in giving information, guidance and support to make optimum educational and occupational decisions. From a community perspective, equitable access to advice, guidance, and information on the development of skills, and supporting informed choices, meet the human capital development agenda. Introducing AI-powered career guidance represents an opportunity to broaden access to human capital development without squandering on equity issues or deepening inequities.

They all share some common elements that are relevant to the study of AI in career counseling: (1) individual agency, self-efficacy and adaptive capacity are key to career success; (2) contextual factors, information, support, environmental opportunities, all play an important role in career pathways; (3) career development is a process that is continuous and adaptive, not linear; (4) effective career support involves addressing both cognitive (knowledge, skills, decision-making) and psychological (confidence, motivation, identity) factors. AI-based systems have the possibility to enhance support in these areas, but must be designed with the psychological and contextual aspects of support in mind as well as information.

Artificial Intelligence in Educational and Career Systems: Conceptual Frameworks and Applications

The use of artificial intelligence in the education sector has led to a significant amount of scholarship exploring opportunities and challenges (Ifraheem et al., 2024). AI technology in education includes intelligent tutoring systems which offer individualised learning, adaptive learning platforms that adjust content difficulty and pacing to student needs, learning analytics systems that detect at-risk students for intervention, natural language processing technology for automated evaluation of student writing and support, and generative AI technology such as a large language model to create content and support conversation (Uthaileang & Kiattisin, 2023). In the context of career counselling, AI can be used in several ways, such as intelligent recommendation systems where AI tailors student matches to educational programs and careers, chatbots that deliver initial career information, predictive analytics systems that identify students who require intervention in career counselling, labor market intelligence systems that collate real-time occupational data, and adaptive career development platforms that adjust skill development activities based on individual student requirements (Bankins et al., 2024).

AI-powered career counselling is a transformative landscape, bridging personalized support, graduate success, labour-market insights, and ethical oversight, as described in recent scholarship. Malik (2024) states that the ethical principles that need to be followed when implementing AI in career counselling include privacy, algorithmic fairness, transparency and human judgment, suggesting that the use of AI should complement and not supplant human counsellors. Building on this human-focused approach, Malik (2025a) presented a multidimensional approach where AI can combine personal traits, educational histories, career preferences, skill needs, and labour-market data to create individual and context-specific career pathways. Malik (2025b) also argues from a cross-national perspective that AI-powered counselling can enhance graduate employability by assessing skills gaps, bridging the gap between educational programs and employer needs, and increasing access to career guidance services, though it is subject to the constraints of digital infrastructure, institutional capacity, counsellor training and readiness, and access. More recently, Malik (2025c) stated that AI-supported career advice systems as 'smart job matching brokers' that can mitigate information asymmetry and skills mismatch using competency mapping, skills intelligence, forecasting and tailored career paths. Together, these research findings indicate that the potential of AI to revolutionize career counselling lies in the integration of technological personalization with human guidance, institutional readiness, ethical management, and labour-market precision.

The findings from the research on the effectiveness of AI in education show us some key trends. The potential for personalization and adaptive learning to enhance learning outcomes appears to be more promising when based on pedagogical considerations (Ifraheem et al., 2024). The effects, however, are significantly different depending on the quality of implementation, teacher training and support, and curriculum and instruction integration. There is evidence that learning analytics systems have the ability to identify at-risk students early, but there is need to test predictive algorithms for bias and validate their performance to prevent them from reinforcing current educational disparities (Malik et al., 2025). Virtual tutoring systems and chatbots have demonstrated positive effects on increasing access to tutoring and on offering additional tutoring support, but are not a substitute for human tutors for more difficult subjects.

Critical across all educational AI applications are issues of transparency, interpretability, and algorithmic bias. In addition, machine learning models can be "black boxes" and make predictions without providing any insight into how the features of the input are related to the prediction. With regard to career counseling, there is a need for transparency, in order to explain why certain careers are recommended to students, which enables a more informed assessment of career recommendations. Algorithmic bias occurs when the history of the data used to train algorithms is unfair (e.g., women may have been underrepresented in technical fields) or when the algorithms learn to perpetuate unfair patterns (Bahangulu & Owusu-Berko, 2025). Biased algorithms may perpetuate gender stereotypes (push women away from STEM careers), ethnic differences, or socioeconomic tracking in career counseling. To address these issues, biases need to be detected and mitigated, training datasets should be diverse, human oversight is needed, and outputs of the systems should be regularly audited for equity implications.

AI-Enabled Career Counseling Technologies: Current State and Evidence

The modern AI-driven career guidance platforms use several technological solutions. Intelligent career matching systems use machine learning algorithms trained on data sets of relationships between individual characteristics (education, skills, interests, personality, demographics) and career outcomes (choice of career, income, job satisfaction). The systems make rank-based suggestions for appropriate occupations or programs of study for individual students (Aithal et al., 2023). These systems have the potential to provide students with exposure to a variety of possible career paths they may not be considering and have the potential to limit subjectivity in the counselor's recommendations.

With conversational AI interfaces via chatbots and virtual counselors responding to queries using natural language processing, students can get answers to their career related queries. The systems can deliver simple information about careers and feedback for interest assessment, and also guidance about educational pathways, without the need for human counselors. LLMs are especially promising in their ability to provide detailed and context-appropriate career advice. Though these systems are trained on mostly English-language texts, their efficacy in other languages and other cultures is unknown.

Predictive analytics systems use educational data mining for predicting student outcomes and identifying students that require intervention in the world of work. Student performance prediction research has shown that machine learning models can predict students' performance with an acceptable level of accuracy, allowing for targeted interventions, such as those based on ensemble methods and dynamic feature selection (Malik et al., 2025). For career counseling, such methods could be used to detect students whose career plans are inconsistent with their academic achievement, interests, and/or available labor market opportunities, which may lead to a counselor intervention.

Labor market intelligence systems are composed of up-to-date information on jobs and job openings, skills and credentials needed for jobs, wage trends, and job needs. More sophisticated systems involve web scraping job boards to gather a wide range of job market data, analysing job surveys, and connecting to employment databases. This information will help counselors to make informed decisions about occupations based on current labor market data, not outdated or stereotypical occupational information.

Career CD learning platforms that support adaptive learning customize the order and content of career skill development experiences to individual learning profiles. These platforms level-up, remediation and deliver multiple learning styles (video, interactive simulations, virtual reality) based on learner needs. These strategies have potential to build career skills such as decision making, work communication, and job search.

However, there is scarce empirical evidence of effectiveness in these promising applications. There have been few studies that investigate the results of AI-driven career counseling against the results of counseling provided by a human counselor, and few studies that report long-term impacts on employment. The majority of the research is on system development and feasibility not on effectiveness evaluation. The implementation studies are predominately in the developed world. This evidence gap impedes conclusions about optimal design and implementation of AI.

Career Counseling and AI Adoption in Developed Countries: Case Examples

Developed economies have made significant strides in their AI-powered career counseling systems, which have been backed by infrastructure, investments, and institutional capacity. There is an increasing number of AI career platforms in the U.S., such as platforms embedded in university career centers, corporate talent management platforms, and independent career counseling platforms (Bankins et al., 2024). These are generally systems that combine resume analysis, searching for jobs, skills gap identification, and customized recommendations. Major universities have developed career technology programs with online assessments, labor market information, and recommendations for educational specializations and occupational goals for students.

Germany provides a good example of how AI-based systems can help vocational education and training (VET) systems. The dual education system, which involves both school-based and work-based learning, is well established in Germany and AI systems are used more and more to match students to suitable apprenticeships, identify skills needed, and tailor learning experiences in VET programs (Hoidn & Šťastný, 2023). The German approach shows how AI-based systems are integrated with robust institutional structures (cooperation with employers, curriculum frameworks, training of counsellors).

Singapore has taken a strategic approach to workforce development and career guidance technology, seeing AI and advanced analytics as key drivers to its economic competitiveness. The government has been spending extensively on the development of career information systems, skills testing, and labor market forecasting for the purpose of national education policy and personal career choices (Nguyen-Anh et al., 2023). The Singapore experience demonstrates how a centralized government plan can ensure that educational institutions, employers and technology providers are aligned to achieve a holistic educational system with an AI tool for career guidance.

Nordic countries have been able to implement AI-based guidance systems without compromising on equity or universality due to the robust educational systems, extensive digital connectivity, and teacher training that are available. These countries highlight the need for AI systems to complement, not supplant, human counsellor support and access to AI career services to be made available in every community (Van der Horst et al., 2021).

Common practices in developed countries involve: significant investment in technology infrastructure and system development, incorporation of AI systems into detailed LMI, professional development for counselors to use AI systems appropriately, regulatory measures to ensure data privacy and algorithmic transparency, and a focus on human-AI collaboration instead of complete automation. In the developed world, however, concerns continue around the issue of algorithmic bias, equity of access for rural or marginalised communities, and the right balance between algorithmic recommendations and human judgment.

Career Counseling and AI Adoption in Developing Countries: Opportunities and Constraints

AI-based career counseling presents unique challenges and opportunities for developing countries. The opportunity arises because of the extent of the need: In many developing countries, the student-to-counsellor ratio is so high that they are in excess of 1000:1. Career counselling is rarely available in educational institutions in Pakistan, Bangladesh and many Sub-Saharan African nations. Consequently, students move into jobs requiring little adaptation, resulting in significant skill mismatches, underemployment and inefficient use of education. AI systems have the promise to deliver career advising at scale without scaling the number of human counselors (Bankins et al., 2024).

Moreover, in many developing countries, the youth population is large which is entering into labor market at a time of rapid transformation of their occupations. There are limited opportunities for information sharing and knowledge of emerging opportunities and skills, thus sustaining cycles of limited opportunity and skill underutilization. Labor market intelligence systems based on AI may deliver essential information to help students make better decisions about their education and career, thus better linking education and employment.

But developing nations have a number of significant challenges that hinder the uptake of AI. The biggest challenge is the lack of infrastructure. The availability of reliable electricity supply is still lacking in rural areas of many Sub-Saharan African and South Asian regions; Internet connectivity is also weak or unavailable in remote communities; bandwidth is also not enough for data-intensive applications; and technology is too costly for institutions and individuals (NIRMANI, 2025). Even if there was good connectivity in the cities, cost is still a major issue for lower income students and resource poor institutions.

These are further challenges due to data scarcity and data quality problems. AI systems need significant quantity of high-quality data to train and validate. Labor market information systems are lacking in many developing countries, and longitudinal data on student outcomes is scarce, as are classifications of occupations. If available, historical data might be reflective of outdated occupational structure and skill requirements. Moreover, in developing countries, the occupational structures are frequently very different from the developed countries' occupational structures, with informal sector jobs dominating in many developing countries, and so the usual occupational classifications are not well-suited.

Human capital and institutional factors are also important. There is a shortage of well-trained employees in developing countries in the field of data science, machine learning, and the development and implementation of AI in education. Counsellors are not trained in technology integration and educational institutions have limited capacity of IT infrastructure and technical support. There is a significantly reduced capacity for investments because the focus on education is principally on simple provision of schools and teachers instead of promoting the enhancement of technology. In many developing countries, policies and regulations addressing data protection, algorithmic governance and technology ethics are still in their nascent stages of development (Folorunso et al., 2024).

Language is also a hurdle, with the majority of AI systems and training data being in English, making it less applicable to non-English speaking contexts. Moreover, the cultural context of career guidance is important, as the conceptualisation and provision of career guidance in Western societies might not adequately reflect the family context, community norms, and cultural norms that influence career decision making in societies outside of Western ones.

Despite the challenges, there are some developing countries that have taken steps to incorporate technology in career guidance. The experience of South Africa with online career information systems and virtual counselling has been found in open distance learning institutions, such as the University of South Africa (UNSA), however the availability is limited due to digital divide issues. Various technology-based career guidance programs have been introduced in India, but their implementation and coverage are limited. Bangladesh has been researching cost-effective technological solutions such as introducing an AI-driven career guidance system for mobile access (Dolhopolov et al., 2022). The preliminary work offers insights into feasibility, challenges, and keys to success.

Responsible and Ethical AI in Career Counseling: Critical Considerations

Whether a situation is in education, healthcare, or any other application, there are a number of key factors that need to be taken into account for responsible AI in career counseling. Algorithmic fairness and bias mitigation is essential and they should not perpetuate the gender, race, ethnicity, disability or socioeconomic bias that has been present in history to guide the career path. Studies have shown that machine learning algorithms tend to perpetuate and amplify bias in the training data (Bahangulu & Owusu-Berko, 2025). Algorithms may cause biases in the workplace by promoting care and career segregation, limiting the abilities of specific groups, or directing people away from non-traditional work. To combat algorithmic bias, diverse data is needed for training algorithms, bias detection and testing is required, fairness constraints must be specified, and human oversight is essential.

To ensure user trust in and appropriate use of the system, transparency and interpretability is a key factor. Students and counselors need to know the rationale behind the specific recommendations that are being made; recommendations from algorithms without explanation may be disregarded or taken on trust. There are different kinds of transparency that are needed by different stakeholders: students need to grasp the system logic at a level understandable to them and know why certain careers are recommended for them; counselors need to understand the system logic and know whether the career is appropriate for them to include in their recommendation; educators and policymakers need to understand the logic of the system and the limitations of the system and assess whether it is appropriate for institutional use.

Career counseling systems handle private, sensitive personal information such as educational records, psychological assessments, and family details, which can lead to large-scale damage if it is misused.These systems also have to deal with sensitive personal data, like educational information, psychological assessments, and family details, which can cause substantial damage if misused, necessitating robust data protection mechanisms. Some developing countries with poor regulatory systems are especially challenged to implement proper data protection. There are standards set by international frameworks (GDPR in Europe, CCPA in California) and many developing countries have no similar data protection standards.

It is not career counseling all the way to the end, but instead human or hybrid systems are suitable models. Algorithms lack the ability to provide human counselors with contextual understanding, ethical judgment, and relationship-based support. The ideal systems are likely to be algorithmically efficient, customised, and involve human judgement and relational support. There are implementation issues, however, such as counselor training, counselor workload, and system design to enable effective human-algorithm collaboration.

Career counseling systems using artificial intelligence should be accessible to students with disability and meet the needs of diverse learners with various learning needs through accessibility and universal design. Systems should be translated into several languages and tailored to the culture. Finally, cost and availability should not be a source of digital inequality, ensuring that only privileged students have access to high-quality AI-powered career guidance (Assefa et al., 2024; Gupta et al., 2025).

Comparative Conceptual Framework: AI Career Counseling Integration across Contexts

Framework Development and Dimensions

Using a comparative analysis of literature and mode of implementation in various contexts, this paper proposes a five-dimensional conceptual framework on how contextual factors influence the outcomes of AI implementation in career counseling. The framework specifies the critical conditions that are needed to support successful implementation, and it suggests that results will be a function of simultaneous development in all five dimensions, instead of development in any single dimension.

Dimension 1: Technological Readiness

Technological readiness includes technical capacity, data systems, and infrastructure for implementing AI. Signals include: quality of digital infrastructure (internet connectivity, reliability of electricity, device availability); data infrastructure (labor market information systems, educational data systems, occupational classifications, longitudinal outcomes data); technical expertise (data scientists, AI developers, educational technologists); and technology investment capacity. It is common to find advanced technical capacity, well-developed data systems and advanced infrastructure in developed countries. These are the main components that developing countries lack, and are a prerequisite for implementation (Folorunso et al., 2024; Ndibalema, 2025).

Dimension 2: Institutional Capacity

Institutional capacity encompasses readiness for technology implementation, such as capacity to prepare counselors, leadership support, and change management capacity. The indicators are: being trained and prepared to integrate technology; commitment of principals/leaders to technology adoption; organizational infrastructure (IT support, equipment, connectivity); staff retention to insure consistent implementation; and institutional culture that supports innovation (Roshan et al., 2024). Where technology is in place, there are often institutional constraints that hinder effective implementation. Insufficient counselor training, lack of IT support, institutional resistance to change, and lack of adequate institutional capacity are just some of the institutional constraints that developing countries may experience.

Dimension 3: Policy and Governance Environment

Policy and governance dimensions include policy and incentive frameworks and strategic planning in AI adoption. They encompass data protection and privacy policies, frameworks for overseeing algorithms, education policies that expressly call for the integration of AI, funding avenues for technology investments, curriculum structures that allow for the use of AI to inform learning, and international coordination of standards and practices (Folorunso et al., 2024). Generally, the policy profiles are more developed in developed countries and less developed in developing countries, or policies may have ambiguous goals or be poorly enforced.

Dimension 4: Human Capital and Labor Market Integration

This dimension will focus on the quality and relevance of LMI, employer engagement and linking education and employment. The indicators are: Quality of labour market intelligence; Employer involvement in setting up the skills required in the labour market; Match between education and the demand in the labour market; Skills forecast capability; Transition pathways to the labour market; Linkages between education and employers (Sairmaly, 2023). Without strong labor market integration, AI systems can only offer useful, relevant information and guidance, if it exists, and can severely reduce the extent to which they can be useful.

Dimension 5: Social Equity and Accessibility

Social equity dimensions refer to who is gaining from the AI-based system and how implementation of the system either exacerbates or diminishes existing inequality. Indicators include: geographic accessibility (urban-rural distribution, rural community access); affordability and cost barriers; digital literacy across populations; representation in system design and data; accessibility for students with disabilities and diverse learning needs; inclusion of marginalized populations; and attention to gender equity (Afzal et al., 2023; Li, 2025). This dimension is key to ensure that an AI-based system is in service to equity or to deepen the digital divide.

Interactions and System Dynamics

These 5 dimensions are interdependent, and growth or development in one dimension without the other dimensions is limited. For instance, if institutional capacity is not built to effectively utilize systems, technological infrastructure could be deployed and not used effectively. Likewise, if AI systems are not implemented with data privacy in mind, it can lead to a loss of trust and uptake. The framework states that success in implementation is dependent on development in integrated dimensions.

In addition, the nature of education outcomes is shaped by various factors at the context level, such as the level of economic development, the quality of governance, cultural factors and historical investments in education. In developed countries there are reinforcing cycles: effective institutions lead to improved data infrastructure, which leads to more effective systems, which leads to greater political will to invest in data further. Weak initial capacity slows down the development of the system, limited initial success reduces support for system development, the reduced support for system development further leads to sustained underinvestment and capacity gaps (Das, 2025).

It also points out that technology transfer from developed to developing countries is not one-size-fits-all because systems developed in developed-country contexts are based on infrastructure, institutions, and policy settings that may not exist in developing countries. Rather, contextually appropriate adaptation is needed which also calls for local technical capacity and understanding of local conditions, and sustained investment (Mubarok et al., 2025).

Visual Representation and Application

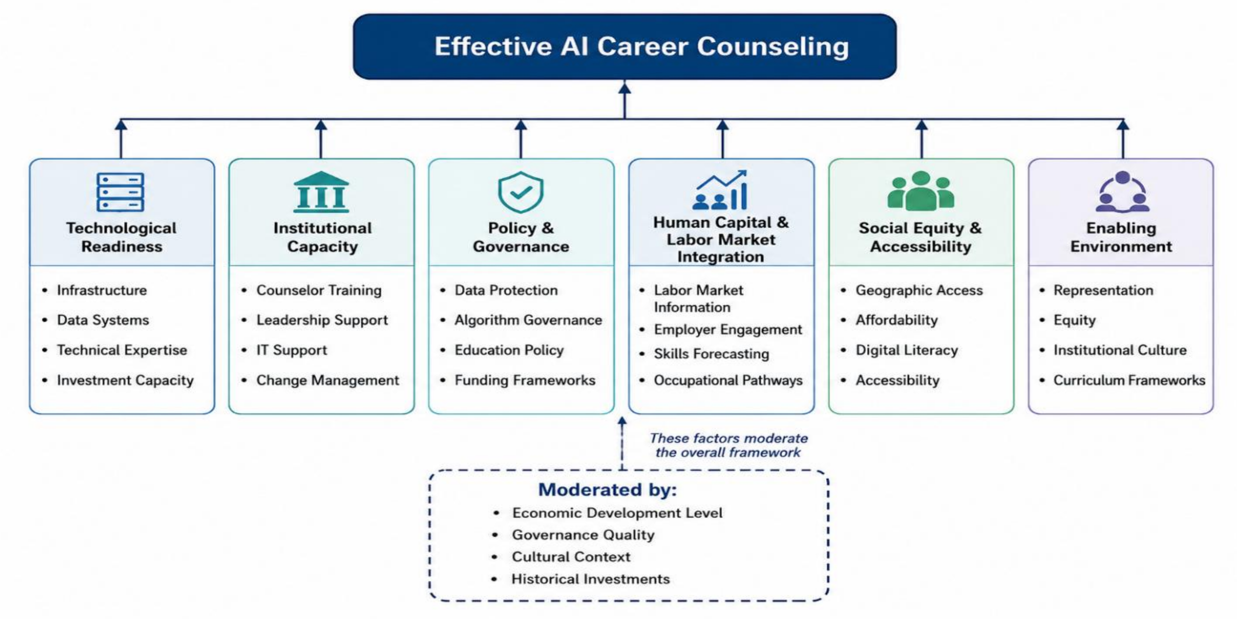

Figure 1: Comparative AI Career Counseling Integration Framework

The framework covers the country, institutional and system level. The five dimensions can be used to compare developed and developing countries at the country level, and can reflect the implementation trajectory, and potential problems. On the institutional level, making comparisons about these dimensions between universities or school systems will help identify gaps in capacity and what priorities should be focused on in terms of capacity development. At the system level, specific AI career counselling systems can be contrasted on these dimensions to forecast barriers to system adoption and adaptations.

Comparative Analysis: Implementation Patterns in Developed and Developing Countries

Technological Infrastructure and AI System Development

Advanced digital infrastructure supports more advanced AI systems in Developed Countries. In most developed countries, the penetration of the Internet is higher than 90%, the connection is reliable in urban areas and in growing numbers in rural areas, the number of devices is significant, and the computational resources allow for complex machine learning models. This infrastructure enables development of data-intensive systems requiring large-scale data collection, processing, and real-time updates. In developed countries, there are several platforms and services available in the field of AI career counseling, including those run by universities and other platforms that are commercial and available to institutional and individual markets.

The U.S. is a good example of this, with several well-developed AI career platforms (such as LinkedIn Career Explorer, Burning Glass Technologies' labor market intelligence, university-integrated systems) providing advanced career matching, skills gap and labor market forecasting. They tend to combine a variety of data sources, such as education records, labor market databases, employer hiring patterns, and salary data. A significant amount of private funding is supplemented by government and university funding for the development of systems (Bankins et al., 2024).

The German career guidance system's infrastructure uses AI to filter the vocational education system and match students with apprenticeships, using complex algorithms to analyze students' skills, interests, and preferences compared to the apprentice's needs. This integration represents Germany's long time practice of vocational education and digital innovation capacity (Hoidn & Šťastný, 2023).

Limited infrastructure constraints the development of the systems in the developing countries. Technical feasibility of cloud-based AI systems is also hindered in many rural regions of developing nations that do not have reliable electricity or internet connections (NIRMANI, 2025). Cost is a major challenge for institutions and students, where there is infrastructure available. Small hardware and computing resources might require more straightforward algorithms or require an offline implementation. Lack of access to detailed data can be a problem for systems wanting to access data that covers full-time labor market participation, education outcome, and occupational classification, which are needed for the training of algorithms.

Implementing AI in career counseling in developing countries is, therefore, still limited in scope and scope, and it is usually done on a smaller scale. Where applied, the systems are generally more simple in their recommendations, tend to be applied to particular regions or institutions, and are not necessarily aimed at nationwide rollout, but are more likely to fit into the existing educational system (Dolhopolov et al., 2022). In the developing world, Bangladesh, India, and South Africa have considered using AI in the domain of career guidance, but there are still infrastructure and institutional challenges to deploy such initiatives in developing nations as opposed to developed ones.

Institutional Capacity and Counselor Readiness

Developed Countries: Counselors trained in recent theories of career development are employed in schools and more and more are competent in using technology in their work. The staff of universities' career centers is usually comprised of professionals who have master's degrees in career counseling, higher education administration or a related area. Technology integration is routinely discussed at the in-service professional development. IT professionals are frequently hired to assist institutions in implementing technology. Career technology is generally considered a critical infrastructure that needs to be invested in over time by leadership.

In many universities, the counselor-to-student ratio is greater than 1 counselor for every 500 students, but this means that there are reasonable caseloads in developed countries to provide at least some face-to-face counseling with the aid of technology. Counselor attitudes towards technology range from negative to positive, with more recognizing the potential for broadening reach and personalization. Research shows that professional development is a strong indicator of counselor confidence in using AI tools, with institutions with a strong focus on professional development seeing improved implementation (Roshan et al., 2024; Thannimalai & Raman, 2018).

Shortage of counselors exists in most of the developing countries. In lots of places, there is not any particular career counselling role in secondary schools or universities. If counselors are available, training is frequently based on traditional ideas and content and focuses on subject matter instead of on current theories or technology in the field of career development. Limited in-service professional development opportunities. There are many counselors who have no access to materials, technology, or office and work in highly resource-poor environments.

Perhaps the biggest hurdle for adopting AI in developing countries is the institutional capacity gap. Even when technology is available, the lack of trained personnel to implement and maintain systems greatly limits their use. A lack of capacity to provide IT support in IT systems in addressing technical issues, maintaining systems and making new systems fit into the existing infrastructure is a common problem in institutions (Ndibalema, 2025). In many cases, leaders in developing country educational institutions focus more on basic provision (buildings, teachers, materials) than on technology enhancement.

Policy Frameworks and Governance

Developed Countries: Developed countries have well-developed policy frameworks on data protection, algorithm governance and technology ethics in education. Data privacy controls in Europe are governed by GDPR, in the USA by FERPA and in the other developed countries by equivalent laws. There is a growing degree of formality in algorithm governance procedures, such as transparency, bias testing and auditability. The topic of technology integration, digital literacy, and equity is a topic that has become prevalent in education policy documents (Capano et al., 2022).

Developed countries often implement ideas and best practice guidance from international policy development by UNESCO, OECD and other organizations. But implementation is uneven; data protection regimes can be observed more as a virtue to be believed in, than one to be executed in practice; algorithm governance is sometimes not catching up with algorithm development.

In developing countries, data protection laws often are not well-developed or monitored. Lots of countries have no privacy legislation as comprehensive as international standards, and, even if it exists, its enforcement capacity is restricted. Regulatory knowledge on emerging technology governance is severely limited, and most developing nations do not have the institutions or the capacity to do so on algorithm governance, AI ethics, responsible technology integration (Folorunso et al., 2024).

In developing countries, education policy tends to focus on increasing access and enrollment, rather than on improving the quality of education or use of technology. Technologies-based career guidance is rarely included in national education strategies, and is therefore left to individual institutions to fill in without policy guidance or funding. However, there may be international guidance, although this is usually not tailored to local conditions or policy contexts.

Labor Market Integration and Information Quality

Developed Countries: Advanced and detailed labor market information systems are available to offer quality data on the demand for jobs, the skills needed, salary trends, and employment forecasts. The government statistical agencies (BLS in the USA, ONS in the UK) carry out periodic surveys of households to measure the labour force and offer detailed information on occupations and skills. Data from private sector organisations (Burning Glass Technologies, LinkedIn, Indeed) gather job posting information that allows for real-time signals of the labour market. Employer involvement in skills definition and forecasting is high and many employers are involved in curriculum development and internships (Sairmaly, 2023).

This labor market infrastructure supports AI systems to give precise, timely career recommendations based on real labor market information. Students and counselors have access to accurate data on employment opportunities, job skills, and job wages for various pathways. Standardized frameworks for system design and data integration are available in the form of occupational classifications (e.g., O*NET in the US, SOC in the UK).

Labor market information systems in developing countries are usually poorly developed or fragmented. A shortage of detailed occupational classification in routine labor force surveys in many developing countries makes it difficult to obtain occupational information. Data quality and availability is often poor due to limited government statistical capacity. There are a number of initiatives in the private sector that provide labour market data in some countries, but many of these tend to focus on employment in the formal sector, which may mask the employment conditions where the informal sector is predominant.

Occupational patterns in developing countries may be very different from those in developed countries. Informal sector employment accounts for a significant share of employment in most developing countries and traditional occupational categorisations may fail to accurately reflect informal occupations. Thus, AI models which have been trained using data from occupations in developed countries are likely to fail to accurately forecast employment opportunities in developing countries. The level of engagement of the employer in skills definition is different in different countries, with some having well-developed partnerships between the employer and education institutions and in others, there is a significant disconnect.

The fact that this gap in the labour market represents a huge hindrance to the use of AI career counseling systems in developing countries. Labor market information is essential for the systems to offer sound advice on occupational opportunities, skills needed for a job, or employment prospects.

Social Equity and Digital Divide Dimensions

Developed Countries: Digital divides have been greatly reduced in developed regions as opposed to developing regions, but there are still digital divides. These include lower coverage among the rural population compared to the urban population, less access to technology among lower income groups, less digital literacy among the older population, and less access for persons with disabilities due to inadequate design of the technology and its environment (Afzal et al., 2023; Li, 2025). There is a significant gender disparity in some technology sectors, for instance: girls and women with equal or higher academic achievement are significantly underrepresented in STEM. Socioeconomic differences impact both technology access and cultural aspects of career aspirations (Assefa et al., 2024).

In developed countries, however, policy attention to ‘digital equity' is significant. There is growing acceptance at institutions of universal design principles, which guarantee access to a diverse learner (Gupta et al., 2025). Regulations cover discrimination and accessibility. The goals of public investment in digital infrastructure are to overcome geographic and socioeconomic barriers. As a result, policy and institutional support for tackling digital inequities is strong, even though these are significant.

Developing countries are much more likely to have significant digital divides when compared to the developed countries (Vesna et al., 2025). There are significant differences between rural and urban areas, with some rural areas not having a reliable electricity supply or connectivity. There are significant barriers to access of technologies, including socioeconomic ones, with the cost of devices and connectivity being a large part of income for poorer households. Gender gaps are frequently greater than in developed nations and there are extra obstacles for girls when it comes to technology and technology education. There is extreme exclusion, for youth in peripheral communities, of access to and skills in digital technologies (Vesna et al., 2025).

Policy attention to digital equity tends to be under-resourced, and, in most developing countries, the capacity of the government to tackle digital inequity is limited by resources and competing priorities. AI-driven career guidance platforms can deepen these inequities if they are not deliberately designed and implemented to address the needs of all communities—especially those in rural areas, who are less likely to have access to these tools and might not benefit from them. At the very least, such a system would make inequity worse because good guidance would be provided for privileged groups but not for disadvantaged groups.

Empirical Findings: Thematic Synthesis of Implementation Experiences

Effectiveness of AI-Based Career Counseling: Evidence and Limitations

There is growing evidence that AI-powered career advising could improve various aspects of career advising quality and availability. Personalization is a proven strength, as AI-based systems can adapt to personal characteristics, such as how the recommendations, learning content, and interaction style are designed, which can lead to better engagement and results (Ifraheem et al., 2024). Labor market information systems offer more timely and detailed occupational information than traditional sources of print information that helps to facilitate better decision making. The advantage of accessibility is realized through the availability of AI systems around the clock, which minimizes waiting periods for counseling and offers support in areas where there isn't a human counselor.

But there are significant gaps in the evidence base and the overall effectiveness cannot be deduced. There have been few rigorous studies that compare employment, income, and satisfaction with work for graduates of traditional counseling to graduates who received guidance via artificial intelligence. System functionality and feasibility are more often the focus of research than impacts of outcomes. Long-term studies that evaluate if AI support helps drive career growth are scarce. The study results are difficult to generalize because of the diversity in system design, contexts in which the systems are implemented, and outcomes studied.

There is so little evidence of predictive analytics in student performance and career outcomes there is both promise and concerns. Predictive models can accurately flag students needing interventions and can be used to flag students for interventions, but haven't necessarily been taught by algorithms using historical data to reduce or compound the biases that already exist about who receives which opportunities (Malik et al., 2025). Likewise, if not adequately designed to mitigate bias, career recommendation systems can perpetuate gender and racial occupational segregation.

Barriers to Implementation in Developing Countries: Case Evidence

However, when examining the efforts to implement in developing countries, several reinforcing barriers emerge. The adoption of AI-based career guidance in Bangladesh faced significant challenges due to infrastructure constraints, low institutional capacity, policy gaps, and a lack of labor market information systems, which had a negative impact on its effectiveness (Dolhopolov et al., 2022). The system remains largely operational but it only serves a few students at certain schools, and the bulk of students still do not have access to AI-driven guidance.

The lack of maintenance infrastructure, inconsistent internet connectivity and limited institutional technical support capacity have posed challenges for the sustainability of the educational technology initiatives implemented by Nigeria, which include career guidance components (Nachega et al., 2021). These examples show that investments in human capacities, institutional infrastructure, and policy enabling environments must go hand in hand with the deployment of technology.

The case of AI-powered career guidance systems in India highlights the potential for large-scale implementation and ongoing equity issues. Although there are hundreds of thousands of youth using platforms, there is also evidence of inequities in usage: urban, English language learners, and those with higher socio-economic statuses benefit disproportionately, while rural, vernacular language, and lower socio-economic status populations are not. This trend indicates that if AI is not intentionally designed to address inclusion and do not have a systemic approach of supporting underserved populations, AI can exacerbate rather than reduce existing educational and economic disparities (Assefa et al., 2024).

The same parallels apply to South Africa's higher education institutions' use of AI for career counseling. Historically marginalized universities have not received the technical infrastructure, training of counsellors, and institutional resources needed for effective implementation of AI career platforms. This leads to greater difference in quality of career guidance in elite institutions and historically marginalized institutions, possibly perpetuating existing patterns of labor market inequality (Enakrire & Ocholla, 2017).

The case studies illustrate that the challenges of implementing AI in developing countries are not solely technical, but much more systemic: a lack of digital infrastructure, as well as weak institutional capacity, insufficient policy frameworks, weak labor market information systems, and a lack of resources shape environments in which even the best-designed AI systems have limited impact. The barriers are interlinked; engaging in infrastructure development without strengthening institutional capacity can only solve one part of the issue, not the other policy barriers and inadequate training of counsellors.

Ethical and Responsible AI Considerations Across Contexts

By examining responsible principles in career counseling, one can uncover context-specific aspects. Algorithmic transparency is a key aspect of responsible AI governance, and poses unique challenges in developing countries where regulatory capacity is low, data protection laws are not as sophisticated, and public awareness of the nature of algorithmic systems is limited, resulting in few accountability mechanisms. The algorithmic auditing requirement and transparency mandates have been introduced in the developed world while most developing countries do not have such arrangements with respect to algorithms (Folorunso et al., 2024).

Algorithmic bias is a major issue in every domain, but can be expressed differently. In the developed world, fair and equitable hiring algorithms and career recommendations have been documented to be based on historical occupational segregation by gender and race (Bahangulu & Owusu-Berko, 2025). Interventions are directed towards bias detection, algorithm auditing, and regulatory oversight. However, concerns are not limited to historical bias; in developing countries, scarcity of data can lead to algorithms providing unreliable recommendations, weak data governance can lead to data misuse, privacy breaches, and discrimination based on caste, ethnicity or other protected data.

Transformations of the role of counselor varies widely between contexts in human oversight. In developed countries, the model of AI augmenting the services of counselors, having them provide data that some AI component uses for decisions, is the new model, with the counselor having central authority and ethics responsibility. AI systems are frequently deployed in developing nations with critical scarcity in counselors, where they are used with minimal human oversight, and where the demand to provide counseling services to vast populations with limited resources puts pressure on needing to replace rather than supplement human counseling. This is a stark contrast in the way this will be implemented and has significant implications for the protection of students, ethical decision-making, and counselling quality.

In contexts of developing countries, where the legal context is less evolved, the security of the data in the institutions is less developed, and information about the students can be accessed for uses other than career guidance, data privacy and protection become increasingly complex. Highly sensitive, personal data can be found in AI systems, including educational records, psychological assessments, career preferences, and family information, which can make them vulnerable to misuse. There is an urgent need to improve data protection laws in developing countries and expand international data security capacity building (Folorunso et al., 2024).

Policy and Practical Implications

Recommendations for Developed Countries

The technological capacity and institutional structures to deploy AI-based career counselling at scale are available in developed countries and the focus should be on responsible and ethical deployment. First, set other algorithmic auditing and transparency standards for AI career counseling systems, including independent oversight procedures to ensure that systems do not discriminate based on protected characteristics, that algorithmic decisions can be explained to students and counsellors. Secondly, conduct longitudinal outcome studies to evaluate outcomes of career pathways with AI-based guidance, employment outcomes and earnings, including differential outcomes across demographic groups. Third, establish comprehensive data protection and privacy rules for student career information, including encryption, access controls, and restrictions on data usage. Fourth, develop human-in-the-loop AI models that do not supplant counselor expertise but are designed to augment it, ensuring that human decision-making is responsible for any important career-related decisions, and that the AI model supports the counselor in providing information and analysis to improve their effectiveness in making these decisions (Wallis, 2021).

Recommendations for Developing Countries

The intertwining hurdles in developing countries are creating basic infrastructure and responsibly incorporating AI. A sequential, 'appropriate to context' approach is required. Priorities are those of the essential digital infrastructure investment – broadband connectivity, device access, power reliability – as prerequisites for implementing AI. Second, invest in human capital side by side: train counselors in traditional counseling skills and in AI-literacy, so that they can understand and make effective use of AI tools. Third, improve data governance and privacy policies by developing policies and engaging in international technical cooperation, while ensuring that there are data protection policies in place before sensitive data is collected and stored in AI systems (Folorunso et al., 2024). Fourth, create low cost and open-source AI career counselling tools available for resource constrained institutions, not commercial platforms geared towards rich markets; international technical cooperation and development agencies need to support this provision of public good.

Recommendations for Universities and Educational Institutions

Human and equity-driven strategies for universities to embrace in using AI. Before implementing AI tools, thoroughly evaluate the institution's needs, limitations of counselors, student needs, infrastructure, readiness for AI implementation, etc. – avoid just implementing for the sake of it, but only to tackle real institutional problems. Second, use AI as a supplement rather than a replacement for human counselling; ensure adequate counsellor staffing, training and support alongside the use of AI systems (Van der Horst et al., 2021). Third, put in place students' protections: ensure transparency of algorithmic decision making; ensure students means to challenge or appeal algorithmic recommendations; ensure consequential decisions that affect students are subject of human review. Fourth, watch for inequities between groups of students; keep systems in place to meet the needs of all students, not just groups, by analyzing data to reduce inequities.

Recommendations for Governments and International Organizations

Broad-based national policies should be created for AI-based career counseling that fit into the larger education and labor market policy frameworks. The first is to create AI governance structures that define ethical guidelines, transparency standards, and accountability measures; and integrate international best practices, while considering local differences. Second, improve the public infrastructure for AI-based career counseling, making it accessible to all education organizations, both public and private, without regard for financial status, and address digital divide issues which would lead to equality (Das, 2025). Thirdly, develop institutional capacity for data governance, cybersecurity and algorithmic literacy for government, educational and labor market information institutions. Fourth, build mechanisms of cooperation and exchange between countries for knowledge sharing, technical assistance, and joint research on the implementation of AI in a fair manner in different contexts.

International bodies like UNESCO, the International Labour Organization (ILO), and the World Bank should provide technical assistance, funding, and evidence on successful implementation approaches in developing countries to help build AI career counselling capacity.

Limitations and Future Research Directions

There are important caveats to this analysis. First, the comparison draws on the existing literature but a lot less developed and rigorous in developed countries where studies are plentiful, and less so in developing countries where there has been little research on AI career counseling. Secondly, AI technologies and applications are evolving quickly, and what is analyzed today might need updating soon, highlighting the need for continued monitoring and regular updating of the framework. Third, country level generalisations obscure considerable variation at the country level; in both developed and developing countries the level of infrastructure, resources and institutional capacity varies considerably across countries. Fourth, because of space limitations, individual-level factors such as student preferences, counselor attitudes, and organizational culture are also important factors that can affect implementation outcomes, though they are not emphasized here.

Future research should be conducted to address future gaps. The need for research to establish actual impacts of AI-based counseling versus traditional counseling approaches exists and studies with a longitudinal design with students in a variety of contexts and demographic groups are urgently needed. Comparative studies across different cultures of students, counselors, and institutional leaders on the perception and reaction of AI career counseling systems would shed light on the cultural aspects of implementation. Investigating context-specific implementation science—such as the specific context adaptations, institutional practices and approaches to policy implementation that facilitate successful integration of AI in developing country contexts—will inform actionable guidance for implementation practitioners and policy makers. AI-based career guidance platforms that are cost-effective, user-friendly, and accessible to all would foster equitable innovation (Akpan et al., 2024).

Conclusion

The potential of AI to revolutionize the field of career counseling is immense, given the need to overcome major hurdles such as accessibility, personalization, and data-driven guidance in today's complex job market. In the developed world, there are numerous examples of systems in place that have improved the effectiveness of counsellors, increased access to counselling and made tailored recommendations based on individual needs and market opportunities. But significant implementation challenges and ethical issues must be considered.

The findings from the comparative analysis highlight significant disparities in technological readiness, institutional capacity, policy frameworks, and resources between developed and developing countries, which play a major role in determining the potential opportunities for implementing AI. Developed countries possess infrastructure and resources enabling substantial AI integration but face challenges of ethical governance, algorithmic bias, and ensuring human-centered, equitable implementation. While developing countries have severe shortages of infrastructure, institutional capacity, and policy frameworks to support the implementation of AI, they also have great potential to leverage AI to overcome a lack of counsellors and to provide more career guidance to vulnerable youth. While there may be some general principles to help guide policy development and implementation, these different contexts demand different approaches and strategies, not models developed in wealthy nations.

The analytical conceptual framework proposed in this paper (strategies focused on technological readiness, institutional capacity, policy environment, human capital integration, and social equity) offers an underpinning to contextual variations and leverage points for equitable integration of AI. Important to this vision is the understanding that technology is just one part of the equation in addressing career counseling challenges – it needs to be part of robust institutional systems, supportive policy contexts, and human expertise. This technology-independent, holistic view is a far cry from the technological determinism that equates complex AI systems with quality results no matter what the context.

Going forward, it is vital that AI tools are integrated into career counseling in a way that involves action on multiple fronts: the creation of digital infrastructure and institutional capacity in developing countries; the development of frameworks and best practices for ethical use of AI in career counseling, safeguarding students, and holding AI systems accountable; the continued relevance of human experts and counselors in the field of career counseling; the production of evidence to support rigorous research on the impact of AI in diverse contexts; and the establishment of international cooperation that ensures career counseling with AI does not further exacerbate existing global inequalities, but instead becomes a public good that contributes to the development of human capital and workforce opportunities globally.

The career is a big one. The trajectory that countries take as they engage with AI in career counselling will affect whether these tools help to increase or decrease educational and economic inequalities, whether young people are guided toward career paths that reflect their true interests and potential, or toward career paths that mirror past inequalities, and whether change in the nature of career counselling will improve human flourishing or simply replace human judgment with algorithmic determinism. The call to the action for policy makers, educators and researchers is clear: there is a need to foster equitable, responsible, human-centred integration of AI into career counselling systems and to ensure technological transformation will contribute to human and social development in all contexts.

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