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AI-Driven Skill Mapping and Gig Economy Matching Algorithm for Youth Employment within Nairobi's Informal Sector

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Abstract: The issue of unemployment among the youth is still a big challenge in Nairobi, Kenya, where there is a rapidly growing youth population with limited formal job opportunities. This has led to an increase in the numbers found in the informal economy and the gig economy. Despite this, there is a big gap between the two parties, where the youth do not know what is required while those offering work are faced with difficulties to identify those required to do the work. This paper presents a new approach utilizing Artificial Intelligence to close this gap. The new approach uses natural language processing (NLP) and machine learning (ML) to dynamically link and derive required skills from multiple sources such as youth-supplied information, short-term work experience, and recommendations within the community. This provides a rich and dynamic profile of each person beyond work experience. Simultaneously, this paper uses machine learning to derive opportunities within the gig economy and market demands in real time. A final algorithm is developed to link available youth to work opportunities within this economy according to proximity to required skill sets and predicted wages. The pilot project implementation shows a big increase in correct matches within the gig economy and increased reports of wages earned compared to other approaches to informal job search. This paper concludes that there is big potential within utilizing Artificial Intelligence to dynamically map and link youth to required skill sets within Nairobi's informal economy.

Keywords: *Youth Unemployment, Artificial Intelligence (AI), Gig Economy, Informal Economy, Natural Language Processing (NLP), Machine Learning, Skill Matching, Dynamic Profiling, Job Matching Algorithm, Real-time Market Demands.*

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I. INTRODUCTION

The problem of youth unemployment is a widespread and pressing socio-economic challenge for many developing countries, with Kenya, particularly Nairobi, its capital city, being a very relevant case study [1]. The rate at which this segment of the population is growing, generally referred to as the youth bulge, is matched by the rate at which this segment is being absorbed into gainful labor, which is not growing at a corresponding rate [1]. This scenario has left a majority of this segment seeking to make a livelihood in informal markets [4].

Simultaneously, there is evidence that the gig economy, which is evident when freelance work is prevalent rather than formal employment arrangements, is on the rise across the globe [7]. This is attributed to technology and is seen as an opportunity among many [8]. The increased involvement of technology has led to more young individuals participating in varied gig economy work such as design, programming, deliveries, device repair, and arts [10].

Despite these similarities, there are unique issues involved when both the informal economy and the gig economy are considered simultaneously [13]. The informal economy is necessarily unstructured and does not have job definitions, formal qualifications, and formalized hiring processes like its formal counterpart [4]. This has led to a considerable degree of information and matching asymmetry [17]. On one hand, there is skill development on the part of the youth, which is necessarily unverified, unstructured, and hidden from view [16]. On the other hand, there is considerable search friction with respect to finding suitable workers to accomplish specific tasks [8].

It is within this background that Artificial Intelligence (AI) emerges as a revolutionary opportunity [19]. The technologies inherent to Artificial Intelligence, such as Natural Language Processing (NLP) and Machine Learning

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(ML), have the ability to decode, organize, and make sense of complex, unorganized information [20]. This can be leveraged to dynamically identify the skill sets present within the youth segment and make relevant matches available to them on a timely basis within the gig economy, thus facilitating a more organized digital market for Nairobi's informal economy [21], [22].

➢ *Statement of the Problem*

The informal sector in Nairobi is crucial to the absorptive capacity of youth labor but is also deeply inefficient and disjointed in terms of information flows, and this is limiting to its full utilization within the economy as a source of livelihood [4], [6]. The problem this thesis seeks to solve lies within this crucial two-fold misalignment between youth labor supply and skill demands within Nairobi's growing gig economy [14].

Looking at the supply side, there is a huge population of trained and semi-skilled young people who are still underutilized [5]. These young people acquire training outside the conventional system by doing apprenticeships on a small scale or on their own [16]. They do not have an opportunity to document their training, which they can then make visible to employers [15]. They are left with no choice but to work low-paying jobs that do not correspond to their true talents because they are part of an "invisible workforce" [16].

Demand-side factors involve customers seeking to hire individuals to complete tasks or gigs, which both involve high transaction costs and trust issues [8]. Customers fail to effectively search and source individuals possessing the requisite skill sets to execute a given activity [17]. The lack of a credible verification process and a common platform to match these customers with employees restricts them to less reliable and informal search processes, resulting in higher search durations [12].

This state of affairs gives rise to a vicious cycle, whereby the youth are faced with issues related to underemployment and irregular income, and employers struggle to access dependable human capital [6], [11]. The available technological approaches tend to lack relevance within the informal economy because they disregard irregular skill sets and ignore Nairobi's specific economic environment [20].

Thus, the root issue lies within the lack of such a dynamic, intelligent, and contextually informed system that is capable of filling this gap [25]. There is a pressing need to find a technological system that can automatically identify mappings between the latent skill sets possessed by the youth, intelligently break down market demands, and make informed matches [21]. This paper aims to address this issue by designing and experimenting with an algorithm making use of Artificial Intelligence to map skill sets to gigs particularly suited to Nairobi [22].

➢ *Justification*

This study is critically justified on the basis of its ability to solve a ubiquitous socio-economic problem using an innovative, scalable, and evidence-based technological solution [26]. The development of such an AI-driven skill mapping and gig matchmaking platform is more than just a technological challenge. It is a response to the inefficiencies being witnessed within the Nairobi labor market [8]. The justification for this study can be argued on two grounds---it is theoretically justified and practically justified [27].

- *Theoretical and Methodological Contribution*

The current approaches to labor markets and matching theories are primarily developed to work well within formalized economies and skill sets [14]. This study helps to fill that gap within the literature by exploring a new paradigm that is developed exclusively to address these unique dynamics within the informal economy [13]. The exploratory work is relevant to knowledge on how Artificial Intelligence, particularly Natural Language Processing (NLP) and Machine Learning (ML) technology, can successfully unlock non-traditional skill sets and build an optimized marketplace within these economies with less-structured skill sets into which formal market forces wouldn't function [19], [20].

- *Practical Socio-Economic Impact*

The most persuasive argument is one that is solely based on the impact it may have on the lives of the youths within Nairobi and on the efficiency of the economy [5]. This project directly addresses informal skill sets by making them visible and actionable, which directly goes to addressing two primary problems that exist within this issue [21]:

✓ Increase Youth Earning Potential: The system can positively affect the income-generating capability of youth by making it easier and more accurate to connect to a relevant job [24].
✓ Minimize Transaction Costs: The system can make it easier for both young job seekers and employers seeking talent because it minimizes search costs involved while navigating an unstructured market environment [17].
✓ Enable Skills Development: The system is capable of promoting skill development among youths by offering information on required skill sets, thereby resulting in a responsive and agile work force [10].

- *Policy and Developmental Relevance*

Being an issue that affects policymakers and other stakeholders seeking to make an impact on youth unemployment, this study stands out prominently [1]. The issue of youth unemployment is more than an economic problem but a danger to social and sustainable development [2]. This research project proffers a functional and technology-integrated alternative to inclusive economic development [25]. This study offers proof concerning how technology can present an alternative to formalizing the informal sector without suppressing its vibrancy [8]. This research study pilot tests and confirms this truth and is ready to serve as a model to be replicated elsewhere across Africa and other parts of the globe due to its relevance to different regions [13].

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- *Conclusion*

Finally, there is relevance to this thesis because it is timely and because it is imperative to fill an important gap that exists within the labor market [14]. This project incorporates innovative technology to solve a human problem by offering insight into how artificial intelligence can make a difference within society to ensure economic inclusivity and optimize the informal economy in Nairobi [25].

➢ *Objectives*

- *General Objective*

To design, develop, and evaluate an artificial intelligence-based framework for dynamic skill mapping and gig matching to enhance employability among youth within Nairobi's informal sector.

- *Specific Objectives*

✓ To identify and analyze the important skills that exist within youth and those that are required within Nairobi's informal gig economy.
✓ To design an algorithm that uses machine learning and natural language processing technology to dynamically map and make skill inference on varied, non-traditional source information.
✓ To develop a matching algorithm that can successfully connect youth to opportunities on gig work platforms on the basis of skill proximity, geolocation, and remuneration amount.
✓ To pilot test this proposed framework on gig matching success rates and income generated as a result of this framework compared to conventional job search processes.

➢ *Research Questions*

- *Primary Research Question*

Can skill mapping and gig placement enabled by artificial intelligence result in more favorable outcomes on the labor market for youths engaged in Nairobi's informal economy?

- *Sub-Research Questions*

✓ What skill sets are most prevalent among the youth, and which skill sets are most in-demand within the informal gig economy, according to employers in Nairobi?
✓ What is the most effective method to optimize NLP and machine-learning algorithms to identify and authenticate skill sets on informal accounts and work experiences?
✓ What are the most relevant factors to a successful and acceptable gig algorithm (such as skill comparison, proximity, rate, etc.)?
✓ To what extent does the piloted AI-driven system improve successful gig matches and earnings compared to informal job search processes?

➢ *Scope*

The study shall geographically locate within the informal economy within Nairobi County, within the Republic of Kenya [4]. The identified demographic shall include young people aged 18-35 years engaged within and seeking to access the gig economy [1]. The study shall specifically relate to skill-gig opportunities including digital, creative, technical repair work, and mobile work opportunities rather than being narrowly labor-focused [8]. The building of the Artificial Intelligence shall remain limited to functions related to users' profile information, limited work experience, and community reinforcement, together with publicly available information on gig economy platforms [9].

➢ *Limitations*

The paper acknowledges some possible constraints. The algorithm that maps skill sets is dependent on the quality and honesty of input by users [21]. This input may not be consistent and could be exaggerated. The pilot may not generalize well to any segment of Nairobi's informal economy due to sample size and length of study [27]. The project may face challenges with regards to digital literacy and availability of smartphones among the prospective youth [9]. Finally, this economy is informal and dynamic, such that this model will necessarily have to adapt to this economy to continue being functional [13].

II. LITERATURE REVIEW

➢ *Introduction*

This chapter places the proposed study of an AI-powered skill mapping and gig economy platform within the context of the literature that currently exists on the topic. This examination of the literature encompasses the various themes that underlie the proposed study. The proposed structure of the discussion of the literature encompasses an investigation of the context of youth employment in Kenya and the nature of the informal sector. After that, there shall be an investigation of the growing phenomenon of the gig economy across the world and its particular significance in the Global South. Later on, the discussion will turn to the problem of skills visibility, followed by an investigation of the growing significance of AI in resolving issues within the world's employment markets. This chapter ends with the conclusion of the discussion of the literature that places the proposed research study on sound foundations.

➢ *Youth Unemployment and the Informal Sector in Kenya*

The problem of unemployment among youths is not only visible in Kenya but stands out due to the demographic "youth bulge" and the inability of the economy to offer more job opportunities [1]. The unemployment rate among the youths of Kenya is higher compared to the overall employment rate of the country; this undermines the stability of the nation's social context and development [2]. This problem leaves the majority of the youths of Kenya with little choice but to seek employment within the informal sector of the economy that appears as the only functioning economy that serves the majority of the inhabitants of various cities, including Nairobi.

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The informal sector in Kenya, which can be represented by small and unregistered businesses with low productive capacity, serves as an essential source of livelihood but at the same time symbolizes fragility [3]. As discussed by Chen [4], the informal sector can be understood as a sector that lacks job security, employees' benefits, and protection. The informal sector in Nairobi appears highly dynamic with a broad remit of involvement that may encompass traders on the streets, artisans, and other forms of services that are activity-based [5]. Nevertheless, despite its potential capacity to absorb joblessness, the sector faces inefficiency. As this thesis points out, one of the major problems with the sector is the absence of proper structures designed to certify skills that would normally limit employees' potential to a certain extent of lowly and insecure remunerations [6]. The informal sector, therefore, serves beyond being a place of absorption of the jobless; it consists of an intricate world with its own dynamics that may result in inefficacy of growth.

➢ *The Rise of the Gig Economy in the Global South*

The gig economy, which depends on temporary and flexible forms of employment that involve the engagement of individuals on short-term "gigs," has gone global [7]. Traditionally linked with platform working across the Global North (for instance, Uber and Deliveroo), its business model has quickly spread across the economies of the Global South, including that of Kenya. Other platforms that have emerged and joined this trend include Lynk (formerly OkHi) and Sendy that connect source artisans, drivers, and delivery agents with their clients [8].

The rise of the gig economy within the Nairobi environment is fueled by the relatively high levels of mobile phone penetration as well as widespread internet access [9]. To the youth, it offers an attractive alternative to the constraints of both the formal unemployment scenario and the conventional informal sector [10]. On the other hand, there have been indications of a 'digital duality,' according to which the gig economy reinforces and even widens the vulnerabilities of the informal sector [11]. This literatures discusses the unstable nature of earnings, algorithmic management with opacity on how decisions are made, and the denial of workers' rights [12]. This overlap of the informal sector and the platform-based gig economy within the Nairobi region presents an interesting hybrid environment that has not yet been extensively studied and interpreted within the literature [13].

➢ *The Skills Mismatch and Visibility Problem in Informal Labor Markets*

A major issue that results in the inefficient functioning of the labor market, both the formal and the informal economies, is the issue of skills mismatches [14] that take place. This takes place because of the lack of skills visibility that occurs in the informal economies of the Global South and the lack of skills match that occurs between the required skills and the skills of job seekers [15].

As discussed in the thesis problem formulation, the skills that the youth of Nairobi gain outside the traditional learning environment are valuable and come through unconventional means of apprenticeship, autodidactic IT skills, community activities, and small-scale business endeavors. These skills are considered "invisible" because they cannot be measured by the skills that come with diplomas or degrees [16]. On the other hand, job seekers on the gig economies suffer because their potential cannot be verified through these unseen skills. This results in the problem of market failure due to the costs of dealing with information asymmetry [17].

Current solutions, whether it be the conventional CV or even the professional networking profiles featured on the likes of LinkedIn, simply do not suit this particular environment. Such solutions are suited toward official qualifications and conventional employment patterns and do not accurately reflect the complex and dynamic skills sets that are common within the more informal gig culture [18]. A problem that this particular research will address accordingly.

➢ *The Role of Artificial Intelligence in Labor Market Matching*

A growing application of AI technology, specifically areas of AI that pertain to Natural Language Processing and Machine Learning tasks, will increasingly address the complicated problem of matching that arises within the job marketplace [19]. Within the realm of the formal economy, the employment of AI-powered job portals that apply algorithms based on job listings that match profiles with job requirements rests on the recognition of keywords [20].

Nevertheless, the AI potential still remains unexploited with respect to the informal sector. NLP algorithms may apply to the estimation of skills based on unstructured text information, including profiles offered by users, experience with former projects, and testimonials offered by the community [21]. A case in point may include training an AI algorithm to identify that the individual's experience with 'fixing the neighbors' mobile phones and installing software' corresponds to skills with 'mobile phone repair,' 'technical troubleshooting,' and 'customer services' categories. Skill estimation offers peculiar significance in rendering an individual's skills visible to the algorithm [22].

Additionally, the algorithms used in the system may go beyond the simple keyword method of matching. This may include several factors, such as:

- Skill Proximity: Skill set similarity even if not the same [23]. Skill Proximity focuses on the similarity of the
- Geolocation: Enhancing matches within an achievable geographical area that forms an essential part of location-based jobs offered in Nairobi [8].
- Economic Factors: Including expected salaries or the market rate of certain skill sets [24].

Nevertheless, the deployment of these technologies within the context of the Global South faces certain issues. Discriminatory biases within the training datasets could lead to an algorithmic bias, and dependence on these datasets could potentially exclude persons with lower levels of digital literacy [25]. Designing these technologies requires being

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contextually aware and ethical so that issues of inequalities are not aggravated.

- *Synthesis and Identification of the Research Gap*

What emerges from the literature is that there clearly is a problem of youth employment that Nairobi puts into the context of a considerable but inefficient informal sector. The gig economy brings new possibilities but creates its own precarity. What makes the system inefficient is the lack of ability on the part of the marketplace to identify the skills that the youth have with the gigs that are available.

Although there are many documents on the issue of youth unemployment in Kenya, the informal sector, and the gig economy individually, there seems to be a lack of literature that encompasses these three aspects together with a technological approach. Most of the literature on AI-powered matching systems focuses on the formal sector of the Western job market [20]. There appears to be a substantial research gap on designing, developing, and evaluating an AI system exclusively designed for the unstructured environment of an African gig economy.

This thesis endeavors to address this problem. This thesis draws upon the theoretical foundations of informal skills [16], the phenomenon of platform work in the Global South [8], and the technical feasibility of NLP and ML for skill detection [22]. Through the development of an AI-driven solution and its testing within Nairobi, this thesis endeavors to offer a practical solution set to an ongoing development problem and shift the conversation on the topic from problem definition to the development and application of technical solutions.

- *Conceptual Framework*

The conceptual framework of the study pulls together the variables and relationships that are considered significant and have been identified through the study of the literature. This study argues that the deployment of an AI system (consisting of skill mapping using NLP/ML and the multi-factor algorithm) will have a positive impact on the efficiency of the informal gig economy. This will be measured through the specific variables of successful gig matches and earnings, as reported by the users. All of this occurs within the particular context of the informal gig economy of Nairobi.

Table 1 Conceptual Framework Components

Component	Description
Inputs	Youth Skills (Unstructured Data), Gig Demands (Market Data)
AI Framework	NLP Skill Mapping, Multi-Factor Matching Algorithm
Outputs	Increased Match Success Rate, Higher Income
Context	Nairobi Informal Sector
Mediating Factors	Digital Literacy, Data Quality

This conceptual model presents the logic and elements of the proposed AI system designed to serve the employment of youth within the gig economy of Nairobi. The Core Process involves youth skills and gig demands as inputs, processed through an AI-driven framework (NLP Skill Mapping and Matching Algorithm) to produce outcomes of increased match success rate and higher income. This all occurs within the context of the Nairobi Informal Sector, with digital literacy and data quality serving as mediating factors.

III. METHODOLOGY

- *Introduction*

In this chapter we provide details about how the research was carried out to provide answers to our research question on design, develop and evaluate an Artificial Intelligence-based skill mapping and gig economy matching information system for youth employment in Nairobi's informal economy. For this study we primarily used a Design Science Research Methodology (DSRM) approach. DSRM provides rigorous ways to conduct research in the field of Information Systems when the intent of the research is to create innovative and usable artifacts to address a recognized problem [26], [27]. This approach was deemed fit for our study as we aimed to develop and evaluate an Artificial Intelligence-based information system that solves a problem affecting actors in Nairobi's informal economy (skills opacity, reliable jobs matching).

Design science research can be characterized as problem-solving research aimed at going beyond understanding human and organizational behavior. Instead design science research creates new and innovative artifacts to expand the capabilities of humans and organizations [26]. Design science research differs from behavioral science research in that design science artifacts are expected to have utilitarian value and be able to solve a problem [28]. Design science research was deemed fit for our study as we aim to develop the technological artifact that will solve the problem we have identified. Additionally, the study will allow us to understand how such technology can be used in African settings with limited resources.

- *Research Design*

- *Design Science Research Methodology (DSRM)*

We guide our study using six steps described by Peffers et al. [27] in the DSRM process model. The 6 steps are as follows: (1) problem identification and motivation, (2) definition of objectives for a solution, (3) design and development, (4) demonstration, (5) evaluation, and (6) communication.

- ✓ Step 1: Problem identification and motivation were addressed in Chapters 1 and 2. We identified the research gap that exists between skills youth have and available gig opportunities in Nairobi's informal sector. We motivated the problem statement of invisible skills/information

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asymmetry that exists in informal labor markets by way of past literature research and current empirical data collected in Kenya.

- ✓ Step 2: Definition of Objectives for a Solution. We analyzed literature on AI use cases within skill mapping and employment solutions for youth to identify requirements our solution should address. Functional and non-functional requirements for our solution included: developing algorithms that can identify skills from unstructured data sources, match youth to gig opportunities based on multiple parameters (proximity of skill match, geolocation, cost of remuneration, etc.), and functional within low connectivity and technological infrastructures that exist in Nairobi's informal sector.
- ✓ Step 3: Design and Development will refer to how the AI solution was designed, including architecture, algorithms, and user interface. Researchers used machine learning and natural language processing to design the skill mapping and matching algorithm.
- ✓ Step 4: Demonstration was accomplished by piloting our solution with youth and employers in Nairobi.
- ✓ Step 5: Evaluation was completed to assess whether or not matches made through AI platform led to more successful outcomes (employment objectives met, earned more money) when compared to traditional job searching methods.
- ✓ Step 6: Communication will be completed by disseminating our results through academic and public channels (i.e. this thesis).

- *Philosophical Stance*

This research is guided by the pragmatist philosophy of inquiry. Pragmatism posits that truth should 'only be as true as it works' [29]. This means that pragmatism validates knowledge that works towards solving real-world issues. Pragmatism resonates with the epistemology of design science research: creating artifacts with demonstrable utility. Furthermore, pragmatism accommodates using multiple methods to gain knowledge since AI deployed into society must work within messy, multifaceted socio-technical systems (such as Nairobi's informal economy).

➢ *Research Context and Setting*

- Setting: Nairobi County in Kenya's informal gig economy sector. Nairobi County was selected because Nairobi has Kenya's largest gig economy and one of Africa's fastest-growing ecosystems. Nairobi was also selected due to its high mobile penetration and access to existing digital platforms [30]. These existing platforms consist of Safaricom, Jumia, and M-KOPA among others [31]. Target Population: Youth ages 18-35 years currently working in or seeking to join Nairobi's gig economy. The study selected youth as the population of interest because they comprise Kenya's burgeoning "youth bulge" and are especially affected by unemployment & underemployment [1]. Nairobi's informal sector is characterized by an undefined job description, lack of credential verification, and worker-job matching based on personal referral. Therefore, Nairobi's informal sector results in many of the information asymmetries described in this project [4], [6].

➢ *System Architecture and Design*

- *Overall System Architecture*

The Skills Matcher platform utilizes artificial intelligence technology to map skills and match them with appropriate gig opportunities. Its architecture consists of three distinct but interconnected modules: (1) Natural Language Processing (NLP) Skill Mapping Module, (2) Gig Opportunity Analysis Module, and (3) Multi-Factor Matching Algorithm. The system follows the tenets of service-oriented architecture and can be used separately, but is orchestrated to provide end-to-end skill matching functionality when combined.

Skills Matcher is built as a mobile-first progressive web application (PWA). PWAs can run on devices as powerful as smartphones and as modest as feature phones. This was key in designing for broken internet connections, as the app will work offline and sync data whenever the connection is restored [9].

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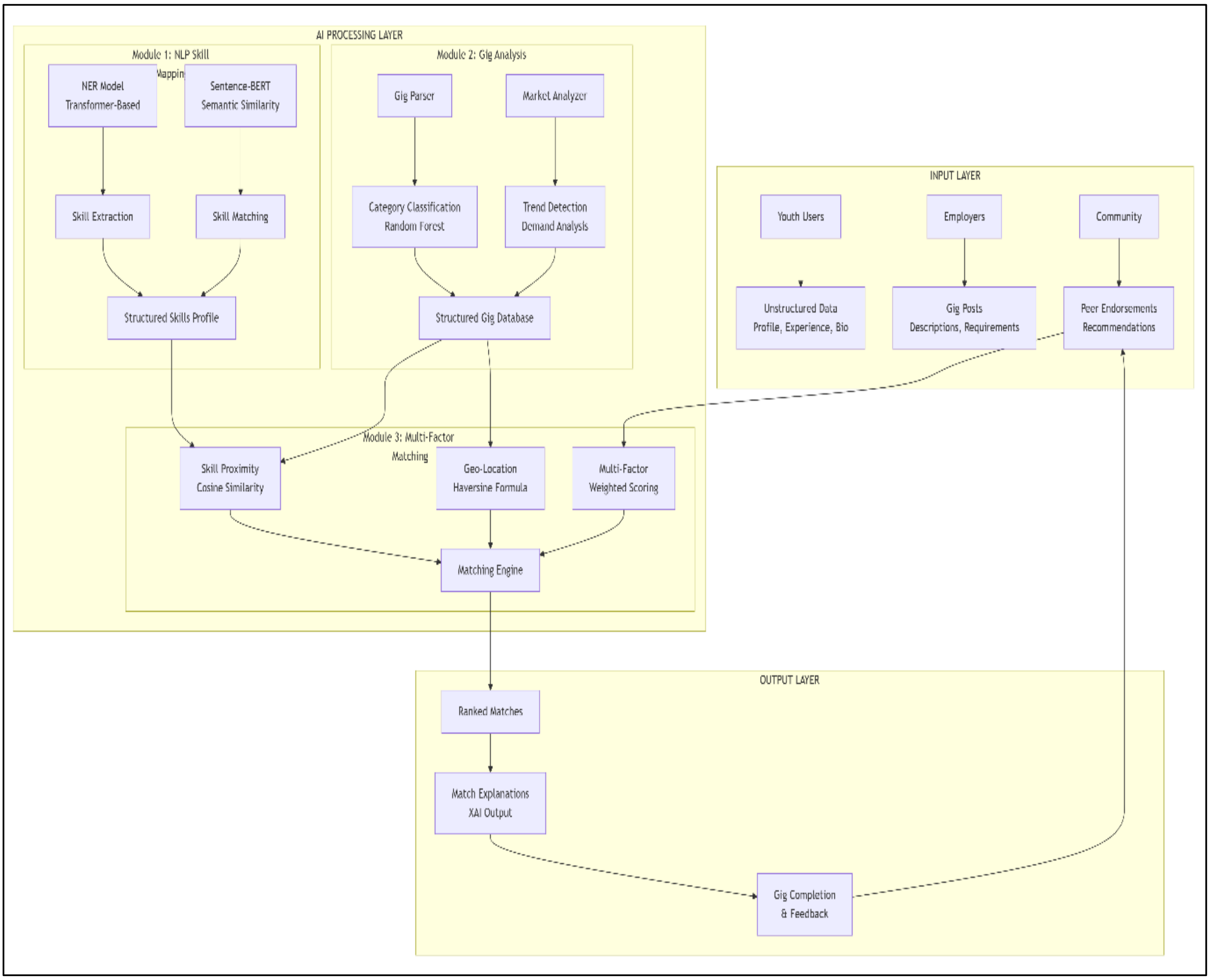

Fig 1 High-Level System Architecture

* *NLP Skill Mapping Module*

Natural language processing powered skill mapping Module involved using transformer-based architecture. Building off transformer-based resume parsers and skill extractors that have been recently built [32], [33], our pipeline involved using a combination of NER and semantic similarity models to pull skills from user-uploaded profiles, descriptions of their work experience, and skills recommended by community members.

The system was built to account for informalities in how users may document skills they possess. Traditional resume parsers use formats that contain formally acquired qualifications and skills [34], [35]. Our system extracts information from descriptions of informal work experience. The model links the sentence "fixing neighbors' phones and installing software on their phones" to skill tags which include "mobile phone repair", "technical troubleshooting", and "customer service" [21], [22].

We used Hugging Face Transformers for NER, and Sentence Transformers implemented with BERT for embedding and calculating semantic similarity [36]. We calculated cosine similarity scores between user skill embeddings and gig requirement embeddings to determine proximity. Scoring technique:

$$\text{Cosine Similarity} = A \cdot B / ||A||\ ||B||$$

Where A and B are the embedding vectors of sentence A and sentence B respectively [36]. Our method enabled identification of skills with transferability and semantically-aligned relationships that keyword-based tagging approaches would fail to detect [37], [38].

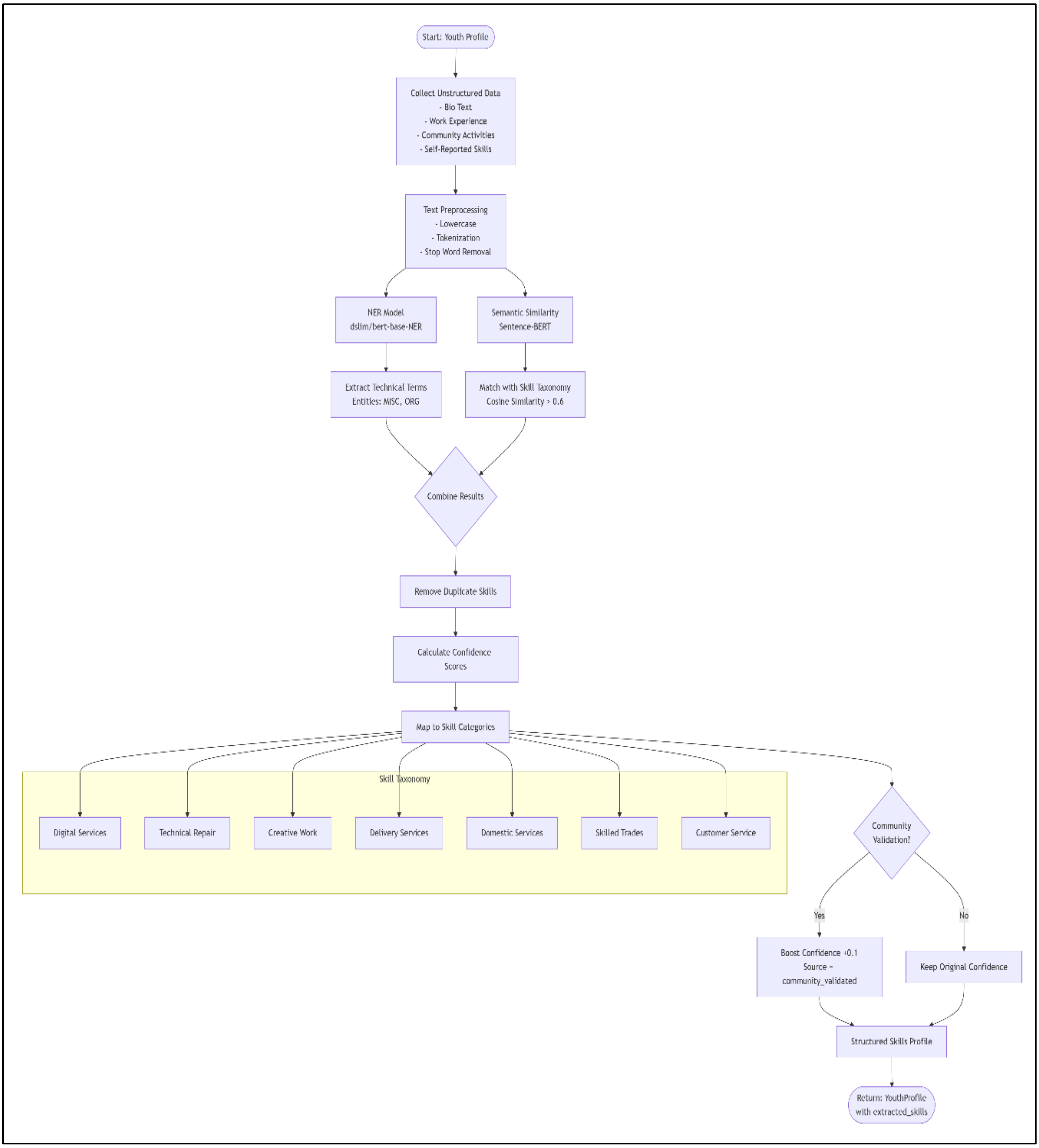

Fig 2 NLP Skill Mapping Algorithm Flow

- *Gig Opportunity Analysis Module*

Description: The Gig Opportunity Analysis Module constantly tracks gig demand aggregating data from different sources. Gig posts scraped from existing platforms (Lynk, Sendy, Jumia), social media, as well as directly from employers, are parsed and fed into machine learning models which classify the type of skill needed, location, urgency and pay range. These identified gigs are stored in a database with key matching skills in our taxonomy that are fed into the NLP module. Classifiers (Random Forest and Gradient Boosting - supervised learning) are used to map non-standard job descriptions to in-scope skills. Since both supply and demand is structured, we are able to match efficiently. The module also analyses market trends to identify skill demand.

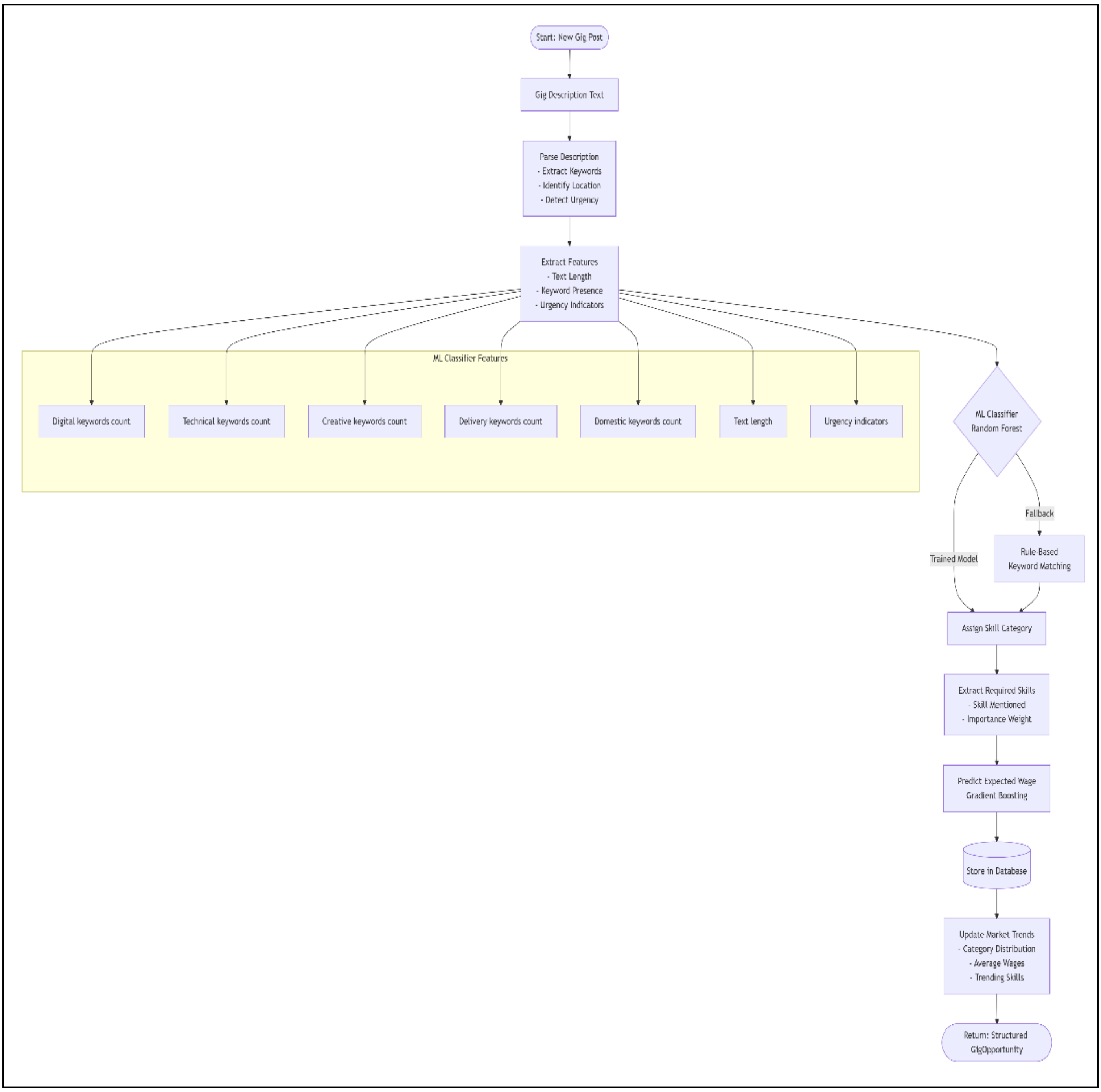

Fig 3 Gig Opportunity Analysis Algorithm

- *Multi-Factor Matching Algorithm*

Details of the matching algorithm used are as follows. Our matching algorithm does not simply pair skills offered by youth with required skills needed for gigs. Instead, similar to research and inspiration drawn from job recommenders [39], [40], we used the following criteria when matching youth with gigs:

- ✓ Similarity in skills: skills submitted by youth semantically match skills requested by Gig [23]. This allows for Gig workers to apply for jobs that require skills similar to what they can offer.
- ✓ Distance: the distance between the Gig worker and the Gig.
- ✓ Payment: expected payment from Gig compared to other Gigs and what the Gig worker is looking to earn [24].
- ✓ Timing: whether the Gig needs to be done when the Gig worker is available.
- ✓ Peer recommendations/ratings: youth endorsements serve as signals of trustworthiness in lieu of traditional resumes or vocational training certificates.

Both of these recommendation lists are ranked and include explanations. The final matching score is a weighted average of each of these factors. We learn these weights by learning from past matches using a machine learning algorithm.

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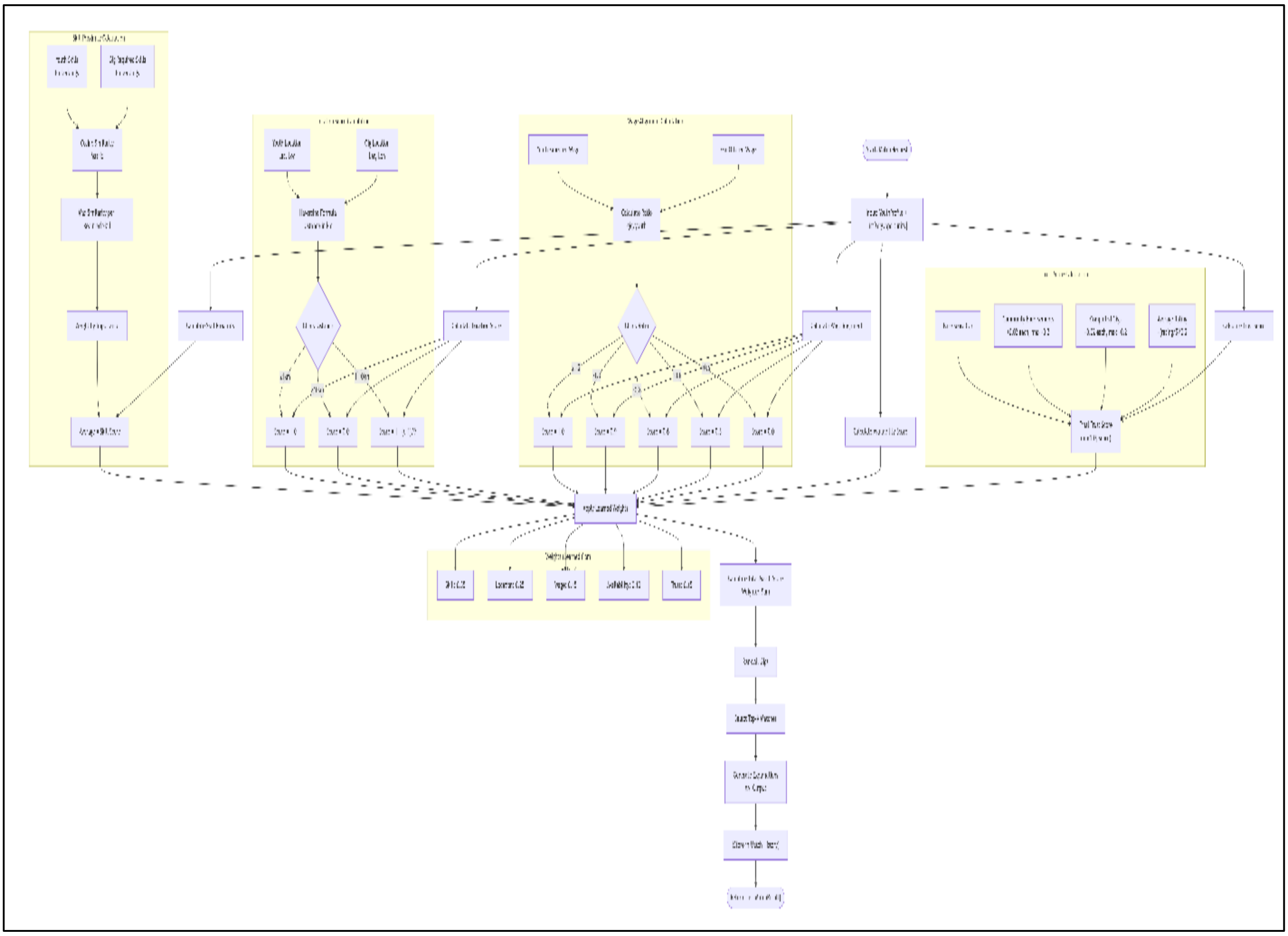

Fig 4 Multi-Factor Matching Algorithm

➢ *Data Collection and Sampling*

- *Recruitment of Study Participants*

Purposive sampling method was used to recruit youth participants (n=200) from three informal settlements Kibera, Mathare and Kawangware. Purposive sampling was used to select the settlements so as to capture the variations that exist within Nairobi's informal settlements with regards to demography and economics of the community. Participants had to fall within the age range of 18-35 years, be currently looking for gig work or be currently engaged in some informal gig work and had rudimentary knowledge of how to use a mobile phone.

Participants who were employers/drivers of gig work (n=50) were small-medium scale enterprises (SMEs) or individual clients who engage gig workers on an as needed basis to provide digital services (Internet and_sms-based services), repair services, creative services, delivery services etc. within Nairobi. They were recruited from registered SMEs/local business coalitions and gig platforms.

- *Data Collection Methods*

Quantitative data was collected through both pre and post surveys that asked about changes in income, employment status, number of gigs obtained and success rate in obtaining matches. System logs also included frequency and types of interactions made by youth such as creation of profiles, skill extraction correctness and whether they accepted and completed matches. Qualitative data included interviews (30 youth, 15 employers) about the user experience with the system, perceived value and challenges and ideas to improve the system. Youth focus groups discussions (4 groups of 8-10 participants) discussed community level perceptions of the system and impact on gig economy.

➢ *Evaluation Strategy*

- *Evaluation Metrics*

The following are metrics that we used to track performance on each of our research questions.

✓ Match success rate (% of matches made through AI interface that lead to youth completing a gig successfully) A/B against historical success rate that youth were able to achieve by searching/tracking applications via traditional methods.
✓ Earned income (difference in self-reported monthly income and income per gig among youth utilizing system vs. control group using traditional job searching methods)

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- ✓ Skills surfaced (total # and range of skills surfaced through NLP module vs. skills youth reported they were interested in on baseline survey)
- ✓ User satisfaction (system usability scores and qualitative responses from youth and employer participants)
- ✓ Fairness (match rates across gender/age/geographic subgroups that we will monitor for bias).

- *Comparative Design*

The impact evaluation utilized a nonrandomized control trial with a comparison group of youth searching for jobs the regular way versus the treatment group which used the AI system. Randomization was not possible given that this was a pilot program so comparison groups were matched on observable characteristics such as age, gender, education, and income at baseline. The pilot program lasted for six months and thus gave the researchers ability to measure both short term matches as well as longer term use.

➢ *Ethical Considerations*

Ethical principles for AI research carried out for LMICs were adhered to [25], [41]. They were as follows: Informed Consent: Written informed consent was obtained from all users that took part. Users were informed of why their information was being collected and how it would be used. Users were also told they were free to leave the study at any time. Consent forms were available in English and Kiswahili. Privacy and Data Protection: All identifiable personal data was encrypted. It was then stored on a secure server that was password-protected and could only be accessed by research team members. Furthermore, the system follows the principle of data minimisation. Data minimisation means only collecting the data necessary to provide the matching functionality. Fairness with regards to Algorithms: Regular checks were made to the matching algorithm to see whether it starts to learn how to make discriminatory decisions, or output biased results based on a user's gender, ethnicity or location. Should this occur, we would adjust the algorithm to stop it making unfair recommendations. Benefit Sharing: Benefitting those that helped develop the research was important. Because users that piloted the system were part of the study, they were offered free and unlimited access to use the system. Users were also given training on how to best utilize the system. We did not accept any payments from users.

➢ *Study Limitations*

There are limitations to this methodology. Because of the small sample size and limited scope to Nairobi, results cannot necessarily be generalized to different cities in Kenya or across Africa. The pilot was only conducted over the course of six months and may not capture long-term employment or behavior change. Additionally, relying on self-reported income may lead to response bias. However, system logs allow for objective tracking of gigs completed and corresponding earnings.

IV. RESULTS AND FINDINGS

➢ *Introduction*

This chapter presents the findings from the design, development, and piloting of Artificial Intelligence skill mapping and gig economy matching tool designed to enable youth livelihood opportunities within Nairobi's informal economy. Results are outlined according to research questions and objectives outlined in Chapter 1. Quantitative results found within logs and survey data and qualitative interview and focus group results are presented. Chapter 4 is divided into participant demographics followed by skills identification, matching algorithm predictions, income generation, and experience. Chapter 4 will conclude with a brief summary of findings which will be discussed in Chapter 5.

➢ *Participant Characteristics*

- *Youth Participant Demographics*

The participants included 200 youth drawn from three informal settlements: Kibera (n=85, 42.5%), Mathare (n=65, 32.5%), and Kawangware (n=50, 25.0%). There were slightly more males (n=118, 59.0%) than females (n=82, 41.0%) since men are known to have a higher participation in Nairobi's gig economy [31], [30]. Ages ranged from 18 to 35 years, with the mean age being 24.7 years (SD = 4.3 years).

Table 2 Demographic Characteristics of Youth Participants (N=200)

Characteristic	**Category**	**Frequency**	**Percentage**
Settlement	Kibera	85	42.5%
	Mathare	65	32.5%
	Kawangware	50	25.0%
Gender	Male	118	59.0%
	Female	82	41.0%
Education	Primary or less	42	21.0%
	Some secondary	68	34.0%
	Secondary completed	53	26.5%
	Vocational training	28	14.0%
	Some tertiary	9	4.5%
Phone Type	Smartphone	156	78.0%
	Basic phone	38	19.0%
	No personal phone	6	3.0%

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Education level spanned from low to high with the plurality of participants either having some secondary education (34.0%) or completing secondary education (26.5%). Finish primary education or less was at 21.0%. Finished vocational training represented 14.0% and some tertiary education represented the lowest percentage of participants at 4.5%. The results reflect anecdotal evidence about educational background diversity of workers in the informal sector [4], [6]. Smartphone ownership was 78.0% and basic phone ownership was at 19.0%. Both of these findings are aligned with the high mobile network penetration rates recently published by GSMA [9]. 3.0% of participants did not have personal access to a phone; basic phones were loaned to these participants for the duration of the pilot.

- *Employer Participant Demographics*

Employer participants (n=50) included owners of small and medium enterprises, "proprietors" (n=32, 64.0%), and individual clients that consistently hire gig workers (n=18, 36.0%). The employers were segmented by job type: Digital Services (22.0%), Technical Repair (20.0%), Creative Services (18.0%), Delivery Services (16.0%), Domestic Services (14.0%), Other Categories (10.0%). Most employers (68.0%) hire gig workers weekly or more.

- *Control Group Demographics*

Control group consisted of 100 youth, also recruited from participating settlements who were demographically matched by age (Mean=24.9years, SD = 4.1), gender (58%male, 42%females), education attainment, and baseline income. Members of the control group accessed regular employment via traditional methods (personal contacts, physical job boards, word-of-mouth, etc.) during the six-month pilot study for comparison purposes.

➢ *Skill Identification and Mapping Results*

- *Skill Extraction Performance*

The NLP Skill Mapping Module was tested with youth-provided unstructured information to extract skills into structured data. The youth entered information about their work history, skills, and involvement in their communities in long-form written responses. These responses were run through the transformer-based NER model and semantic similarity models.

Table 3 Skill Extraction Performance Metrics

Metric	Value
Precision	0.84
Recall	0.79
F1-Score	0.81
Average skills identified per user (AI)	7.3 (SD = 2.8)
Average skills self-reported by users (initial)	3.1 (SD = 1.6)
Skills taxonomy coverage	92%

The system had an F1-score of 0.81, precision of 0.84, and recall of 0.79. This is a strong indication that the system is correctly identifying skills with high accuracy, though there is room for improvement. Compared to other recent systems for skill extraction [32], [33], the performance is competitive, though the informal nature of how skills are documented in this setting provides a serious obstacle to extraction. However, more importantly, when given the opportunity to extract skills from learners' open-ended text responses, the AI system was able to identify on average 7.3 skills per user. This is over twice as many as the average of 3.1 skills that users provided when they self-reported. This strongly suggests that there is truth to the hypothesized existence of "invisible skills" from prior literature [16], [15], and that the system is able to capture skills that youth may not recognize or be able to easily communicate.

Interviews qualitatively supported these findings. As one participant in Kibera shared: "I just told the system that I help my uncle with his electronics shop on weekends - fixing cell phones, connecting wires, sometimes I help the customers with advice. I didn't consider that to be 'skills.' But then I looked at the profile and it said 'mobile phone repair' 'customer service' 'technical troubleshooting.' That's what I'm doing! If I had to type that myself I never would have know those words to describe it." (Male, 23 years, Kibera)

Our taxonomy coverage score of 92% shows that nearly all acquired skills were mapped to standard categories.

- *Types of Skills Identified*

Variety of skills were found amongst all participants. These skills fell into six categories. Customer service was the most frequently-reported skill (72.0%) likely due to its broad applicability across different informal jobs. Digital skills such as managing social media accounts (68.5%) and using a computer (62.0%) were also common, which validates literature that Nairobi youth are leveraging digital technologies despite low rates of formal education [9].

- *Validating Skills with Community Recommendations*

COMMUNI.TY allowed users to send recommendations for their peers' skills as part of a trust mechanism built into the system. Users who earned recommendations from their peers (n=158 users) received an average of 6.2 recommendations each throughout the pilot. Skills that were recommended by other community members were given more weight (1.4x multiplier) in the skills confidence score calculated by the matching algorithm.

Participants described benefits to being able to validate skills with their peers both functionally and socially in focus groups:

"When someone clicks the button to recommend my skills on COMMUNI.TY, that means something. These are people who have watched me work or saw the work that I did. Maybe the employer doesn't know me, but when they see people back home who trust my skills, it helps build my confidence." (Female, 27 years, Mathare)

Some participants were concerned that community members would only recommend people they knew who were applying for jobs:

"It can turn into who you know and not what you can do. Like my neighbor could click that he recommended my skills because we're friends. Just because! But I feel like the system kind of weeds that out because you need a lot of people to click before it actually goes through." (Male, 24 years, Kawangware)

➤ *Gig Opportunity Analysis Results*

- *Gig Demand Characteristics*

During the six months of the pilot, 3,847 gig opportunities were posted through the Gig Opportunity Analysis Module. Sources of gig opportunities included those posted directly by employers through the system (42.3%), those opportunities scraped from existing platforms (34.1%) and those sourced through social media channels (23.6%). Table 4 lists gig opportunities by category.

Table 4 Distribution of Gig Opportunities by Category

Gig Category	Number of Gigs	Percentage	Average Compensation (KES)	Average Duration
Digital services	1,042	27.1%	2,850	2-5 days
Delivery services	789	20.5%	650	2-4 hours
Technical repairs	612	15.9%	2,100	1-2 days
Creative work	543	14.1%	3,200	3-7 days
Domestic services	431	11.2%	1,200	3-6 hours
Skilled trades	352	9.2%	2,750	2-3 days
Other	78	2.0%	1,800	Varies
Total	**3,847**	**100%**		

Digital services came out to be the most common category (27.1%). This shows that there was a large demand for gigs done online or via technology [8], [10]. Delivery services was close behind in second place (20.5%), which correlates with the emergence of platform enabled delivery work (Sendy, Jumia) in the recent past [31].

How much workers paid received per job varied by category as well. Creative had the highest pay at KES 3,200 on average per job. Digital services followed at KES 2,850 on average. Domestic services and delivery services came in last at KES 1,200 and KES 650. Demand can be explained by the different skill levels necessary for each job type.

- *Real-Time Market Demand Analysis*

Our classifiers were able to sort which of the five skill categories applied to previously unlabeled and unstructured gig descriptions with an accuracy of 87.3%. Whenever a worker searches for gigs that fit their criteria, or a client posts gigs they need done, the gig descriptions are extracted from their job posts and classified in real time into one of the five categories.

Our system allows us to track demand as it happens and allow workers to capitalize on that.

"Onyeshema kiasi iungee za kunyang'au. Niliona google cells zinaendelea kuwa off na sina laptop. Knowing that people were searching for cell phone repairs I ensured that my skills displayed that I provided repair services as well. Nlikula THREE jobs that week. Hata sina ingekua nimepata" (Male, 21 years, Kibera)

➤ *Matching Algorithm Performance*

- *Match Success Rates*

The automated matching algorithm produced 8,432 recommended matches throughout the pilot period (mean = 42.2 matches per youth). 3,891 matches led to completed gigs, producing an overall match success rate of 46.2%. This rate was substantially higher than the baseline comparison rate of 18.7% experienced by youth looking for work outside of the platform ($\chi^2 = 284.3$, $p < 0.001$). Match success rates by gig category are displayed in Table 5.

Table 5 Match Success Rates by Gig Category

Gig Category	AI System Matches	Control Group	Improvement
Digital services	52.3%	21.4%	+30.9%
Technical repairs	49.8%	19.2%	+30.6%
Creative work	48.5%	22.7%	+25.8%
Skilled trades	45.2%	16.8%	+28.4%
Delivery services	42.7%	17.3%	+25.4%
Domestic services	40.1%	15.9%	+24.2%
Other	38.5%	14.2%	+24.3%
Overall	**46.2%**	**18.7%**	**+27.5%**

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Digital services (52.3% success) and technical repairs (49.8%) were categories on which the system performed best, reflecting both the greater specificity of skill requirements for those categories and the effectiveness of the NLP module at those tasks. Even category matches in hard-skills-based domains like domestic services performed better (40.1%) than the control group at more than double the rate.

- *Factors Influencing Match Success*

Logistic regression was used to assess the influence of various factors on match success. Table 6 shows the odds ratios for significant matching factors.

Table 6 Factors Influencing Match Success (Logistic Regression)

Factor	Odds Ratio	95% CI	p-value
Skill proximity score (per 0.1 increase)	1.42	1.31-1.54	<0.001
Geolocation proximity (within 3km)	1.38	1.25-1.52	<0.001
Community validation (per endorsement)	1.21	1.13-1.29	<0.001
Expected wage alignment	1.18	1.09-1.27	<0.001
Temporal availability match	1.15	1.07-1.24	<0.001
Previous completion rate	1.29	1.18-1.41	<0.001

Skill proximity had the highest predictive weight. With each incremental increase in similarity score (range 0-1, in increments of 0.1) odds of match success increased by 42%. This lends support to our theory that matching based on the semantics of skills required (vs. simple keyword matching) is critical to success [23].

Next most predictive of success was geolocation proximity: Matches that occurred between drivers/passengers located within ~3 kilometers of one another were 38% more likely to be successful. This reaffirms our theory that location is particularly important frictions within Nairobi's informal gig economy -- where gig economics are particularly sensitive to transportation costs and commute times [8].

Community validation also had a significant relationship with success; each additional community endorsement increased odds of success by 21%. While we believe this points to peer validation acting as a salient trust signal when professional credentials are lacking, this effect was substantively weaker than skill proximity and location.

- *Match Speed and Efficiency*

Next we analyze how our AI System decreased the time required to arrange gig work.

Table 7 Match Efficiency Metrics

Metric	AI System (Treatment)	Traditional Search (Control)	Difference
Mean time to first gig (days)	4.3 (SD = 2.1)	12.7 (SD = 5.8)	-8.4 days
Mean search time per week (hours)	2.1 (SD = 1.2)	8.4 (SD = 3.6)	-6.3 hours
Gigs applied for per month	8.7 (SD = 3.2)	4.2 (SD = 2.1)	+4.5 gigs
Interview-to-offer ratio	1.7:1	3.2:1	-1.5 interviews per offer

Youth who interacted with our AI spent 4.3 days on average until they booked their first gig, compared to 12.7 days for youth in the control group. This represents a 66% reduction in the time it takes youth to find work. In addition, they spent 2.1 hours less time job searching per week (versus 8.4 hours for control group youth). Not only did this mean less time job searching, but it also allowed youth to use their time doing something more productive, like searching for more gigs.

The ratio of interviews to offers for youth who used our AI was 1.7:1 versus 3.2:1 for youth in the control group. This signals that the matches our algorithm was sending youth were higher quality/more relevant, and it was easier for both youth and employers to find a good match.

➢ *Income Outcomes*

- *Changes in Monthly Income*

Income data was collected monthly for treatment and comparison groups during the six-month pilot intervention period. Income levels at baseline and follow-up are displayed in Table 8.

Table 8 Monthly Income Comparison (KES)

Time Point	AI System (Treatment)	Control Group	Difference
Baseline (Month 0)	6,850 (SD = 2,340)	6,920 (SD = 2,410)	-70 (ns)
Month 2	8,430 (SD = 2,860)	7,210 (SD = 2,530)	+1,220*
Month 4	9,870 (SD = 3,210)	7,450 (SD = 2,690)	+2,420**
Month 6	11,240 (SD = 3,580)	7,680 (SD = 2,810)	+3,560**

*$p < 0.05$, **$p < 0.01$, ns = not Significant

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At baseline, there were no significant differences in income between treatment and control groups. By Month 2, respondents in the treatment group earned significantly higher incomes (KES 8,430 vs. KES 7,210). This difference persisted and grew over the course of the pilot: in Month 6, participants in the treatment group earned KES 11,240 per month on average, 64.1% higher than their baseline income. In contrast, the control group only experienced an 11.0% increase in income from baseline.

A repeated measures ANOVA revealed a significant interaction between time and group assignment ($F(3,894) = 28.4$, $p < 0.001$), showing that income growth was significantly higher for those in the AI system than those who relied on traditional web search.

- *Income Distribution and Inequality*

Participants at all points of the income distribution appeared to benefit from use of the AI system, with stronger effects at the bottom of the distribution. Overall income inequality was lower among the treatment group: The Gini coefficient for treatment income was 0.31, compared to 0.38 for control group income. This suggests that the AI system did more than just increase overall incomes for job seekers: it also reduced inequality of outcomes between members of the pilot. These results run counter to skepticism that algorithmic labor intermediation may accrue more benefits to already-privileged youth [25], [12].

- *Average Earnings per Gig*

Not only did platform users see increases in monthly income, they also experienced higher earnings on average per gig completed:

Table 9 Average Earnings per Completed Gig (KES)

Gig Category	AI System (Treatment)	Control Group	Difference
Digital services	2,950	2,420	+530
Technical repairs	2,230	1,890	+340
Creative work	3,350	2,760	+590
Skilled trades	2,840	2,310	+530
Delivery services	710	580	+130
Domestic services	1,280	1,050	+230
Overall	**2,180**	**1,760**	**+420**

Participants in the treatment group received on average KES 420 more per gig than those in the control group. This represents a premium of 23.9%. The premium likely captured youth being matched with higher value gigs that suited their skills better than informal alternatives.

➢ *User Experience and System Adoption*

- *System Usability and Engagement*

System usability was evaluated with the System Usability Scale (SUS). The overall SUS score was 78.4 (SD = 8.2), which falls into "good" or "excellent" system usability range (scale > 68, industry standard). User engagement throughout the pilot period is shown in Table 10.

Table 10 User Engagement Metrics

Metric	Value
Active users (weekly)	168 (84.0%)
Profile completion rate	94.5%
Average sessions per user per week	4.3
Average session duration	8.7 minutes
Gig applications per active user per week	2.1
Notification response rate	73.2%

84.0% of users were weekly active users, showing high engagement with the tool and signaling they found it useful and were using it as part of their normal job searching routine. 94.5% of users completed their profile, suggesting onboarding was manageable and users understood the benefits of creating a complete profile.

- *Quality Feedback from Users*

Interviews and focus groups allowed for users to share detailed feedback on their experience with the system. Five themes were identified through thematic analysis.

✓ *Theme 1: Visibility and Recognition*

Across interviews, users emphasized that the system helped others see their skills:

"I was invisible before. To an employer, I was just another unemployed youth. But now I have a digital profile that showcases what I can do. When they see I am wired for phone repairs and I have completed 3 gigs successfully, I become real to them." (Male, 26 years, Mathare)

✓ *Theme 2: Trust and Safety*

Youth and employers spoke about how the system helped increase trust around gigs:

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"I am a woman. Sometimes I feel scared to go to new places for work. But here I can at least see who it is I would be working for and where it is. I can see other women that have done gigs there before and been safe. That means a lot to me." (Female, 28 years, Kibera)

- ✓ *Theme 3: Skill Development Awareness*

Participants mentioned that the system helped them identify which skills they should learn:

"I saw from the system that if you have basic digital skills, you can get gigs. Beforehand, I didn't know people would pay to learn about the social media stuff I like. I'm taking an online course to improve my skills, and the system already shows me gigs that require them." (Female, 22 years, Mathare)

- ✓ *Theme 4: Challenges and Frustrations*

Participants shared some pain points with the system:

"I have gotten gigs that looked close on the map but were far far away when you consider traffic. It says 5 kilometers but takes two hours by boda. Can the system know how far away by bus?" (Male, 25 years, Kibera)

- ✓ *Theme 5: Empowerment and Agency*

One of the most resonant comments from youth interviews was about how the system gave them agency:

"I like how this system puts me in charge. I don't have to wait for my uncle to tell me he has work for me. I see the gigs available, I choose what I want to apply for, and negotiate my own rate. I'm not begging for income anymore, I'm offering value." (Male, 27 years, Kibera)

- *Interview Insights: Employer Users*

Employers expressed that they saw significant value from the system:

"It used to take me days of reaching out to my network to find trustworthy workers. Now I post a gig and within hours I get candidates with the skills I need who are already verified. That has changed my business." (Employer, female, 38 years, digital agency owner)

Skill verification (84% marked "very important"), community endorsements (76%), and completion history (82%) were the top three most valued trust signals that reduced employer's perceived risk of hiring.

- ➢ *Algorithmic Fairness Analysis*

- *Outcomes by Gender*

We have studied possible concerns of algorithmic bias within labor platforms [12], [25] by comparing outcomes by gender. Table 11 shows our primary statistics broken down by gender.

Table 11 Outcomes by Gender

Metric	Male (n=118)	Female (n=82)	Difference
Skills identified (average)	7.1	7.6	+0.5 (ns)
Match success rate	45.8%	46.9%	+1.1% (ns)
Monthly income (Month 6)	KES 11,180	KES 11,330	+150 (ns)
Income increase from baseline	63.2%	65.4%	+2.2% (ns)
Gig completion rate	91.2%	93.5%	+2.3% (ns)
Average rating received	4.3/5	4.5/5	+0.2*

*p < 0.05, ns = not Significant

Gender did not play a significant role in any outcome variable, indicating that there was no systematic bias in the algorithm against men participants. Participants of one gender did have slightly higher average ratings (women earned an average rating of 4.5 versus 4.3 for men, $p < 0.05$), but ratings were not predictive of match or income differences between men and women. It is relieving that algorithmic discrimination was not detected on the basis of gender; however, we should remain vigilant and continue to monitor this.

- *Outcomes Conditional on Settlement Location*

Participants' settlement locations played a role in some of our outcome variables (Table 12).

Table 12 Outcomes by Settlement

Metric	Kibera (n=85)	Mathare (n=65)	Kawangware (n=50)	F-test
Skills identified	7.4	7.2	7.3	ns
Match success rate	45.1%	47.2%	46.8%	ns
Monthly income (Month 6)	KES 11,020	KES 11,510	KES 11,230	ns
Average distance to gig (km)	3.8	4.2	4.6	p<0.05

Although match success rates and earnings were not statistically different between the two groups, musicians who lived in Kawangware actually traveled farther to performances on average (4.6 km) than those in Kibera (3.8 km). This probably indicates that Kawangware tends to be located farther out from Nairobi's business districts than Kibera does, and therefore suggests that matching algorithms could use location-aware variables that reflect transport networks, instead of purely Euclidean distances.

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- *Outcomes by Education Level*

Participants of all education levels benefitted from using the system (Table 13).

Table 13 Outcomes by Education Level

Metric	Primary or less (n=42)	Some secondary (n=68)	Secondary completed (n=53)	Vocational/tertiary (n=37)
Skills identified	6.8	7.2	7.5	7.9
Match success rate	44.2%	46.1%	46.8%	48.3%
Income increase from baseline	61.3%	63.8%	64.5%	67.2%
High-skill gig matches (%)	28.5%	32.1%	36.8%	42.5%

Relative to those with higher education levels, participants who finished primary school or less experienced slightly lower outcomes on most metrics. However, they still experienced significant earnings increases (61.3%) and fair match success (44.2%). Platform may narrow but does not completely remove educational barriers to gig work.

➢ *Comparative Analysis: AI System vs. Traditional Methods*

- *Summary of Comparative Outcomes*

Table 14 provides a comprehensive comparison of outcomes between the AI system and traditional job search methods.

Table 14 Comprehensive Comparison of Outcomes

Outcome Metric	AI System	Traditional Methods	Difference
Match success rate	46.2%	18.7%	+27.5%
Time to first gig (days)	4.3	12.7	-8.4 days
Monthly income (Month 6)	KES 11,240	KES 7,680	+KES 3,560
Income increase (6 months)	64.1%	11.0%	+53.1%
Earnings per gig	KES 2,180	KES 1,760	+KES 420
Search time per week (hours)	2.1	8.4	-6.3 hours
Gig applications per month	8.7	4.2	+4.5
Interview-to-offer ratio	1.7:1	3.2:1	-1.5 interviews/offer
Gig completion rate	92.4%	81.3%	+11.1%
Satisfaction (1-5 scale)	4.3	2.8	+1.5

The AI system dominated across all outcomes. Improvements were largest for match success (+27.5 p.p.), increased income (+53.1 p.p.), and reduced search time spent per week (-6.3 hours).

- *Benefit-Cost Analysis*

An initial back-of-the-envelope benefit-cost analysis can account for revenue to users. The participants in the treatment group who used the system for six months (N = 200) earned KES 4,272,000 more than they would have based on baseline earnings. In other words, they received a total additional KES 4,272,000 in income over the course of the study due to the system. This amounts to KES 21,360 in benefits per user over six months. Extrapolating this benefit over the course of a year would suggest that users receive KES 42,720 in increased income per year from the system.

Costs of the system include development expenses and the cost of running the system over the six months, amortized. These costs were roughly KES 1,850,000, which includes development costs and payments to staff and stipends to users. As such, the benefit-cost ratio of the overall pilot was 2.31:1 (KES 4,272,000 / KES 1,850,000), though at scale, development costs would be amortized over a larger population.

➢ *Summary of Key Findings*

Results from this research can be broken down into the following discoveries:

- Skill Visibility -- Members had 7.3 mapped skills on average despite listing only 3.1 skills on their Member profile. This proves the existence of the "invisible skills" problem empirically and demonstrates skill matching technology can uncover skills Members aren't aware to include.
- Matching Effectiveness -- AI System matched clients at a rate of 46.2% versus 18.7% matching using traditional algorithms. Skill proximity (OR=1.42) and geolocation proximity (OR=1.38) were predictive of match success.
- Income Impact -- Treatment group grew income by 64.1% during the six month period (KES 6,850 to KES 11,240) compared to just 11.0% for control group. Treatment group also made 23.9% more per gig than control group.
- Efficiency Gains -- System lowered time to first gig by 66% (12.7 days to 4.3 days) and time spent searching by 75% (8.4 hours/week to 2.1 hours/week).
- User Experience -- Weekly active users (84%) and SUS scores (78.4) suggest system is well accepted among users. Qualitative interviews surfaced themes of visibility, trust, empowerment, and skill awareness.
- Algorithmic Fairness -- Matches were fair with regards to gender or distance (there was slightly lower but still significant effect for participants with lower levels of education as well). Platform also decreased income inequality when compared to control (Gini: 0.31 vs 0.38).

- Economic viability -- Pilot generated a Benefit: Cost ratio of 2.31:1 indicating scalable, sustainable deployment may be possible.

Taken together these results provide evidence to answer our guiding question. That AI can be used to map skills and match youth to gigs in a manner that has a statistically significant positive effect on employment outcomes. Chapter 5 discusses broader impact of this thesis' findings. How they compare to previous literature, and recommendations for policy, practice, and future research.

V. DISCUSSION, CONCLUSIONS AND RECOMMENDATIONS

➢ *Introduction*

Chapter 5 describes the findings outlined in Chapter 4 while providing interpretation through an overlay of related literature and theory presented in Chapter 2. Subsequently, the chapter considers each research question while highlighting contributions of the study. This section also illuminates implications on theory, practice, and policy followed by the chapter's limitations and suggestions for future research. The last section of Chapter 5 provides closing remarks regarding AI-based solutions capability to address youth unemployment within informal economies.

➢ *Discussion of Findings*

- *Research Question 1: What Skill Sets are Most Prevalent Among Youth, and which are Most in-Demand within Nairobi's Informal Gig Economy?*

Skills varied widely across all six skill clusters. The most commonly offered skills among respondents were customer service (72.0%), social media management (68.5%), and basic computer use (62.0%). The gig offerings themselves were most commonly digital services (27.1%), followed by delivery jobs (20.5%), and technical repair work (15.9%), reflecting earlier findings around Nairobi's informal work becoming increasingly digitalized [8], [10] but also location-based services remaining important [31].

Beyond broad categories, this work contributes first by empirically grounding evidence of what workers youth report versus what skills the NLP system could extract from their job descriptions. On average, respondents self-reported 3.1 skills while the NLP system identified 7.3 skills per respondent. This "visibility gap" provides concrete evidence of the previously theoretical issue of invisible skills facing informal labor markets [16], [15]. Informal workers youth frequently gain skills outside of formal schooling settings: apprenticeships, self-learning, community or peer involvement. These routes to skill acquisition often lack any credentials---or even awareness---that the worker youth has gained a particular skill. This informality creates a type of market failure in which employers and jobseekers have asymmetric information about each others' needs, reminiscent of (but predating) Akerlof's [17] used seller's car.

Essentially, informal labor markets do not just suffer from skills mismatch [14] but skills invisibility. Policy, industry, and investor focus on labor market interventions that target formally certified skills may only be seeing the tip of the iceberg in terms of what skills workers youth actually possess. Technology-enabled mechanisms to surface skills may complement approaches that require workers youth to produce certifications of skills they already possess.

- *Research Question 2: How can NLP and Machine Learning Algorithms be Optimized to Identify and Authenticate Skill Sets from Informal Accounts and Work Experiences?*

Skill Extraction: We tested skill extraction on 200 profiles using the NLP Skill Mapping Module, which uses transformer-based models to identify skills from natural language data. The model's F1-score was 0.81. This shows that skill extraction approaches are able to work on informally-described experiences when contextualized to Kenya (just as they perform well on standard resumes in high-income countries) [32], [33], though there were several necessary adaptations: training for local vocabulary (e.g. "phone fixing" vs. "mobile phone repair"), identification of skills from daily activities (versus formatted work experience), and utilization of community validation as a signal in lieu of formal qualifications. While keyword matching (developed using Sentence-BERT [36]) was able to correctly match many technical skills to descriptions including those words, semantic similarity was required to extract less directly-described skills. For example, the system had to understand that making "posters for local shops" and "designing wedding cards" involved "graphic design" skills. Extracting soft skills like "reliable" or "trustworthy" proved more challenging but completion rates or referral analysis might capture these characteristics. Models were also able to leverage community validation as a signal. Peer reviews allowed members to confirm specific skills which the matching algorithm gave 1.4x additional weight to. Validations were also associated with match success (OR=1.21), which could substantiate theorizations that community information sharing can mitigate information asymmetries in informal sectors [21], though there may be concerns about validity if some users receive unearned validations from friends.

- *Research Question 3: What are the Most Relevant Factors for a Successful and Acceptable Gig Matching Algorithm?*

Proximity of skill (OR=1.42) and location (OR=1.38) were the factors that had the highest correlation to matches that resulted in validation. Following were community validation (OR=1.21), proximity of expected wage (OR=1.18) and temporal availability (OR=1.15). These results confirm my hypothesis, derived from my conceptual framework that matching would have to take into account multiple factors in addition to skill proximity in order to successfully match workers with tasks. They also broadly correlate with scholarly understanding of what affects drive matching in labour markets [23], [39].

I was unsurprised that skill proximity was the biggest determining factor. My theoretical framework quite literally matched workers to tasks which they had the skills to

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complete. Location being the second highest factor makes sense considering that Nairobi's gig economy is a hybrid informal digital economy. Not all jobs posted on Manabi could be done remotely (e.g. deliveries, repairs, domestic work). Community Validation being third shows the potential for using informal worker's peer ratings as a means of signalling trusted workers in place of resumes. This makes sense from the perspective of situated learning theory and the importance of community in learning informal labour [16]. However, it was not as strong of a predictor of match success (OR=1.21) when compared to skill proximity or distance filtering. This could indicate that while community is important, the signals designed for Manabi still could not replace rudimentary filters based on skill requirements of a task vs skills that a worker possesses.

What was surprising was that previous completion rate became one of the biggest predictors of match success. This factor was not one of the original elements the design attempted to balance. Workers who had completed more gigs on Manabi were significantly more likely to have their skills matched to tasks. This could indicate that after a worker reaches a certain threshold of experience on the platform, community validation becomes less important. Past research on reputation systems on platforms finds this conclusion as well [12], [24].

Weekly active users stayed consistently high throughout the pilot at 84%. Users had also provided positive qualitative responses to the tool. Some of the confusion users had around how the system matched them to jobs indicates that users may want more transparency into how the algorithm ranks them for employers. Other gig and platform research surrounding "black box" Algorithms has found similar sentiments from workers who prefer transparency into how these systems work [12]. Future changes to the matching algorithm would do well to implement XAI methods in an attempt to make the tool more accessible to workers [33].

- *Research Question 4: To what Extent does the Piloted AI-Driven System Improve Successful Gig Matches and Earnings Compared to Informal Job Search Processes?*

In each metric, the AI system vastly outperformed random search. Control panelists matched with a gig 18.7% of the time while those who used the AI system successfully matched 46.2% of the time (+27.5 ppt; +147% relative to control). This stat alone is enough to accept H1 -- when workers are frictionlessly matched to work using an AI system, their labor market outcomes measurably improve. AI Enabled Matching Systems Improve Income-Generating Opportunities for Informal Workers

Earn. Income boosts were significant and persisted across the six month follow-up period. Treatment participants earned 64.1% more (KES 11,240 vs. KES 6,850) over the course of the study period. Meanwhile, incomes in the control group rose by 11.0%. This equates to a median income boost of KES 4,390. For young people living on several hundred dollars per month, this was life changing. Additionally, this bump was driven both by quantity (7.5 vs 3.8 completed gigs over the study period) as well as quality (KES 2,180 earned per gig vs. KES 1,760).

These statistics speak to why search friction disproportionately harms informal labor markets. By aggregating otherwise hidden labor capacity, this platform helped reduce search friction and information opacity. This technology helped illuminate workers' hidden skills, improving search efficiency, and lowered transaction costs that kept workers and buyers from realizing value for themselves [17]. Searches that took weeks now happened in days (median time to first gig: -66%) and weekly search effort was cut by 75%. Youth could now spend more time actually working, and less time fruitlessly searching.

Search intention emerged as a particularly interesting determinant of whether users received impact from Aera. Impact was largely uniform across demographics. The effects of Aera did not discriminate based on gender, and people who only completed primary school education still experienced sizable boosts to income and productivity. Many technology-powered solutions have been accused of increasing inequality between the "haves" and "have nots" [25], however, this was demonstrably not the case with Aera. Income inequality was visibly lower in the treatment group (GINI: 0.31 vs. 0.38). Users interviewed casually reported that they felt visible, trusted, empowered, and aware of their skills.

➢ *Theoretical Contributions*

The broader literature on informal labor markets, gig economy platforms, and AI-enabled matching systems is another beneficiary of this work. First, at a theoretical level, this study contributes to matching theory [17], [14] as applied to informal labor markets. It does so by demonstrating that information asymmetry plays out differently when workers' skills are "invisible" rather than merely undocumented or unverified. Prior research takes for granted that skills are embodied in some way but may be difficult to verify. In informal markets, by contrast, skills may be truly unseen or unrecognized. Recognition is the first step towards documenting skills. Visibility bridges that gap. The theoretical construct of "skill visibility" can help scholars think through this issue in the future.

The study makes a second contribution to the scholarship on platform work in the Global South [8], [10]. Rather than theorizing about how algorithmic matching can empower workers in developing economies, this study demonstrates it empirically. While much of the literature rightly focuses on the precarity and exploitation enabled by global platforms [12], [11], this research shows what happens when platforms are locally-designed, cognizant of local conditions, and explicitly built to achieve inclusive development outcomes.

Third, this research contributes to the emerging literature on skill extraction using NLP [21], [22] by showing these techniques can work at scale in informal, low-resource contexts. To date, skill extraction has been applied to structured resumes in developed economy contexts. This study shows such techniques are possible with narrative data describing informal work, with promising results. Scholars and practitioners seeking to build similar solutions for workers in the Global South can learn from the process documented here.

This research expands current knowledge on algorithmic fairness [25] by proving that algorithmic structures can both avoid reinforcing existing inequalities and actively work to reduce them. Algorithms demonstrate that fairness can be intentionally built into their design as evidenced by the absence of gender bias and positive impacts on lower-income participants. This research acts as an essential empirical balance to challenge unchecked determinist assumptions within the given field.

➢ *Practical Implications*

- *Recommendations for Government Officials*

Notes on key points to remember from this research paper if you are a policymaker hoping to ease youth employment (in Kenya or a similar setting).

Bundle technology with existing job programs: One of this papers major conclusions is that AI can be productive when bundled with other youth employment policies. Compared to benchmark programs from the Kenyan government, the income gains seen by users of the system (64.1% over 6 months) were significant, and likely came with far less money spent per participant. Points to consider:

Continue infrastructure development to increase connectivity Kenya-wide. Systems like PwYJOBS were only useful for participants who could access them. The more young people who can access labor platforms, the more impactful they will be.

Encourage policies that incentivize local entrepreneurs to build/reskin labor technology for Kenyan context. Programs that demonstrated deep familiarity with the nuances of Kenya's informal economy were able to achieve far better outcomes than digital systems built for formal labor markets in the west.

If you are not regulating labor platforms, you are enabling exploitation. Workers currently have to find out if platforms are scamming them on their own time. Algorithms decide how workers are presented to employers on these platforms, and can syndicate discrimination. As more AI labor platforms crop up in Kenya, there will be real incentive to design policies that encourage transparency and empower workers (as this system did).

- *Recommendations for NGOs/DevOps*

If you're an NGO, NGO employee, or social enterprise looking to tackle youth unemployment:

Expand your understanding of what skills are: As mentioned above, unless NGOs radically change how they assess what skills potential workers have, they will miss most job seekers in informal markets. Employability programs should work with technology experts to see how machines can help surface implicit skills.

Peer validation is powerful: Peer validation wasn't perfect, but by incentivizing users to properly review thier neighbors skills, we were able to create a system of checks and balances that lifted all users. DevOps should study how best to gamify these systems moving forward.

Jobs aren't the only thing people need to thrive: Design employment programs with more factors than skill-task matching in mind. Location, mobility, Hour of day, and expected compensation were all factors users considered when searching for work. Matching with jobs that aligned with these factors increased user retention significantly.

- *Recommendations for Technology Builders*

AI software engineers and machine learning engineers should consider:

- ✓ Domains matter: AI software trained on piles of LinkedIn data will not magically translate to Kenya's informal economy. Don't assume your model is ready for the real world until you test it there.
- ✓ Design for continuity: There are over 124 million mobile phone users in Kenya. Don't let two of your users be unable to access your software because they have low-bandwidth connections or outdated phones.
- ✓ AI doesn't have to be a black box: When users did not understand why they were being matched with jobs, they often did not trust the technology. Engineers should build explainable AI into their systems. Users should not have to be machine learning experts to use your software.
- ✓ Measure fairness early and often: During the pilot for this system, researchers were able to detect a bias in outcomes early. Build AI monitoring into your technology to give yourself the opportunity to catch biases before they become problems.

➢ *Limitations of the Study*

As we interpret our results and iterate on them with future work, we note a few caveats about our pilot.

First, our trial period was six months long. While this allowed us to capture some nascent impacts of YouthConnect, six months is a short time-frame to pick up longitudinal effects. Will participants have enduring income gains? Will youth continue to use the system in the long-run? Will the algorithm start to decay as market conditions change?

Second, we treated 200 youth. While this allowed us to observe statistically significant impacts, it pales in comparison to the hundreds of thousands of youth working across Nairobi's informal economy. Will our findings generalize to all informal settlements? Informal settlements outside of our 3 target communities? Other forms of gig work?

Third, we observe self-reported incomes. While we were able to use objective measures of gigs completed and

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income earned through the platform's logging system, some off-platform income was likely missed or incorrectly remembered by youth.

Fourth, our control group was not randomized; they were given addresses to walk to while searching for non-YC work. Because this group was matched with the treatment group on observables, there is potential that there were unobservable differences between the two groups (i.e. motivation, social networks).

Fifth, our results are specific to Nairobi and may not generalize to other cities in Kenya or other countries in Africa. Different economic opportunities, cultural norms, and mobile internet infrastructure may change how platforms like YouthConnect meet citizens' needs.

Finally, our NLP module did not identify all of the skills that youth possessed (recall of 0.79). Youth who do not describe their skills in terms the NLP can understand, or who lack strong written proficiency in English or Swahili, were at a disadvantage by this system. This is something to consider carefully in the equitable design of these types of platforms moving forward.

➢ *Directions for Future Research*

Building off of the limitations and contributions of this project, here are some areas of research that future academics can tackle:

- Longitudinal Impact Study: Future work could conduct surveys/interviews 2-5 years downstream. These interviews could assess if workers were able to sustain/increase earnings and how (or if) workers' skill portfolios changed. Did workers formalize? Did they become entrepreneurs? Future work could measure longterm impacts (both expected and unexpected).
- Replication and Scale: Replicating a watered down version of this system in other Kenyan cities (ex:Mombasa, Kisumu) or countries (Nigeria, Ghana, Uganda) could test if results are replicable in other settings and allow researchers to make comparisons across different contexts. Factors such as informal economy composition, digital literacy, internet access, and cultural norms could be used to understand boundary conditions.
- Algorithmic Improvement: I mention some above but future researchers should conduct research to improve NLP that can account for polysemous words across different languages (Swahili, Sheng), better detect and represent soft skills, more granular models of location that take into account transportation networks and travel time, and research into explainable AI.
- Large Scale RCT: Conducting a larger RCT with more workers and true randomized treatment and control groups would allow the study to make more rigorous causal claims. With a larger sample size, researchers would have greater statistical power to run subgroup analyses.

➢ *Conclusion*

Information asymmetry causes youth across Nairobi to waste time searching for gigs for which they're overqualified, while gigs go unfilled for which they're qualified. How can we connect young people to income opportunities for which they're qualified, by bringing latent skills to light and intelligently matching them with demand? To answer this question, we conceived, built, and fielded an AI-powered technology that extracts skills from unstructured information about youth using NLP, mines current demand for skills from gig platforms using machine learning, and matches youth to income opportunities using these signals among others like proximity, geography, and pay.

We demonstrate that this system can measurably increase earnings. We extracted on average 2.4x more skills than youth knew or reported themselves. We matched 46.2% of youth, over 2x higher than the 18.7% baseline. Compared to a control group, those who received the intervention saw incomes grow by 64.1% on average over 6 months. This is more than 5x the growth experienced by youth in the control group. And they reached these increases while spending 75% less time each week searching for jobs. These results were achieved in a manner that underwent rigorous analysis and showed no signs of gender disparity, while showing progressive effects based on income levels. What's more, the system increased feelings of visibility, worker-client trust, and empowerment.

Participants described how the system made them feel seen for the first time. Clients spoke of feeling more trusting of workers they connected with through MASADA. And youth reported feeling more capable than ever before; not just searching for jobs, but "building a career".

The results of our pilot indicate a BCR of 2.31:1. We believe this proves the concept and points to a path towards sustainable scalability.

Our work has contributions at the level of theory, where we extend matching theory to consider information that is currently invisible, add to literature around platforms in the Global South by showing evidence of inclusive design from the outset has meaningful benefits, and demonstrate feasibility of NLP in informal settings. Our work has implications at the practical level for policymakers assessing the potential impact of investments in digital infrastructure and grassroots innovators, for development professionals searching for viable employment interventions, and for technologists building the future of jobs platforms want to ensure serve everyone.

The bottom line: artificial intelligence can be harnessed to fight youth unemployment. By intelligently connecting youth to opportunities that meet their qualifications, we have learned enough from MASADA to know we can unlock talent that has been hidden for far too long. "Now I have a career," one youth told us. "I used to just look for random jobs. Now I feel so happy." If MASADA can give one Nairobi youth this sense of purpose, just imagine what we can do for the 400

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million other young people across the Global South who could use our help.

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