



AI-supported Skills Elicitation, Guidance, and Personalized Matching

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Implementing Partners



Funding Partners



Building Evidence While Building Solutions:

Our Ongoing Research in AI-Supported Employment Systems

- Today we are sharing **ongoing research** that is **embedded directly into Tabiya's implementation work** with partners in South Africa and Kenya
 - We're inviting feedback while our studies can still adapt—shifting from post-hoc evaluation to collaborative learning
- We develop theoretically grounded **graph-based matching** based on skills elicitation from unstructured text (conversations with AI & semi-formal job descriptions)
- **Two RCTs** examining different applications:
 - How AI can enhance skills-elicitation matching and correct labor market beliefs (South Africa, Harambee Youth Employment Accelerator / SAYouth.mobi)
 - The quality and effectiveness of AI-powered vs. human career guidance (Kenya, Swahilipot Hub Foundation)

About Tabiya (→ tabiya.org)

Open-Source Solutions for Economic Opportunity in LMICs

- Tabiya is a non-profit spin out from the University of Oxford
 - *Mission:* Build and share open-source tools for labor market applications
- Interoperable, integrated data systems to link demand- and supply-side data:
 - Basis for all tools: Structured occupation and skills taxonomy (ESCO based) that captures informal and traditionally "unseen work" including care work
 - Skills elicitation, CV building, vacancy processing, and matching tools
 - Connectors with CRM systems and existing digital public infrastructure
 - *Today's focus:* **GenAI-supported conversational agents and matching**
- Everything open-source, freely available for governments, NGOs, and researchers to adapt and improve

Broader Policy Context and Literature

From Credential-Based to Skills-Based Hiring and Matching

Skills-Based Hiring: US employers (Google, IBM, Delta) and states removing degree requirements

- HICs: Promises more equitable access, addresses talent shortages
- LMICs: Opportunity for recognizing informal economy skills (60-90% of work)—street vending, domestic work, agriculture, care work

Evidence on Barriers

- **Information Asymmetry:** Key barrier is credible skills signaling. Verifiably demonstrating skills leads to employment and earnings gains (Carranza et al., 2022) – not realistic at scale
- **Pronouncement-Practice Gap:** Despite policy changes, hiring outcomes have not shifted. Degrees still proxy for unobserved attributes (Fuller, Langer & Nager, 2024) – what are alternatives?

Where AI Could Help (or Harm): Signal deteriorating but skill-leveling?

- AI compresses skill distributions (Brynjolfsson, Li & Raymond, 2023), but also reduces skill signal to noise ratio (Wiles & Horton, 2025).
- Training of recommender systems (esp. content-based & collaborative filtering) often encodes human biases (Zhang & Kuhn, 2022)
- Our taxonomy makes "unseen" informal competencies visible and matchable



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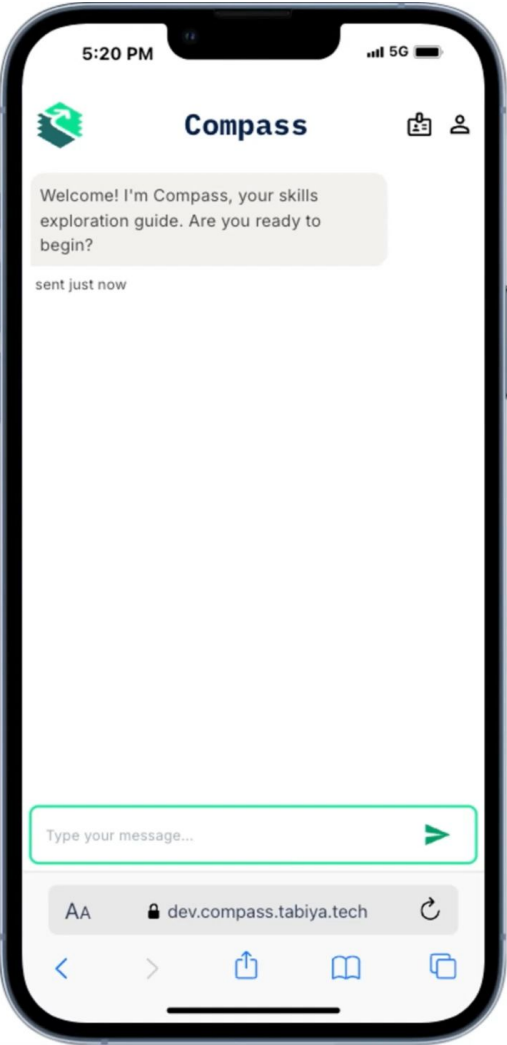
Skills Elicitation, Extraction, and Graph-Based Embeddings for Matching

Two-Sided AI-Taxonomy-Linkage

Labor supply

Taxonomy Bridge

Labor Demand



Full Skills Entity			
Skill	ESCO code	Skill Type	Occupation
		Knowledge	
		Competence	
		Language	
		Attitude	

18 days ago

Salaried Financial Advisor - Bredasdorp

Old Mutual Life Assurance Company

Member since Feb 2023

Location: Caledon, Western Cape

Date posted: 08 September 2025

Closing date: 31 December 2025

Salary: R 7,000.00 per month - Base pay with commission and benefits

Job type: Full-time / permanent

Industry: Insurance

Vacancy

Description

Role overview:

This role provides advice on a specific range of products to a specific allocated market and is individually accountable for achieving results through their own efforts.

What is a financial advisor?

- The role of a financial advisor demands the utmost professionalism, integrity, and a customer-centric approach.
- An accredited financial advisor commands the respect and trust of those customers who are entrusting their and their families' financial futures to them.
- The role calls for formal in-house training, the completion of the prescribed Regulatory exams, and accreditation with the Financial Services Regulatory Authority, and requires continuous professional development.
- As an accredited financial advisor with Old Mutual, you will represent the ideals and

Fine-tuned BERT classifier

LLM-reranker with full context

Technical Approach

Graph-Based Embeddings for Skills Matching (1/2)

Challenge: Keyword-based matching is inefficient – no accounting for skill transferability, hierarchies, distances between capabilities <> requirements

Objective: Develop data-driven measure of skill proximity for users

Methodology:

1. **Graph Representation:** Taxonomy as multi-relational graph (skills = nodes, relationships = edges)
2. **Learn Embeddings (Node2Vec):** Generate high-dimensional vectors via random walks; skill meaning revealed by network neighborhood/context, not just its label or definition
3. **Match Score Calculation (extending Bied et al., 2023):**
 - Cosine similarity of embeddings to calculate distances between jobseeker j & opportunity o
 - Calculate utility score U ("fit") using coverage across essential/optional skills and skill groups
 - Calculate vacancy side success proxy p
 - Get final job seeker ranking: $\text{rankscore}(u, j) = U(j, o) \times p$

Delivery: 2-sided skills elicitation via Chatbot with agentic AI orchestrating (Google Gemini on GCP), BERT classifiers, and context-aware LLM re-rankers

Technical Approach

Graph-Based Embeddings for Skills Matching (2/2)

Formally, inspired by Bied et al. (2023), we define skills coverage (Cov) across essential skills (E_j), optional skills (O_j), and skillgroups, where κ represents proximity = cosine similarity of skill embeddings.

$$\text{Cov}_{\text{ess}} = \frac{1}{|E_o|} \sum_{s \in E_o} \kappa_{j,s}, \quad \text{Cov}_{\text{opt}} = \frac{1}{|O_o|} \sum_{s \in O_o} \kappa_{j,s}. \quad (1)$$

$$U(j, o) = \theta_{\text{ess}} \text{Cov}_{\text{ess}} + \theta_{\text{opt}} \text{Cov}_{\text{opt}} + \theta_{\text{grp}} \text{SkillGroupRecall}, \quad (2)$$

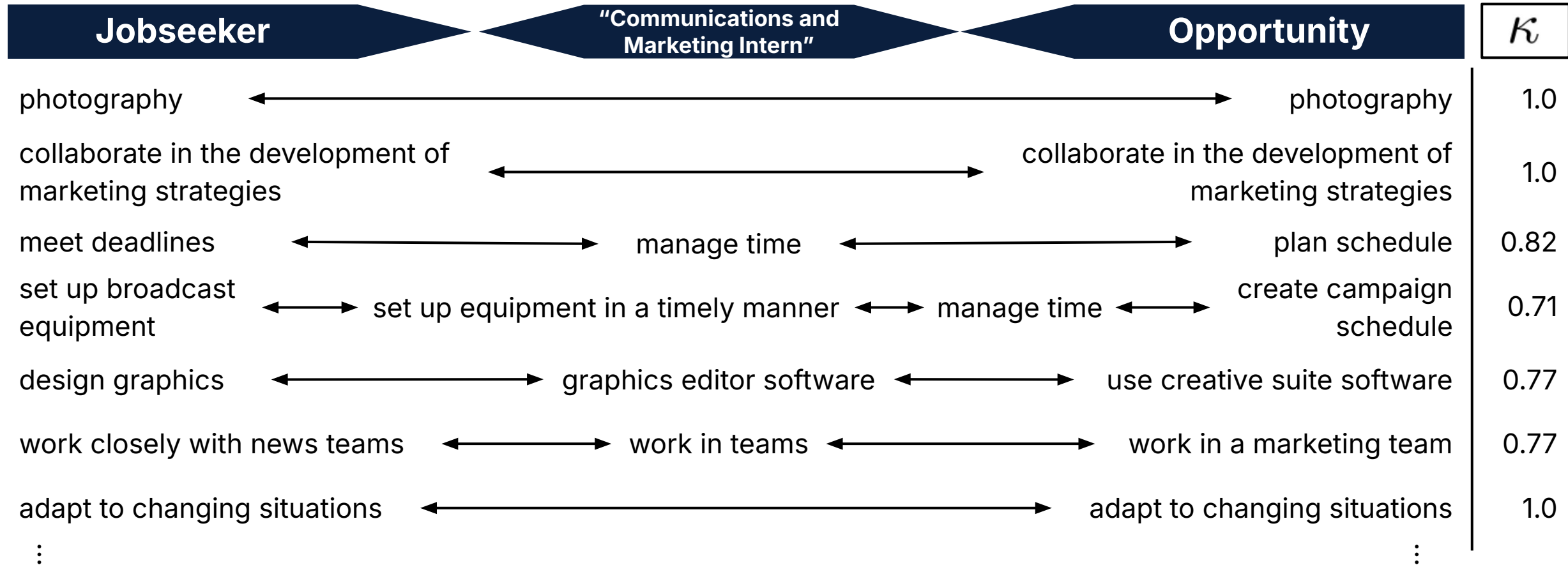
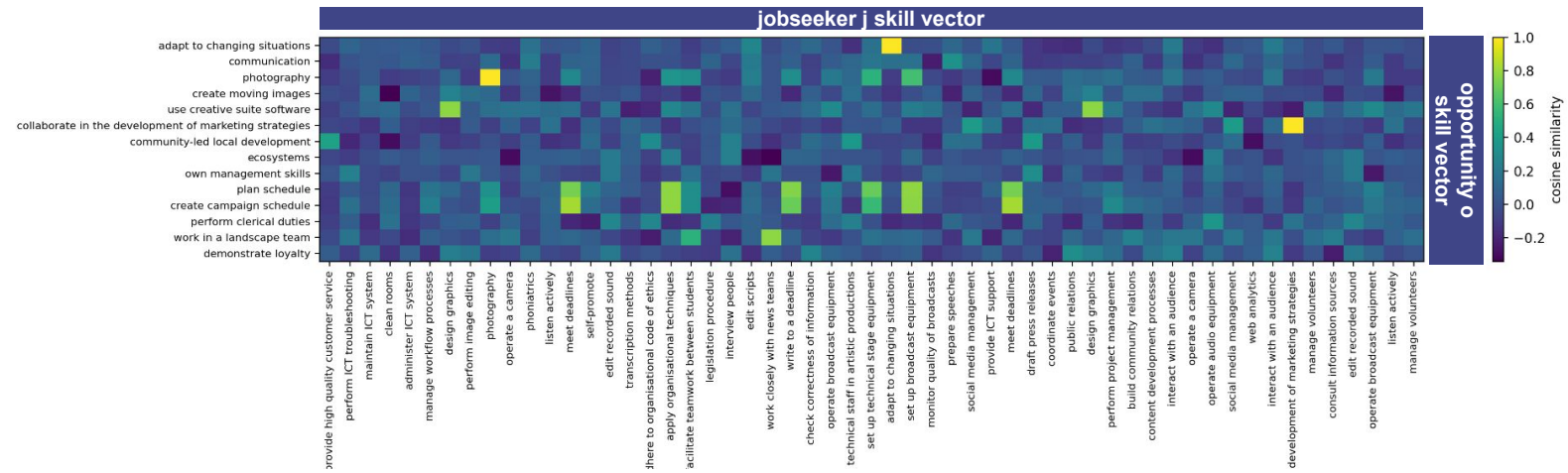
where *SkillGroupRecall* (0–1, rewards breadth across competency areas) = share of required skill-groups with any skill member at $d \leq 1$ i.e., an exact match ($d=0$) or a one-hop hierarchy neighbor ($d=1$).

$$\hat{p}_o = \text{OSI}_{o,\ell} \times s_o. \quad (3)$$

where *OSI* is an opportunity supply index at a given location, and s_o represents opportunity staleness.

$$\text{rank_score}(j, o) = U(j, o) \times \hat{p}_o. \quad (4)$$

Matching: Example





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Two Empirical Applications

Two Implementation Contexts, Two Matching Challenges

Labor supply

Labor demand

**South
Africa**
(national)

AI-facilitated **skills elicitation** and its signalling effects

Skills-based matching
& aggregate
competitiveness
information

Repository of ~4,000 entry
level jobs (from SAYouth.mobi
API) mapped to taxonomy

Kenya
(Mombasa)

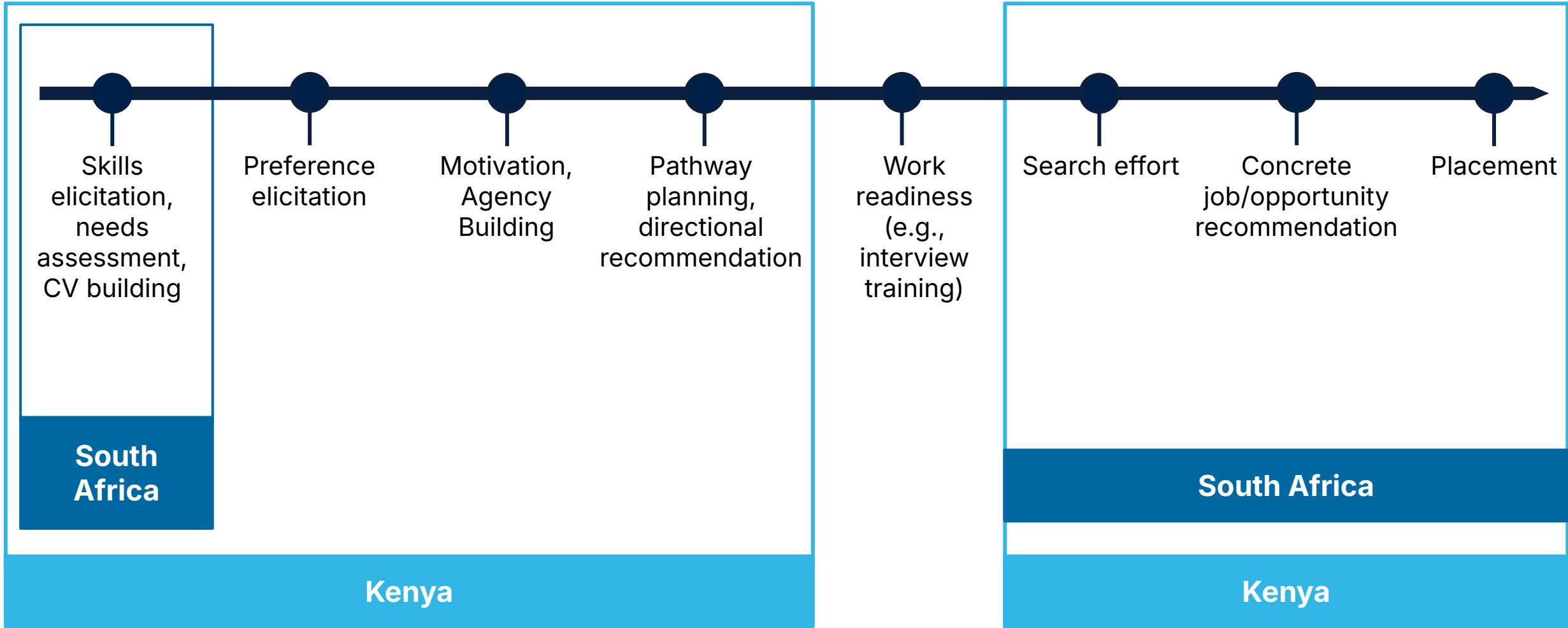
AI-facilitated career
guidance, agency building
& **recommendation**,
compared/complemented
with human advice

Human counselors

Recommendation
and
quality of advice

Semi-formalized collection
of training opportunities,
pathways, and concrete jobs

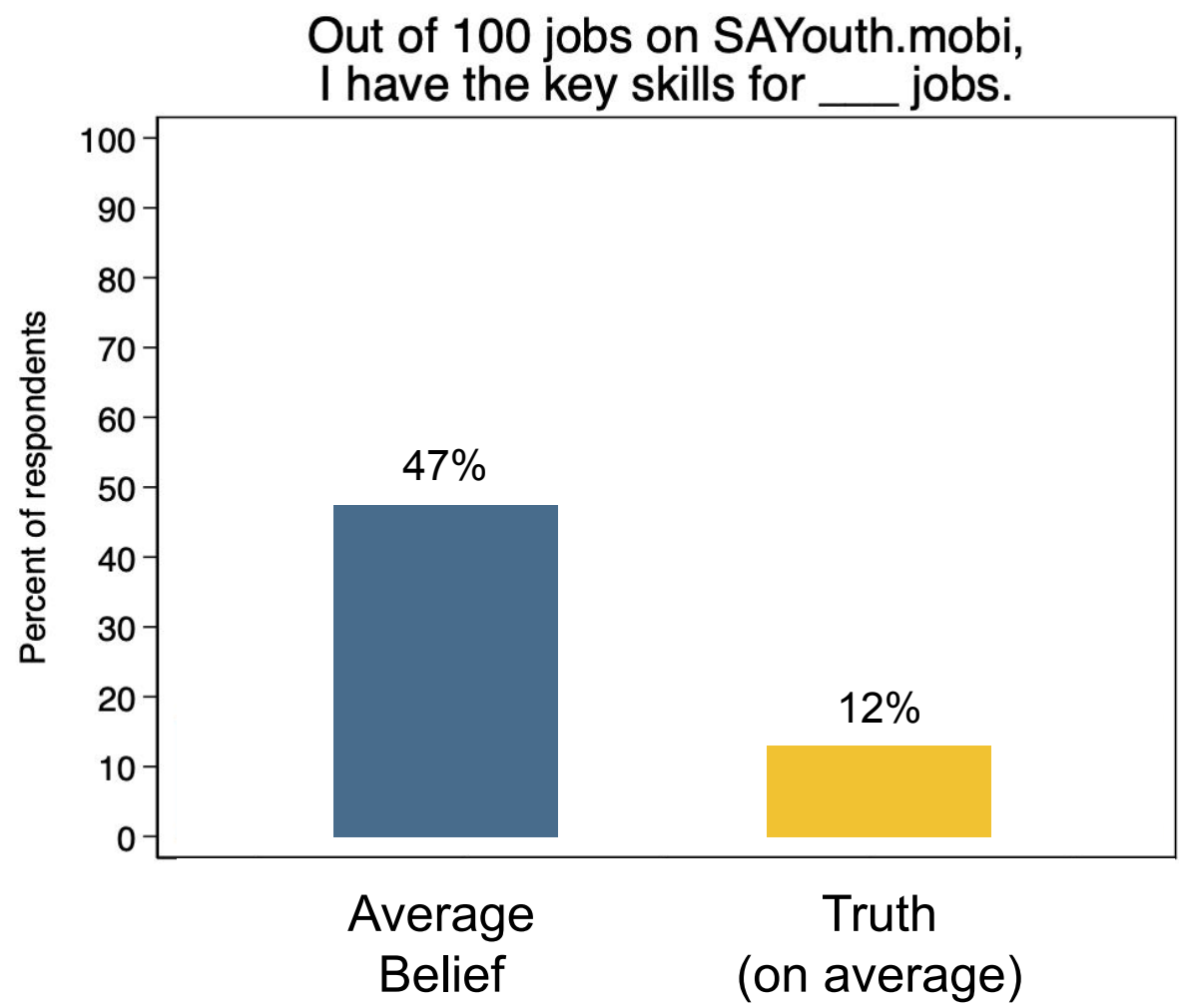
We Intervene at Different Moments of the Jobseeker Journey



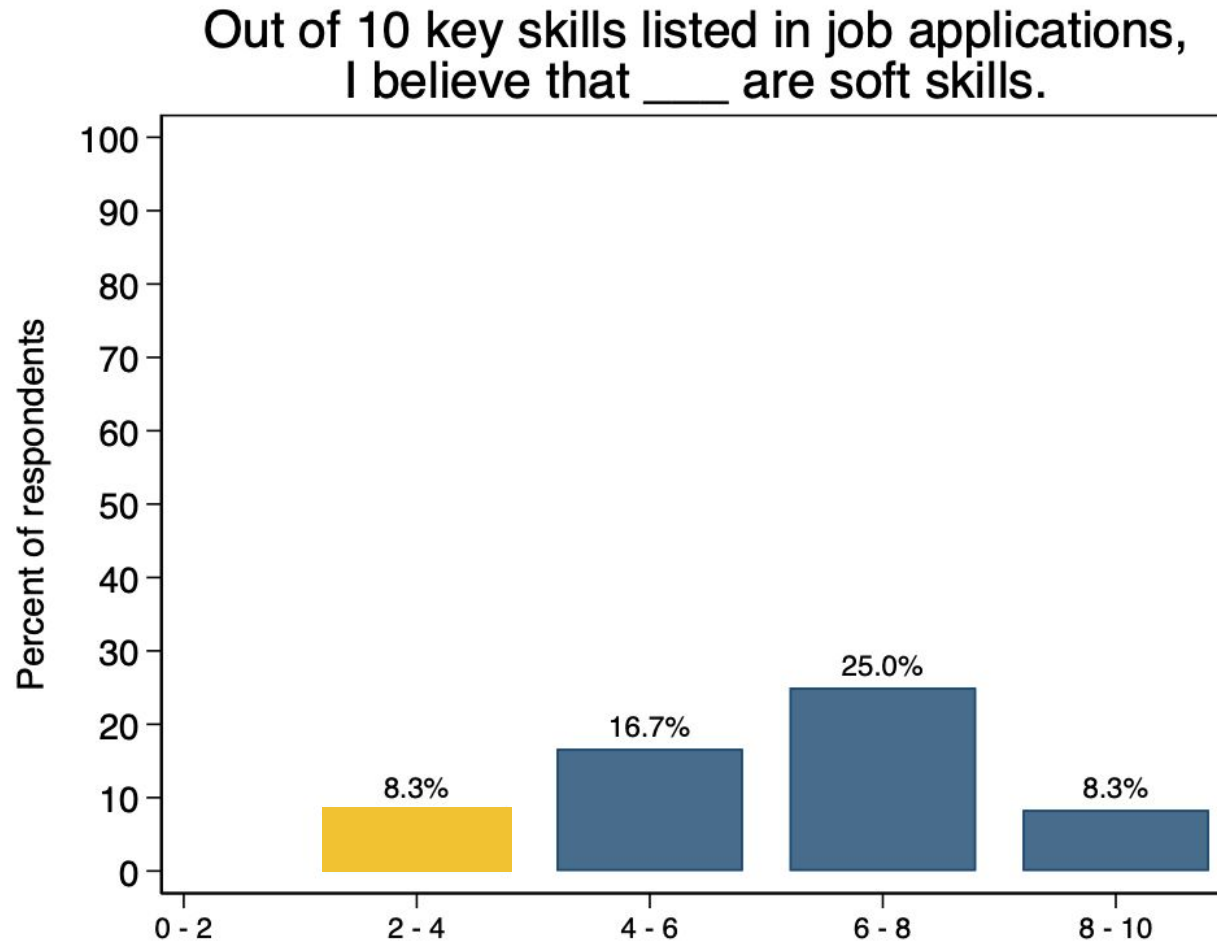
Intervention: Agentic AI system

Outcome Measurement

South Africa: Pilot Data on Beliefs and Preferences



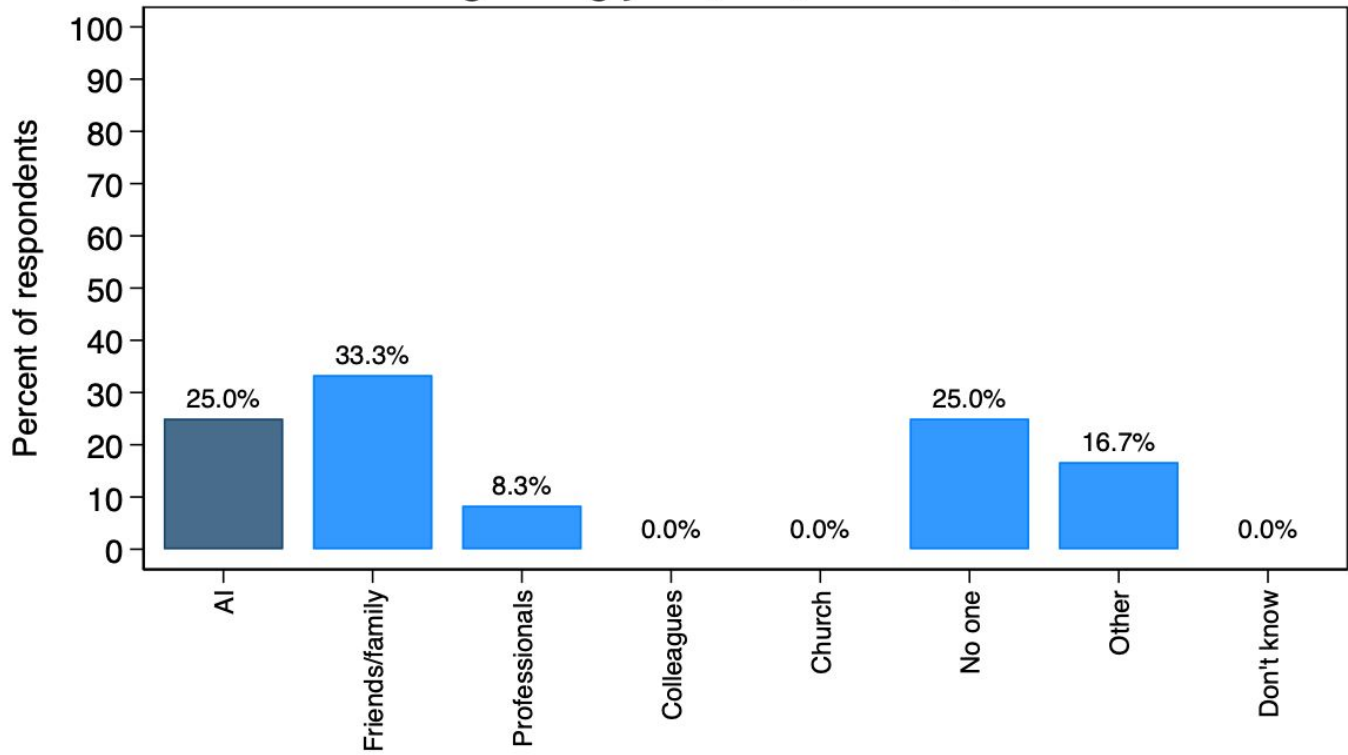
South Africa: Pilot Data on Beliefs and Preferences



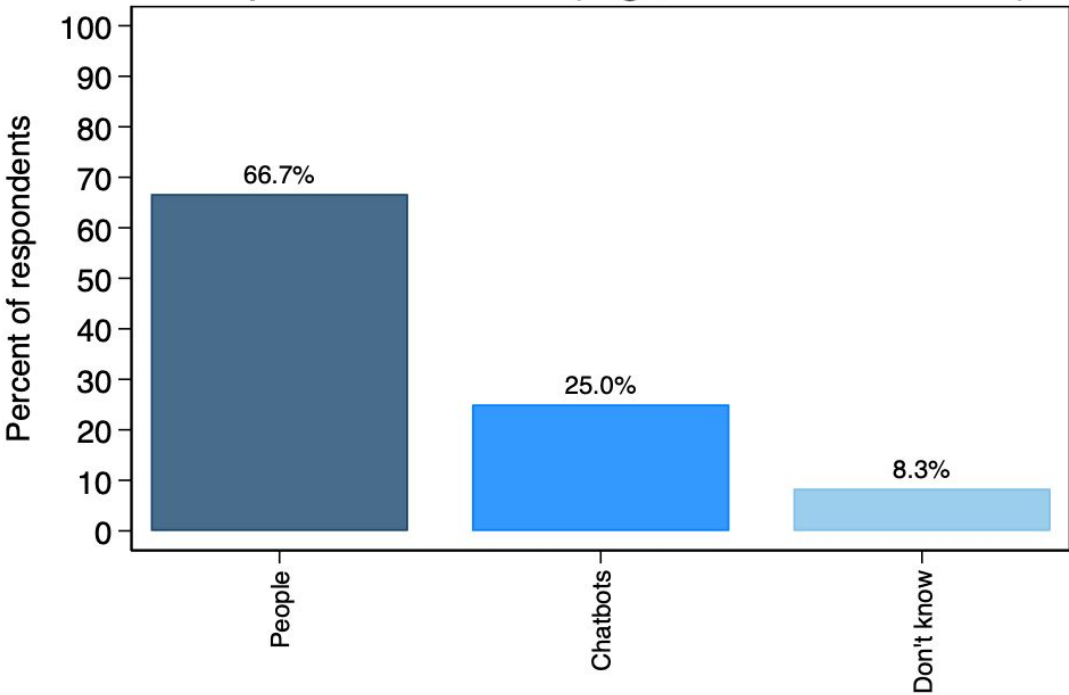
In our current database of entry level jobs posted on Harambee's [SAYouth.mobi](https://sayouth.mobi), on average **~8%** of key demanded skills are soft skills.

South Africa: Pilot Data on Beliefs and Preferences for AI-based guidance

Who do you ask for help regarding jobs, CV, career, etc.?



Who listens better when you share concerns? People vs. chatbots (e.g., ChatGPT/Gemini)



Kenya: Recommendation Focus, Test Against Humans

Motivation: Mentorship addresses search costs, information asymmetries, and uncertainty in human capital investment decisions – but quality mentors don't scale

Conceptual Frame: Real option theory, learning under uncertainty, preference discovery vs. eval

- Under uncertainty → invest in transferable skills (theoretical basis for recommendations)
- θ = latent preferences/constraints; S = option set; $u(\theta, x)$ = utility
 - **Discovery:** Improve identification of θ , expand S (youth often only see narrow paths)
 - **Evaluation:** Better predict (θ, x) → outcomes and rank options

Core Questions:

1. Do AI recommendations complement or substitute human mentors?
2. Who better surfaces preferences – and with what biases?
3. What type of guidance increases agency under low self-efficacy?

Design: Cross-randomize feedback to humans/AI; compare Human vs AI vs Hybrid arms

- Outcomes: Search breadth, skill investments, placement, retention, earnings
- Mechanisms: Belief updates, agency, confidence, advice uptake, perceived constraints

Kenya: Qualitative Insights on AI for Career Counseling

Perceived Risks

- **Signal inflation:** AI CV-polish leads to documents looking the same → Employer shift to referrals → Exclusion risk
- **Cultural misfit:** Models may feel “not Kenyan,” can’t reference local anchors (e.g., chief)

Perceived Opportunities

- **AI as infrastructure:** Data plumbing + mentor co-pilot increases mentor throughput and interview rates, even without changing youth skills
- **AI as for work readiness:** Coaching for language, behavior, dresscode & interview skills
- **Pathway discovery:** Map transferable skills to adjacent roles; aggregate local opportunities.

Perceived Limitations

- **AI as mentors:** Mentors themselves **do not** believe that AI can replace them; they mention that personal relatability and authentic shared experience is key
- **Lacking Accountability:** If reminders and feeling accountable to a person drives effort → AI may not succeed
- **Referral economy:** Employers prefer intros over platforms; “mindset” often trumps formal skills

Summary of Approach and Next Steps

- We develop open-source **graph-based skills matching** via conversational AI
 - Moves from heuristic to **learned, quantitative skill distance** based on taxonomy
 - Uncovers non-obvious matches via vector-space proximity of transferable skills
 - Fully interpretable – decomposes matches to show exact skill substitutions
 - Theoretically grounded (Bied et al, 2023) and informed by both sides of the market
- We implement and evaluate in **two contexts for improved matching & recommendation**
 - In South Africa, we support jobseekers with AI-facilitated skills elicitation and CV building, preparing them for more targeted search and signalling.
 - In Kenya, Youth faces limited information and symptoms of learned helplessness – requiring personalized mentorship. With humans being the bottleneck, AI-facilitated pathways planning may relieve constraints more effectively than simple signalling.
- Expect **first results in late January 2026**



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Thank you

We'd love your feedback and welcome collaboration opportunities.

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