Beyond Digital Access: AI Literacy, Digital Capabilities and Sustainable Livelihood Pathways for Young People in the Digital Economy Human Capability, Youth Employment and Inclusive Growth

Asher.O. Ojuok[1], John.O. Anyango[2], Charles. J. Odhiambo[3]

[1]University of Nairobi, Nairobi, Kenya

[2]Jomo Kenyatta University of Agriculture and Technology, Juja, Kenya

[3]University of Nairobi, Nairobi, Kenya

***Corresponding Author**

DOI: https://doi.org/10.51244/IJRSI.2026.1310000243

Received: 01 November 2026; Accepted: 06 November 2026; Published: 17 November 2026

ABSTRACT

Connectivity programmes often assume that a young person who gets online will be able to find a way to earn. Evidence provides partial support: faster internet has increased employment in a number of African countries [17]. However, many young Africans with internet access continue to work in informal, low-paid and insecure jobs. Generative artificial intelligence (AI) raises a further question: who is able to benefit from these technologies, and under what conditions might they widen existing disparities? This paper asks what needs to connect digital access to sustainable livelihoods for young people in Kenya and, by implication, in other African contexts. It develops the Capability-to-Livelihood Pathway Framework, comprising five interrelated components: access conditions; a four-level capability stack connecting foundational digital literacy, functional AI literacy, critical AI literacy and occupational application; conversion factors that shape whether capabilities can generate income; livelihood pathways; and outcome measures focused on security and progression rather than income at a single point in time. The framework is developed through an integrative conceptual synthesis of scholarship on digital inequality, AI and employment, youth employment programmes, and relevant policy and labour-market evidence, using Kenya as the principal contextual case. Four propositions are advanced for empirical testing. The paper's central contribution is to shift the measure of programme success from skills delivered to livelihoods sustained.

Keywords: AI literacy; digital capabilities; youth employment; sustainable livelihoods; digital inequality; platform work; Kenya; Africa

INTRODUCTION

Consider two nineteen-year-olds from Kisumu, Kenya who both own a similar smartphone and a similar prepaid bundle. However, one has finished a certified short course and maintains an account of paid tasks on a freelancing site and sells products via a WhatsApp list. The second individual uses his smartphone to watch videos, get football scores, and send M-Pesa. Both individuals are statistically equal when it comes to connectivity, yet their socio-economic status varies.

Digital inclusion policy has long treated that difference as a lag that more of the same would close: wider coverage, cheaper handsets, more training places. A few years ago, scholars studying digital inequality had established that inequality is structural. Van Deursen and van Dijk [39] illustrate how digital inequality starts as one of physical access before changing to material access, skills and finally the tangible benefits realized from

using the digital technologies. Helsper [16] expands the argument by illustrating that digital inequalities are socially structured because people with more resources extract greater value from technology.

The generative AI technologies further complicate the question. Text-drafting tools, translation tools, code writing and question-answering tools make tasks more affordable and recent field studies have shown that the biggest benefits are accrued by workers with little experience [6, 32]. Whether a young Kenyan can realize such benefits depends on whether she can effectively use the technology, assess its results and market the outcome. This is all a matter of capability, not access.

This article asks what must stand between access and livelihood, and what a programme designer, a county youth officer or a funder should measure to know whether it does. Its answer is a framework, set out in Section 5, that treats AI literacy as one level in a stack of capabilities and treats the conversion of capability into income as a separate problem with its own causes.

The paper is the second of five. The first examined how public institutions should govern AI systems that act on citizens. Here, young people appear as workers, traders and learners and not as subjects of public decisions. The papers concerning cloud computing infrastructure, IT assurance and monitoring and evaluation are used only in those cases when they place restrictions on what livelihood program is capable of achieving.

The logic follows the path from the global to the continental to the national level. Section 2 analyses of international experience related to digital inequalities, AI literacy and impact of AI on employment. Section 3 examines the African context, while Section 4 focuses on Kenya.

CONCEPTUAL REVIEW METHODOLOGY

This article adopts an integrative conceptual review design. Its purpose is theory development rather than estimation of a pooled effect or reporting of a new empirical dataset. The review brings together four bodies of material: (i) peer-reviewed research on digital inequality and digital inclusion; (ii) scholarship on AI literacy, human–AI interaction and AI-related work; (iii) studies and reviews of youth employment, skills development and labour-market intermediation; and (iv) Kenyan, African and international policy documents and statistical reports relevant to digital access, employment and livelihoods.

Sources were considered relevant where they addressed at least one of the framework's constructs—access, capability, conversion conditions, livelihood pathways or livelihood outcomes—or provided contextual evidence about Kenya and comparable African labour markets. Priority was given to peer-reviewed studies, established research reviews, official statistical publications and policy documents issued by recognised public institutions. Investigative journalism and other non-academic reporting were used only where they documented a specific labour practice not adequately covered by formal datasets; such material is treated as illustrative rather than representative evidence.

The cited source base is concentrated in 2019–2025, while earlier foundational work is retained where it provides a necessary theoretical basis. The review is conceptual and purposive, not a systematic review: it does not claim exhaustive coverage, a reproducible database search, formal risk-of-bias scoring or meta-analysis. The manuscript does not report database-specific search strings or screening counts, and no such figures are inferred here. The synthesis identifies relationships and propositions for testing but does not establish causal effects.

Synthesis proceeded in three stages. First, recurring constructs and mechanisms were extracted, including material access, skills, critical evaluation, labour-market signalling, finance, language, working conditions and resilience. Second, these constructs were compared across the four bodies of literature to identify points of convergence and gaps, especially the limited connection between AI literacy models and livelihood outcomes in informal and platform-based work. Third, the constructs were organised into the five components of the Capability-to-Livelihood Pathway Framework, and the proposed relationships were expressed as four propositions for empirical examination.

For greater reproducibility in a future update, the authors should retain a search log recording databases and institutional repositories consulted, exact search dates and terms, duplicates removed, inclusion decisions and excluded source categories. Because this article is a purposive conceptual synthesis based on the cited source set, the absence of a formal systematic-search log is acknowledged as a limitation rather than concealed.

The Global Position: From Access To Outcomes

According to the International Telecommunication Union [19], some 2.6 billion people are not yet online. This is still a significant number but one that is declining. Most of those whose lives would be influenced by any policy on livelihoods are already online, but their differentiating factors would be the nature of their connectivity and the manner of their utilization. According to Ragnedda [34], individuals who connect but are unable to derive benefits from that connectivity can be called the digital underclass, while van Deursen and van Dijk [39] have examined the process of stratification through the device, connectivity, and payment for usage.

AI literacy is the most recent endeavor to coin the name of this missing competence. This competence has been described as the set of competencies that allow people to critically reflect upon AI technologies, collaborate with them and use them as a tool; the total of seventeen competencies is extracted for this definition. Ng et al. [31] organize this competence by distinguishing between knowing and understanding, using and applying, evaluating and creating, and finally ethical concerns. According to Laupichler et al. [24], the majority of the research focuses on higher education and does not discuss the issue related to adult and informal learning. The competence framework proposed by UNESCO [38] for students encompasses twelve competencies in four dimensions and three progression levels. However, as stated by Selwyn [36], the issue is that the promise of AI in education is outpaced by the evidence.

Nearly all of these frameworks assume a classroom. A young Kenyan who left school at seventeen and trades in a market is outside them. That mismatch is the first reason the framework in this article is built around work and not around curricula.

The evidence on what AI does to work is mostly experimental and mostly from high-income workplaces. In a study of professional writing tasks, access to ChatGPT cut completion time by about 40 per cent and raised rated quality by about 18 per cent, and it narrowed the gap between stronger and weaker writers [32]. Brynjolfsson et al. [6] find that customer-support agents using a generative assistant resolved 14 per cent more issues per hour, with gains of about 34 per cent among novices and little effect on the most experienced. Dell'Acqua et al. [10] describe a "jagged frontier" in a field experiment with management consultants: tools improved performance on tasks inside their competence and reduced the correctness of answers on tasks just outside it. A worker who cannot tell which side of the frontier she is on will do worse with the tool than without it.

Exposure studies consistently indicate this pattern even at the occupational level. For example, Eloundou et al. [11] demonstrate that large language model exposure is greatest in occupations that earn more money and require greater levels of education. Exposure levels estimated by Cazzaniga et al. [8] amount to 40 per cent of global employment, 60 per cent in advanced nations and 26 per cent in poor countries. Gmyrek et al. [12] note that the automation exposure level for employment in poor countries stands at 0.4 per cent for the highest exposure group against 5.5 per cent in advanced nations due to lower digitisation of occupations. Low exposure is not a shield but a sign of absence of AI in current occupations of young people in these nations.

There is evidence of uneven results of training programs. As noted by Kluve et al. [23] after reviewing impact evaluations of youth employment programs, there are positive but limited average results. Larger results occur in developing countries and when the intervention includes multiple elements and meets local demand. A short training course implemented separately falls into the latter category.

The African Position: A Young Workforce, Uneven Access, Adverse Terms Of Inclusion Of all continents, Africa possesses the youngest population, and the Digital Transformation Strategy of the African Union [2] considers digital literacy and employability an integral part of capitalizing on that advantage. As noted by the International Labour Organization [18], in most parts of sub-Saharan Africa the central youth-employment

challenge concerns the quality and security of work, not unemployment alone. Young people in Africa do work; they work informally, for little pay, without a contract and without any security in case of difficult times.

There is great inequality in access. According to ITU [19], internet usage in Africa stands at just above 33 percent of the population. According to GSMA [14], more than half of the people within the region residing within the reach of mobile broadband do not access it due to issues such as handset cost, poor literacy and skills levels and uncertainty about relevancy and security. According to the World Bank [42], skills form one of the three foundations of readiness for AI with infrastructure and data forming the other two.

Where access exists, there have been tangible impacts on the nature of work. Hjort and Poulsen [17] use the differential availability of submarine cables to establish that faster internet led to increase in employment across educational classes and increased movement towards skilled employment. According to Choi, Dutz and Usman [9] for the World Bank, digital technologies have the potential to increase productivity and improve the quality of employment in Africa provided there is investment in skills and given the predominance of informal employment in the sector.

Studies of training and job search show where the bottleneck sits. Alfonsi et al. [3] test vocational training in Uganda against firm-provided training and find that both raise employment and earnings, through different channels. Abebe et al. [1] find that in Addis Ababa the cost of distance and the difficulty of signalling skills to employers held back job search, and that interventions aimed at those two frictions changed outcomes. Carranza et al. [7] show in South Africa that giving employers verified information about workseekers' skills improved outcomes for those assessed. Skill is rarely the only gap. A trained young person with no way to prove what she can do often loses to a less capable one with a referral.

Platform labor and data labor reveal the danger in a different guise. Anwar & Graham [4, 5] reveal that African platform laborers appreciate their flexibility and autonomy but still struggle with unstable pay and lack of protection as well as recourse should the platform alter its terms. Wood et al. [41] highlight how algorithmic management undermines the autonomy promised by platform work. Gray & Suri [13] explain the work involved in AI products in terms of a labor force hidden from view. Muldoon et al. [28] provide a typology to show that data work is highly stratified, with routine tasks being the lowest paid and without any possibility of upward mobility. Perrigo [33] reported that Kenya-based workers who labelled harmful content for an AI developer earned under two dollars an hour. Heeks [15] names the pattern adverse digital incorporation: a person is included in a digital system, but on terms under which most of the value goes to others.

Language is a further filter. Joshi et al. [20] find that most of the world's languages, including nearly all African ones, receive very little attention in language technology. Nekoto et al. [30] show with the Masakhane community that participatory methods can produce translation benchmarks for more than thirty African languages. A course taught in English, on tools that fail in Dholuo or Kikuyu, serves a narrower group than its enrolment figures suggest.

Kenya: A High Base Of Digital Use And A Thin Record Of Outcomes

More than three out of four Kenyans are below 35 years old [21]. Formal sector firms do not employ as fast as the youth joins the labour market, while the informal sector represents more than eight out of ten jobs [22]. This means that an employment-focused policy looks at only a fraction of the entire labour market. For many young Kenyans, what matters is livelihood formation from various streams of income and vulnerability to various types of shocks.

Kenya starts from a stronger digital base than most of the continent. Mobile money is a daily instrument for payment and credit. Suri, Bharadwaj and Jack [37] find that access to digital loans in Kenya made households more resilient to shocks, reducing the chance that they forwent expenses after a negative event. The capability to use digital finance exists at scale. What has not been shown is that it extends to AI tools used for income.

Policy has also taken care of skills at every stage. The Digital Economy Blueprint [26] recognized digital skills and values as a pillar. The Kenya National Digital Master Plan 2022–2032 [27] continues to carry skills as a pillar from amongst four, while talent is recognized as one of the programmatic areas in the Kenya Artificial Intelligence Strategy 2025–2030 [35]. Delivery has run through several channels: the Digital Literacy Programme and the Competency Based Curriculum in basic education, technical and vocational training, the Ajira Digital programme for online work, internships in public bodies under the Presidential Digital Talent Programme, and plans for community digital hubs under the Jitume initiative.

Publicly available programme reporting should be interpreted carefully because it often reports inputs and outputs—such as infrastructure, enrolment, training, registration or placement—rather than sustained livelihood outcomes. These measures are useful for monitoring delivery, but are not equivalent to evidence of sustained earnings, income stability, decent-work conditions or progression. This article does not claim that no longitudinal data exist in any implementing agency; rather, a consolidated, publicly accessible longitudinal evidence base linking participation in the programmes discussed above to these livelihood outcomes was not identified in the sources reviewed. Programme targets, participation counts, placements and independently evaluated livelihood effects should be reported separately.

Several constraints are especially salient in the Kenyan context, although they are not necessarily unique to Kenya. These include the cost and reliability of electricity and data, with particular implications for remote and arid and semi-arid areas; unequal access to devices and time, including constraints associated with unpaid care responsibilities; accessibility barriers for persons with disabilities; and language choices that shape whether training and AI tools are usable. These factors vary across counties, households and occupations and should be measured rather than assumed to affect all young people in the same way.

The Capability-To-Livelihood Pathway Framework

The framework is not intended to replace established perspectives. Its originality lies in integrating their complementary insights into a work- and livelihood-centred model for digital and AI capability development, with explicit conversion mechanisms, multiple income pathways, feedback effects and measurable sustainability outcomes. Table 1 summarises this distinction.

Table 1. Positioning the Capability-to-Livelihood Pathway Framework in relation to established perspectives

Established perspective	Principal contribution	Gap addressed	Advancement offered
Digital inequality perspectives [16, 34, 39]	Explain inequalities in access, skills, use and benefits derived from digital technologies.	Do not by themselves specify an AI-related capability sequence linked to livelihood pathways and longitudinal livelihood indicators.	Adds capability levels, conversion factors, livelihood routes and sustained outcome measures.
AI literacy frameworks [25, 31, 38]	Define competencies for understanding, using, evaluating and engaging ethically with AI.	Often organised around education settings; do not necessarily explain conversion into income under informal, platform or enterprise conditions.	Connects AI literacy to occupational application, market access, work terms and livelihood security.
Sustainable livelihoods [29]	Emphasise assets, vulnerability, institutions and capacity to sustain livelihoods through shocks and change.	Do not specifically disaggregate AI-related capabilities or digital work pathways.	Treats digital and AI capabilities as livelihood resources and specifies digital-era conversion factors and pathways.
Youth employment evidence [1, 3, 7, 23]	Shows that training, employer demand, signalling and intermediation affect employment and earnings.	Often evaluates particular interventions or labour-market frictions rather than integrating access, AI capability, work conditions and long-term sustainability.	Integrates programme design, capability, conversion and 6-, 12- and 24-month outcomes.

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue X October 2026

The framework has five interrelated elements: access conditions, capabilities, conversion factors, livelihood pathways and sustainable livelihood outcomes. They are analytically distinguishable but should not be interpreted as a rigid one-way sequence. Access enables opportunities to develop and exercise capabilities; conversion factors shape whether capabilities can be used productively; and livelihood pathways provide routes through which value may be generated and captured. Each component can constrain the others. Improved and more secure livelihoods may enable young people to reinvest in devices, data, training, working capital and professional networks, while adverse outcomes may erode these resources and reduce future opportunities.

5.1 Access conditions

Access means a working device, affordable data, reliable electricity, a language the tools handle, and a safe place to learn and work. The framework treats access as a threshold to be verified, not as an outcome to be reported. A programme should state the cost of completing its course in data, time and transport as a share of a participant's weekly income. A course that needs two gigabytes a week excludes those whose income arrives irregularly, however open its enrolment rules.

5.2 The capability stack

Table 2 sets out four analytically distinct capability levels. They are cumulative in the sense that higher-order occupational application generally depends on foundational digital competence and the ability to use and critically assess AI outputs. They are not a rigid instructional ladder: learners may encounter AI tools before mastering other digital tasks, and a particular occupation may require greater depth in one level than another. Assessment should profile demonstrated competence at each level rather than assume that every learner progresses at the same pace.

Table 2. The capability stack and the evidence that a level has been reached

Level	Capability	Observable evidence	Kenyan illustration
1. Foundational digital	Operate devices and accounts, search, communicate, manage money and passwords safely [40]	Completes a task set unaided: opens an account, submits an online application, verifies a payment	Using M-Pesa, e-Citizen and email to complete a business licence application
2. Functional AI literacy	Use generative tools for defined tasks, write usable instructions, check output against a source, recognise failure modes	Produces a client-ready draft together with a log of the errors found and corrected	Drafting a Kiswahili product description, then correcting the tool's translation mistakes
3. Critical AI literacy	Recognise automated decisions, understand data rights, assess privacy, bias and fraud risk, contest outcomes	Identifies the consent and data protection issues in a scenario and names the route of complaint	Questioning an app-based loan refusal with the lender, then the Data Protection Commissioner
4. Occupational application	Embed tools in a trade or service, price the result, keep client relationships	Verified paid work, or a documented change in a business such as time saved or revenue gained	An agrovet owner using a language model to draft farmer advisories in local languages

Level 1 draws on the European DigComp framework [40], adapted to the tasks Kenyan users perform. Level 2 is where most current short courses stop, and it is the level most exposed to the jagged frontier identified by Dell'Acqua et al. [10]: a learner who can operate a tool but has not learned to check it will make confident errors for paying clients. Level 3 links this paper to the first in the series. A young person who knows that credit scoring, hiring screens or benefit eligibility may be automated can ask who decided and how to contest it. Level 4 is

where income is made, and it is the level most programmes never reach. Selwyn's [36] caution applies throughout. AI literacy taught as a compliance exercise, or as enthusiasm for a product, will not change anyone's earnings.

The four levels distinguish different questions sometimes collapsed under the broad label of "digital skills". Level 1 asks whether a person can access and operate the digital environment safely and independently. Level 2 asks whether the person can use an AI system to complete a defined task and check its output against a relevant source or standard. Level 3 asks whether the person can critically judge the system's limitations, data practices, risks and decisions, and take appropriate action when an output is harmful, biased or contestable. Level 4 asks whether the person can embed the tool in a real occupation or enterprise, deliver a quality-controlled service, price the value created and sustain a client or employer relationship.

The distinction between functional and critical AI literacy is consequential. Functional competence concerns task execution and output checking; critical competence concerns judgement about the system, its social and institutional effects, and the rights and risks surrounding its use. Occupational application is different from both: it is not simply more advanced prompting, but the integration of digital and AI capabilities with domain knowledge, quality assurance, customer or employer requirements, pricing and work organisation. A person may demonstrate critical understanding without market access. The levels are a cumulative capability architecture with context-specific profiles, not a universal certification ladder.

The rationale draws on digital competence models for foundational operation [40], AI literacy scholarship on use, evaluation and ethical understanding [25, 31, 38], and research on the limits of AI-assisted performance [10]. The framework's additional step is to distinguish occupational application as the point at which competence is tested against actual work requirements and livelihood value, rather than treating tool use or classroom assessment as evidence of employability.

5.3 Conversion factors

Capability is converted into income by means which cannot be controlled by the learner. By reformulating the sustainable livelihood framework to fit contemporary situations, Natarajan et al. [29] consider such conditions as part of the livelihood rather than the context. Six are especially important for young Kenyans.

Verification. Neither the employer nor the client sees capability. Credible signals are found to influence hiring decisions in both Carranza et al. [7] and Abebe et al. [1]. Portfolio work from a known institution is more powerful than attendance certificate. Finance. Availability of working capital, instalment system, or float for client payment makes the difference if the person is trained or not to begin his or her venture. Time and care. Free care work determines who is capable of completing the course and engaging in evening or non-standard work. Place. Concentration of recruitment in Nairobi results in graduates from Turkana or Kwale being left with a skill but no market for it. Language. Equipment and courses in Kiswahili and other local languages increase the number of those able to complete the training and deal with customers. Terms of work. Payment and rating policies set by platforms determine the share of the value created by the worker.

The last factor gives the framework a design test drawn from Heeks [15]. A pathway shows adverse incorporation if its terms are set elsewhere, if the worker cannot contest them, and if the value she creates is captured by a party she cannot bargain with. In Kenya the Data Protection Act of 2019 and the Employment Act supply some legal ground for contesting such terms, though few young workers know how to use either.

These conversion factors interact rather than operate independently. A verified portfolio may have limited value where a young person lacks reliable connectivity or access to a buyer; finance may enable enterprise entry but expose the worker to debt if demand is weak; and language accessibility may improve course completion without producing income where local markets do not value the resulting service. Programme designers should assess the combination of conditions that supports or blocks each pathway, rather than treat any single factor as sufficient.

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue X October 2026

*5.*4 Livelihood pathways

Four pathways account for most of the routes by which capability turns into income in the digital economy. Each has a different entry level, a different main barrier and a different risk, and Table 2 sets them side by side.

Table 3. Livelihood pathways, conversion barriers and risks

Pathway	Entry capability	Main conversion barrier	Livelihood risk
Enterprise adoption (traders, farmers, artisans)	Levels 1–2, with level 4 in the person's own trade	Working capital; trust in tool output; low-bandwidth tools	Dependence on one tool provider; price changes outside the user's control
Freelance and platform services	Levels 2–4	Verified skills; access to international payment; platform terms	Volatile income; account deactivation without appeal
Data and AI-supply work (labelling, moderation, translation)	Levels 1–2	Contract terms; psychological safety; absence of a career ladder	Low pay; no progression; exposure to harmful content
Wage employment (business process outsourcing, ICT, public service)	Levels 1–4	Credential recognition; Nairobi-centred hiring; reliance on referrals	Automation of entry-level tasks reduces the number of starting posts

A fifth route, further learning, runs beside all four, since many young people alternate between training and work. The pathways are not exclusive. A Kisumu fish trader may sell through a catalogue, take occasional freelance translation work and hold a temporary data-entry contract in the same year. Programmes that aim at a single destination miss this pattern. They should be designed around a portfolio of income sources, and the framework asks that outcomes be measured for the portfolio.

5.5 Sustainable livelihood outcomes

According to Natarajan et al. [29], a livelihood will be deemed sustainable if it is able to resist shock and allow progress, and income at a particular point of time will not prove that. The suggested livelihood framework has six criteria, all evaluated at the 6, 12 and 24 month period after training: median monthly income; variance of monthly income during the year; share of work done by a person that is protected by social security or agreements; progress to higher-value activities; membership in a collective, cooperative or association capable of bargaining; and ability to resist a shock, such as a month without work, due to savings or credit. The sixth criterion is important since AI applications evolve rapidly, and a livelihood based on a particular tool may become obsolete due to a change in a provider's pricing decision.

5.6 Design rules

Framework component	**Main content and relationship**
1. ACCESS CONDITIONS	Device, data, electricity, language, safety and time
↓ enables or constrains	Access shapes opportunity to acquire and exercise capabilities
2. CAPABILITY STACK	Foundational digital literacy → Functional AI literacy → Critical AI literacy → Occupational application
↓ mediated by	Verification, finance, time and care, place, language and terms of work
3. CONVERSION FACTORS	Conditions enabling or constraining use of capabilities in a specific market
↓ shape	Enterprise adoption | Freelance/platform services | Data/AI supply work | Wage employment
4. LIVELIHOOD PATHWAYS	Multiple and overlapping income routes; further learning cuts across all pathways

↓ contribute to	Income and stability, work protection, progression, collective voice and resilience
5. SUSTAINABLE LIVELIHOOD OUTCOMES	Measured at 6, 12 and 24 months
↺ FEEDBACK	Outcomes strengthen or weaken future access, capabilities, finance and opportunities; programme evidence informs redesign

Figure 1. Dynamic relationships in the Capability-to-Livelihood Pathway Framework (authors' conceptualisation)

Feedback relationships and dynamic adjustment. The relationship between the five components is recursive. A young person who earns more consistently may be able to purchase a reliable device, pay for data, finance further training, obtain working capital and build a stronger portfolio. Improved livelihood security can strengthen future access and capability, creating a positive feedback loop. Conversely, unstable earnings, unpaid platform disputes, equipment failure or a household shock can reduce access to devices and training, weaken occupational participation and reinforce disadvantage. Evidence about earnings, retention and work quality should inform subsequent curriculum design, buyer partnerships and financing arrangements. The framework should therefore be evaluated over time, not only at course completion.

There are five principles to guide programme design. Begin with demand: identify the consumers or purchasers of the work being trained to do prior to enrolment of the cohort, and train for skills they will pay for. Train students on the tools that they will need: those that work in low bandwidth, mobility and in Kiswahili and local languages. The training will be linked to evaluation and placement: an evaluated portfolio and a path to first paid job is part of the curriculum, not provided later as an aftercare program. Finance the initiative: a device or an account if needed for the path. Test the impact over 24 months using a comparison group, so any difference between the two groups can be attributed to the training.

Application To Kenyan Scenarios

Stylized examples of three cases demonstrate the functioning of the framework; they are created only for illustrative purposes and do not refer to any specific organization.

Although Kenya provides the principal contextual case, the framework is an adaptable analytical structure rather than a claim that all African countries share the same labour-market or institutional conditions. Application elsewhere should retain the five core components but re-specify indicators and relationships using country-level evidence. Relevant dimensions include informal-work prevalence and regulation, digital-payment infrastructure, language ecology, electricity and broadband reliability, education and vocational systems, social-protection coverage, platform regulation, access to finance, and the geographic concentration of employers and buyers. Country-specific policy and labour-market mapping should precede application; Kenyan programme assumptions or thresholds should not be transferred without validation.

An AI literacy program is introduced in a county youth polytechnic. This program includes training in prompting using tablets provided within a national program, and enrollment is very high. In respect of this case, the framework starts with asking a question regarding accessibility – tablets can be used only in the workshop, and students have no opportunity to practice at home using their own mobile phones. Then the question related to the stack arises – assessment is based only on attendance, and the program cannot prove that students have achieved level 2. There is no buyer for these skills, so level 4 is missing.

The fish vendor in Kisumu uses a chatbot to communicate with clients. She uses mobile money and WhatsApp Business, hence, level 1 is achieved. The chatbot provides answers in Kiswahili and English while dealing with questions related to price. There is a limitation in achieving level 2 because she cannot be sure when the bot mistranslates a Dholuo word. There is a dependency risk within the enterprise pathway because she cannot choose another service provider once there is an increase in cost or change in conditions.

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue X October 2026

An organization in Nairobi employs two hundred youths in labeling jobs. The jobs are entry level, paying better than the casual wage, but the contracts are short-term, there is measurement-based supervision, and there is offensive content. The framework would categorize the job as having an adverse incorporation risk. Barriers to conversion include the contract terms, and lack of a career ladder to more valuable jobs. The organization would be required to disclose wage and career advancement data, give psychological support, and pay for development into quality assurance or annotation design jobs for those who would like it. With such conditions, the framework would categorize the pathway as one that exploits youths but does not develop their livelihoods.

PROPOSITIONS, LIMITATIONS AND CONCLUSION

7.1 Propositions for empirical testing

The framework implies relationships that can be tested with programme records, survey follow-up and randomised or quasi-experimental designs.

P1. Among trainees who receive equal hours of instruction, those whose curriculum is tied to a named buyer or employer segment will show more stable earnings at 12 months than those who take a generic AI literacy course.

P2. Credentials issued after assessment of performance will raise the probability of paid work within 12 months relative to attendance certificates, with larger effects for young women and for applicants outside Nairobi.

P3. In platform and data-work pathways, workers whose capability stops at levels 1 and 2 will retain a smaller share of the value they create than workers who reach levels 3 and 4, and the difference will be largest where contract terms are not negotiable.

P4. Training delivered in Kiswahili or a local language on low-bandwidth tools will show smaller completion gaps between urban youth and youth in arid and semi-arid counties than English-only online courses.

A first test could be conducted in two or three counties selected to represent different connectivity, language and labour-market conditions. Eligible applicants not admitted because places are limited may provide a comparison group, provided selection processes and baseline differences are documented. Earnings stability should be pre-specified, for example as within-person variation in monthly net income over a defined period, complemented by months with paid work. Verified credentials should be based on a documented practical assessment with an identifiable issuer and verifiable result. Value retained should be defined as worker net remuneration relative to total task payment where observable; otherwise, use stated proxies such as effective hourly earnings, control over pricing and ability to retain clients. Completion gaps should be reported as percentage-point differences between pre-specified groups.

Proposition	Operational definition	Outcome indicators	Potential data sources	Suggested testing
P1 Buyer-linked training	Named buyer/employer segment, documented consultation, work trial or purchase commitment; comparator: generic course.	Monthly net income; within-person income variation; months with paid work; share of income from targeted skill at 6 and 12 months.	Training records, buyer agreements, income diaries/surveys, platform or sales records with consent.	Longitudinal comparison; random assignment where feasible, otherwise matching or difference-in-differences.
P2 Performance-verified credential	Performance-assessed credential with rubric, identifiable issuer	Any paid work within 12 months; time to first paid task; number of paid	Assessment records, credential registry, employer confirmation,	Randomised or quasi-experimental comparison; logistic

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue X October 2026

	and verifiable result; comparator: attendance-only certificate.	tasks; earnings; effects by gender and location.	participant follow-up and payment records.	regression and survival analysis.
P3 Higher capability and value retained	Demonstrated profile across Levels 1–4; moderator: ability to negotiate contract terms.	Net worker remuneration as share of task payment where observable; effective hourly earnings after fees and unpaid time; control over pricing, clients and disputes.	Practical assessments, worker surveys, contracts, platform statements and client payment records where available.	Longitudinal multivariate analysis; interaction test for capability and contract negotiability; define denominator consistently.
P4 Local-language, low-bandwidth training	Language of instruction/support, bandwidth requirement, data cost and offline/asynchronous access.	Completion and pass rates by urban/rural or ASAL location; absolute percentage-point gap; attendance and interruption rates.	Learning records, provider records, participant location and connectivity survey.	Cluster-randomised or phased rollout where feasible; otherwise matched comparison adjusted for baseline differences.

Table 4. Proposed operationalisation and empirical testing of the four propositions

7.2 Limitations

This is a conceptual paper: the framework and propositions have not been empirically tested. The Kenyan analysis relies on published statistical reports, policy documents and secondary research rather than original fieldwork. The review is integrative and purposive rather than systematic; it does not claim exhaustive coverage or formal quality appraisal of every potentially relevant source. Publicly available programme reporting does not always permit a clear distinction between targets, enrolment, completion, placement and independently evaluated livelihood effects. The paper should therefore be read as a theory-building contribution and research agenda, not as an evaluation of the effectiveness of the named Kenyan programmes. The strongest experimental evidence on generative-AI productivity cited here comes largely from higher-income organisational settings [6, 32], and its transferability to informal enterprises and low-resource work settings remains uncertain.

The 24-month measurement the framework proposes is expensive, and small programmes may not be able to afford it. Shared evaluation services, in which a county, a university or a funder collects follow-up data for many programmes, are a plausible answer, and their design is left to the fifth paper in this series. The six indicators also overlap, and weighting them into a single index would require judgement that this paper does not attempt.

CONCLUSION

Connectivity remains an important condition of digital inclusion, but it cannot by itself explain whether young people secure sustainable livelihoods. The Capability-to-Livelihood Pathway Framework integrates insights from digital inequality, AI literacy, sustainable livelihoods and youth employment research to explain how access and capabilities are converted—or fail to be converted—into income and work security. Its distinctive contribution is the explicit connection of four capability levels to conversion factors, multiple livelihood pathways, feedback relationships and longitudinal outcome indicators. The framework is a conceptual proposition requiring empirical validation, not a validated causal model.

Programmes designed around this logic may report fewer immediate success stories because they require demand to be identified before training, work quality to be assessed, and outcomes to be followed over time. They make

it possible to distinguish participation, certification, first placement and sustained livelihood improvement. Future research should test the propositions across different Kenyan counties and adapt the framework to other African settings through country-specific analysis of labour markets, institutions, infrastructure and social protection. The practical test is not simply whether young people acquire digital or AI skills, but whether those capabilities help them secure, improve and sustain livelihoods on fair and resilient terms.

REFERENCES

1. Abebe, G., Caria, A. S., Fafchamps, M., Falco, P., Franklin, S., & Quinn, S. (2021). Anonymity or distance? Job search and labour market exclusion in a growing African city. The Review of Economic Studies, 88(3), 1279–1310.
2. African Union. (2020). The Digital Transformation Strategy for Africa (2020–2030). African Union Commission.
3. Alfonsi, L., Bandiera, O., Bassi, V., Burgess, R., Rasul, I., Sulaiman, M., & Vitali, A. (2020). Tackling youth unemployment: Evidence from a labor market experiment in Uganda. Econometrica, 88(6), 2369–2414.
4. Anwar, M. A., & Graham, M. (2020). Digital labour at economic margins: African workers and the global information economy. Review of African Political Economy, 47(163), 95–105.
5. Anwar, M. A., & Graham, M. (2021). Between a rock and a hard place: Freedom, flexibility, precarity and vulnerability in the gig economy in Africa. Competition & Change, 25(2), 237–258.
6. Brynjolfsson, E., Li, D., & Raymond, L. (2025). Generative AI at work. The Quarterly Journal of Economics, 140(2), 889–942.
7. Carranza, E., Garlick, R., Orkin, K., & Rankin, N. (2022). Job search and hiring with limited information about workseekers' skills. American Economic Review, 112(11), 3547–3583.
8. Cazzaniga, M., Jaumotte, F., Li, L., Melina, G., Panton, A. J., Pizzinelli, C., Rockall, E., & Tavares, M. M. (2024). Gen-AI: Artificial intelligence and the future of work (IMF Staff Discussion Note SDN/2024/001). International Monetary Fund.
9. Choi, J., Dutz, M. A., & Usman, Z. (Eds.). (2020). The future of work in Africa: Harnessing the potential of digital technologies for all. World Bank.
10. Dell'Acqua, F., McFowland, E., Mollick, E. R., Lifshitz-Assaf, H., Kellogg, K., Rajendran, S., Krayer, L., Candelon, F., & Lakhani, K. R. (2023). Navigating the jagged technological frontier: Field experimental evidence of the effects of AI on knowledge worker productivity and quality (Harvard Business School Working Paper 24-013).
11. Eloundou, T., Manning, S., Mishkin, P., & Rock, D. (2024). GPTs are GPTs: Labor market impact potential of LLMs. Science, 384(6702), 1306–1311.
12. Gmyrek, P., Berg, J., & Bescond, D. (2023). Generative AI and jobs: A global analysis of potential effects on job quantity and quality (ILO Working Paper 96). International Labour Organization.
13. Gray, M. L., & Suri, S. (2019). Ghost work: How to stop Silicon Valley from building a new global underclass. Houghton Mifflin Harcourt.
14. GSMA. (2024). The state of mobile internet connectivity report 2024. GSMA.
15. Heeks, R. (2022). Digital inequality beyond the digital divide: Conceptualizing adverse digital incorporation in the global South. Information Technology for Development, 28(4), 688–704.
16. Helsper, E. J. (2021). The digital disconnect: The social causes and consequences of digital inequalities. SAGE.
17. Hjort, J., & Poulsen, J. (2019). The arrival of fast internet and employment in Africa. American Economic Review, 109(3), 1032–1079.
18. International Labour Organization. (2024). Global employment trends for youth 2024: Decent work, brighter futures. ILO.
19. International Telecommunication Union. (2024). Measuring digital development: Facts and figures 2024. ITU.
20. Joshi, P., Santy, S., Budhiraja, A., Bali, K., & Choudhury, M. (2020). The state and fate of linguistic diversity and inclusion in the NLP world. Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics (pp. 6282–6293). ACL.

21. Kenya National Bureau of Statistics. (2019). 2019 Kenya Population and Housing Census, Volume IV: Distribution of population by socio-economic characteristics. KNBS.
22. Kenya National Bureau of Statistics. (2024). Economic Survey 2024. KNBS.
23. Kluve, J., Puerto, S., Robalino, D., Romero, J. M., Rother, F., Stöterau, J., Weidenkaff, F., & Witte, M. (2019). Do youth employment programs improve labor market outcomes? A quantitative review. World Development, 114, 237–253.
24. Laupichler, M. C., Aster, A., Schirch, J., & Raupach, T. (2022). Artificial intelligence literacy in higher and adult education: A scoping literature review. Computers and Education: Artificial Intelligence, 3, 100101.
25. Long, D., & Magerko, B. (2020). What is AI literacy? Competencies and design considerations. Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems (pp. 1–16). ACM.
26. Ministry of ICT, Innovation and Youth Affairs. (2019). Digital Economy Blueprint: Powering Kenya's transformation. Government of Kenya.
27. Ministry of Information, Communications and the Digital Economy. (2022). Kenya National Digital Master Plan 2022–2032. Government of Kenya.
28. Muldoon, J., Cant, C., Wu, B., & Graham, M. (2024). A typology of artificial intelligence data work. Big Data & Society, 11(1).
29. Natarajan, N., Newsham, A., Rigg, J., & Suhardiman, D. (2022). A sustainable livelihoods framework for the 21st century. World Development, 155, 105898.
30. Nekoto, W., Marivate, V., Matsila, T., Fasubaa, T., Fagbohungbe, T., Akinola, S. O., et al. (2020). Participatory research for low-resourced machine translation: A case study in African languages. Findings of the Association for Computational Linguistics: EMNLP 2020 (pp. 2144–2160). ACL.
31. Ng, D. T. K., Leung, J. K. L., Chu, K. W. S., & Qiao, M. S. (2021). Conceptualizing AI literacy: An exploratory review. Computers and Education: Artificial Intelligence, 2, 100041.
32. Noy, S., & Zhang, W. (2023). Experimental evidence on the productivity effects of generative artificial intelligence. Science, 381(6654), 187–192.
33. Perrigo, B. (2023, January 18). Exclusive: OpenAI used Kenyan workers on less than $2 per hour to make ChatGPT less toxic. TIME.
34. Ragnedda, M. (2020). Enhancing digital equity: Connecting the digital underclass. Palgrave Macmillan.
35. Republic of Kenya. (2025). Kenya Artificial Intelligence Strategy 2025–2030. Ministry of Information, Communications and the Digital Economy.
36. Selwyn, N. (2022). The future of AI and education: Some cautionary notes. European Journal of Education, 57(4), 620–631.
37. Suri, T., Bharadwaj, P., & Jack, W. (2021). Fintech and household resilience to shocks: Evidence from digital loans in Kenya. Journal of Development Economics, 153, 102697.
38. UNESCO. (2024). AI competency framework for students. United Nations Educational, Scientific and Cultural Organization.
39. van Deursen, A. J. A. M., & van Dijk, J. A. G. M. (2019). The first-level digital divide shifts from inequalities in physical access to inequalities in material access. New Media & Society, 21(2), 354–375.
40. Vuorikari, R., Kluzer, S., & Punie, Y. (2022). DigComp 2.2: The Digital Competence Framework for Citizens. Publications Office of the European Union.
41. Wood, A. J., Graham, M., Lehdonvirta, V., & Hjorth, I. (2019). Good gig, bad gig: Autonomy and algorithmic control in the global gig economy. Work, Employment and Society, 33(1), 56–75.
42. World Bank. (2024). Digital progress and trends report 2023: Strengthening AI foundations. World Bank.