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Editorial

Journal of Economics and Behavioral Studies (JEBS) provides a distinct avenue for quality research in the ever-changing fields of economics & behavioral studies and related disciplines. Research work submitted for publication consideration should not be limited to conceptualization of economics and behavioral developments but comprise interdisciplinary and multi-facet approaches to economics and behavioral theories and practices as well as general transformations in the fields. Scope of the JEBS includes: subjects of managerial economics, financial economics, development economics, finance, economics, financial psychology, strategic management, organizational behavior, human behavior, marketing, human resource management and behavioral finance. Author(s) should declare that work submitted to the journal is original, not under consideration for publication by another journal and that all listed authors approve its submission to JEBS. Author (s) can submit: Research Paper, Conceptual Paper, Case Studies and Book Review. Journal received research submissions related to all aspects of major themes and tracks. All submitted papers were first assessed by the editorial team for relevance and originality of the work and blindly peer-reviewed by the external reviewers, depending on the subject matter of the paper. After the rigorous peer-review process, the submitted papers were selected based on originality, significance and clarity of purpose. The current issue of JEBS comprises papers of scholars from Uganda, Kenya and Tanzania. Linking Big Data Analytics Capabilities to Humanitarian Supply Chain Resilience, Determinants of Youth Unemployment in Kenya, Estimating Technical Efficiency and Yield Losses Among Smallholder Coffee Farmers, Influence of Governance Quality on Youth Unemployment and Investment Practices and Household Income among Small-Scale Women Entrepreneurs were some of the major practices and concepts examined in these studies. The current issue will therefore be a unique offer where scholars will be able to appreciate the latest results in their field of expertise and acquire additional knowledge in other relevant fields.

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TABLE OF CONTENTS

Description	Pages
Title	I
Editorial	II
Editorial Board	III
Table of Contents	IV
Papers	V
Linking Big Data Analytics Capabilities to Humanitarian Supply Chain Resilience: The Mediating Mechanism of Inter-Organizational Coordination Wilbroad Aryatwijuka, Henry Mutebi, Ronald Twongyirwe, Naster Tumebembeire, Miriam Tugiramasiko	1
Determinants of Youth Unemployment in Kenya: Exogenous Growth Theory Nuwatuha George, Robert Mugabe, Benjamin Musiita	19
Estimating Technical Efficiency and Yield Losses Among Smallholder Coffee Farmers in Uganda: A Stochastic Frontier Analysis Phiona Natuha, Onesmo Selejio, Aloyce S Hepelwa	29
Influence of Governance Quality on Youth Unemployment in Kenya: Institutional Growth Theory Nuwatuha George, Robert Mugabe, Benjamin Musiita	43
Investment Practices and Household Income among Small-Scale Women Entrepreneurs in Bwera Sub-County, Kasese District, Uganda Richard Drabe Aguta	51

PAPERS

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Linking Big Data Analytics Capabilities to Humanitarian Supply Chain Resilience: The Mediating Mechanism of Inter-Organizational Coordination

*Wilbroad Aryatwijuka[1], Henry Mutebi[2], Ronald Twongyirwe[3], Naster Tumebembeire[4], Miriam Tugiramasiko[5]
[1]Department of Procurement and Marketing, Mbarara University of Science and Technology (MUST), Uganda
[2]Department of Procurement and Supply Chain Management, Makerere University Business School, Uganda
[3]Department of Environment and Livelihoods Support Systems, Mbarara University of Science and Technology (MUST), Uganda
[4]Department of Accounting and Finance, Mbarara University of Science and Technology (MUST), Uganda
[5]Department of Human Resource Management, Mbarara University of Science and Technology (MUST), Uganda
Email: *waryatwijuka@must.ac.ug, hemutebi@gmail.com, rtwongyirwe@must.ac.ug, tnaster@must.ac.ug, miriamt@must.ac.ug
Corresponding Author: Dr Wilbroad Aryatwijuka

Abstract: This study examines the relationships among big data analytics capabilities (BDAC), inter-organizational coordination capabilities (IOCC), and humanitarian supply chain resilience (HSCR), with particular emphasis on the mediating role of IOCC. Drawing on Dynamic Capability Theory (DCT), the study explains how humanitarian organizations leverage data analytics and inter-organizational coordination to strengthen supply chain resilience in uncertain and disruption-prone environments. A quantitative cross-sectional survey was conducted among 88 humanitarian organizations operating in Uganda. Data were analyzed using partial least squares structural equation modeling (PLS-SEM) in SmartPLS to assess the hypothesized direct relationships and the mediating effect of IOCC. The findings reveal that BDAC has a significant positive effect on both IOCC and HSCR. IOCC also significantly enhances HSCR. Furthermore, IOCC partially mediates the relationship between BDAC and HSCR, indicating that the resilience benefits of big data analytics arise both directly and indirectly through strengthened inter-organizational coordination. The cross-sectional design limits the ability to capture how analytics capabilities, coordination mechanisms, and resilience evolve. Future research could employ longitudinal and qualitative designs to examine the dynamic processes through which humanitarian organizations develop and deploy these capabilities across different stages of disruptions. Humanitarian organizations should complement investments in big data analytics and digital infrastructure with mechanisms that strengthen information sharing, joint planning, resource coordination, and collaborative decision-making among supply chain partners. Integrating analytics with strong coordination capabilities can improve preparedness, responsiveness, and recovery from humanitarian supply chain disruptions. This study extends the application of DCT to humanitarian supply chains by demonstrating that IOCC constitutes an important mechanism through which BDAC translates into HSCR. By empirically examining the interplay among analytics, inter-organizational coordination, and resilience in the context of humanitarian organizations in Uganda, the study contributes evidence from an underexplored developing-country humanitarian setting.

Keywords: *Big data analytics capabilities; inter-organizational coordination capabilities; humanitarian supply chain resilience; dynamic capability theory; humanitarian organizations; Uganda; PLS-SEM.*

1. Background of the Study

The increasing frequency, severity, and complexity of humanitarian emergencies have heightened concerns about the capacity of humanitarian supply chains to respond effectively. In 2023, 399 natural-hazard-related disasters affected approximately 93.1 million people and caused 86,473 deaths globally (CRED, 2024). Such disruptions disproportionately affect resource-constrained regions, including Sub-Saharan Africa, where inadequate infrastructure, financial resources, information systems, and institutional capacity can constrain humanitarian response. Uganda remains particularly vulnerable to recurrent floods and landslides. For example, the May 2020 floods and landslides in Kasese District damaged roads, bridges, schools, health facilities, and other critical infrastructure (Kasese District Local Government, 2020). These challenges are compounded by Uganda's substantial refugee burden, with more than 1.5 million refugees hosted in 2024 (UNHCR, 2025). The COVID-19 pandemic further exposed vulnerabilities in humanitarian supply chains through movement restrictions, supply shortages, shifting demand, and disruptions to procurement and

transportation. In Uganda, relief operations were additionally affected by logistical bottlenecks, procurement challenges, fragmented information flows, and weaknesses in beneficiary data management (Aryatwijuka et al., 2023). These experiences demonstrate the need for humanitarian organizations to anticipate disruptions, generate timely information, coordinate multiple actors, and rapidly adapt their operations.

These challenges underscore the importance of Humanitarian Supply Chain Resilience (HSCR), which reflects the capacity of humanitarian supply chains to anticipate, withstand, adapt to, and recover from disruptions while maintaining or rapidly restoring essential services. Previous studies identify flexibility, integration, collaboration, visibility, procurement effectiveness, and other organizational capabilities as important resilience enablers (Pereira et al., 2019; Iftikhar et al., 2021). Recent research, however, suggests that resilience increasingly depends on complementary configurations of technological, operational, and relational capabilities (Jiang et al., 2024). Consequently, attention has shifted towards Big Data Analytics Capabilities (BDAC), which enable organizations to mobilize data, technological, human, and managerial resources to generate actionable insights from large and diverse datasets. In humanitarian operations, BDAC can improve needs forecasting, disruption detection, resource allocation, beneficiary targeting, decision-making, and operational visibility. Recent evidence demonstrates that BDAC contributes to resilience through complementary capabilities such as supply chain integration and flexibility (Jiang et al., 2024; Lee et al., 2024), while humanitarian-specific evidence links BDAC, information alignment, and collaboration to HSCR (Tetteh et al., 2024).

Nevertheless, the resilience value of BDAC may not be fully realized without Inter-Organizational Coordination Capabilities (IOCC) that translate analytical intelligence into collective action. IOCC reflects organizations' capacity to coordinate across organizational boundaries through information sharing, joint planning, role alignment, collaborative decision-making, and synchronized resource deployment. This is particularly important in humanitarian operations involving multiple interdependent actors, including humanitarian organizations, governments, donors, suppliers, logistics providers, local authorities, and affected communities. Although BDAC may identify emerging needs, shortages, vulnerable populations, and operational disruptions, such intelligence may have limited value where actors cannot jointly interpret information and coordinate decisions and resources. Inadequate coordination can contribute to duplication, logistical difficulties, inefficient resource utilization, and delayed humanitarian assistance (European Commission, 2024). Thus, BDAC provides analytical intelligence, while IOCC enables that intelligence to be transformed into coordinated humanitarian action and resilience.

Despite growing research on BDAC and supply chain resilience, the mechanisms through which analytics capabilities generate resilience in humanitarian supply chains remain insufficiently understood. Recent studies have examined complementary mechanisms including supply chain integration (Jiang et al., 2024), flexibility (Lee et al., 2024), information alignment and collaboration (Tetteh et al., 2024), and organizational ambidexterity (Kong & Feng, 2025). However, comparatively limited empirical attention has been devoted to IOCC as a mediating mechanism between BDAC and HSCR, particularly in resource-constrained Sub-Saharan African humanitarian settings. This gap is important because humanitarian supply chains are inherently inter-organizational and depend on multiple actors transforming information into coordinated decisions and collective action.

Drawing on Dynamic Capability Theory (DCT), this study examines the relationships among BDAC, IOCC, and HSCR. DCT argues that organizations operating in dynamic environments require capabilities to sense changes, seize appropriate responses, and reconfigure resources as conditions evolve (Teece et al., 1997; Teece, 2007). In this study, BDAC primarily strengthens sensing by enabling humanitarian organizations to identify and interpret emerging disruptions, while IOCC facilitates seizing and reconfiguration through joint planning, information sharing, resource mobilization, and coordinated action. Accordingly, the study examines the direct effects of BDAC on IOCC and HSCR, the effect of IOCC on HSCR, and the mediating role of IOCC in the relationship between BDAC and HSCR among humanitarian organizations operating in Uganda. In doing so, the study extends DCT to humanitarian supply chains and demonstrates how analytical and inter-organizational capabilities jointly contribute to resilience in a resource-constrained context.

The remainder of the paper is organized as follows. Section 2 presents the theoretical foundation and literature review; Section 3 describes the methodology; Section 4 presents the empirical findings and hypothesis testing; and Section 5 discusses the theoretical and practical implications, limitations, and directions for future research.

2. Theoretical Framework and Development of Hypotheses

The Dynamic Capabilities Theory

This study is anchored in Dynamic Capability Theory (DCT), which explains how organizations operating in uncertain environments integrate and reconfigure resources and competencies to respond to change (Teece et al., 1997; Eisenhardt & Martin, 2000; Teece, 2007). DCT conceptualizes dynamic capabilities around three interrelated processes: sensing, seizing, and reconfiguration. These processes are particularly relevant to humanitarian supply chains, where organizations must continuously detect disruptions, mobilize resources, coordinate multiple actors, and adapt operations under conditions of uncertainty and resource constraints.

Within this study, Big Data Analytics Capabilities (BDAC) primarily represent a sensing capability. BDAC enables humanitarian organizations to collect, integrate, and analyze data from multiple sources to identify emerging risks, forecast humanitarian needs, detect supply chain bottlenecks, and improve situational awareness. Recent evidence indicates that BDAC contributes to supply chain resilience, particularly when complemented by other organizational capabilities (Jiang et al., 2024; Lee et al., 2024; Kong & Feng, 2025).

Inter-Organizational Coordination Capabilities (IOCC) facilitate seizing and reconfiguration by enabling humanitarian organizations to share information, undertake joint planning, synchronize decisions, mobilize complementary resources, and coordinate activities with external partners. IOCC therefore enables organizations to translate intelligence generated through BDAC into coordinated action and to reconfigure resources and operational arrangements as humanitarian conditions change.

The complementarity between these capabilities provides the central theoretical mechanism underlying HSCR: BDAC (sensing) → analytical intelligence → IOCC (seizing and reconfiguration) → coordinated humanitarian action → HSCR.

DCT also explains the proposed mediating role of IOCC. While BDAC can directly enhance HSCR through improved forecasting, visibility, disruption detection, and decision-making, it can also indirectly enhance resilience by improving the information available for inter-organizational coordination. IOCC translates this intelligence into joint planning, resource mobilization, synchronized action, and operational adaptation, thereby strengthening HSCR.

Accordingly, this study extends DCT to humanitarian supply chains by demonstrating how digital sensing capabilities and inter-organizational coordination capabilities complement each other in building resilience. Applied to humanitarian organizations in Uganda, DCT explains the direct relationships among BDAC, IOCC, and HSCR and, importantly, the mediating role of IOCC in translating analytics capabilities into resilient humanitarian supply chain outcomes.

Hypotheses Development

Big Data Analytics Capabilities and Humanitarian Supply Chain Resilience

The role of Big Data Analytics Capabilities (BDAC) in strengthening Humanitarian Supply Chain Resilience (HSCR) has gained increasing attention as humanitarian operations face growing uncertainty, rapidly changing demand, and resource constraints. BDAC refers to an organization's capacity to integrate data, technological, human, and managerial resources to transform large and diverse datasets into actionable insights. In humanitarian operations, BDAC can improve situational awareness, forecasting, disruption detection, resource allocation, operational visibility, and timely decision-making.

Existing research supports the resilience-enhancing role of BDAC. Earlier studies demonstrate that big data analytics improves visibility, coordination, and responsiveness within humanitarian supply chains (Dubey et

al., 2018). More recent evidence shows that BDAC contributes to proactive and reactive supply chain resilience when combined with complementary organizational capabilities (Jiang et al., 2024; Lee et al., 2024). Kong and Feng (2025) further demonstrate that technical, managerial, and data-driven dimensions of BDAC contribute to resilience, while humanitarian-specific evidence identifies BDAC as an important antecedent of HSCR (Tetteh et al., 2024). Collectively, these studies suggest that analytics capabilities enable organizations to anticipate disruptions and make more informed and adaptive decisions.

This relationship is supported by Dynamic Capability Theory (DCT), which proposes that organizations operating in uncertain environments require capabilities to sense changes, seize appropriate responses, and reconfigure resources accordingly (Teece et al., 1997; Eisenhardt & Martin, 2000; Teece, 2007). Within this framework, BDAC primarily represents a sensing capability, enabling humanitarian organizations to identify emerging threats, forecast beneficiary requirements, detect supply chain constraints, and generate timely operational intelligence. BDAC should therefore be viewed not merely as technological infrastructure but as an organizational capability integrating technology, data, analytical expertise, and managerial competencies.

This capability is particularly important in humanitarian supply chains characterized by uncertain demand, urgency, infrastructure disruptions, resource scarcity, and multiple interdependent actors. Strong BDAC can reduce information uncertainty and enable timely adjustments to procurement, inventory, transportation, and distribution activities. However, much of the existing evidence originates from commercial and manufacturing supply chains, while empirical research within resource-constrained humanitarian environments, particularly in Sub-Saharan Africa, remains comparatively limited. This provides an important contextual basis for examining whether BDAC strengthens HSCR among humanitarian organizations operating in Uganda.

Accordingly, this study argues that humanitarian organizations with stronger BDAC are better positioned to anticipate disruptions, improve operational visibility, allocate resources effectively, and adapt their operations to changing humanitarian conditions. Consistent with DCT, BDAC is therefore conceptualized as a strategic sensing capability that contributes to HSCR. Hence,
H1: Big Data Analytics Capabilities have a positive and significant effect on Humanitarian Supply Chain Resilience.

Big data analytics capabilities and Inter-organizational coordination capability
Effective coordination across organizational boundaries is essential in humanitarian operations involving multiple interdependent actors. Such coordination depends substantially on the availability and timely exchange of reliable information. Big Data Analytics Capabilities (BDAC) can strengthen this informational foundation by enabling humanitarian organizations to acquire, integrate, and analyze diverse data, thereby improving shared situational awareness, reducing information asymmetries, and supporting coordinated decision-making.

Previous research supports the contribution of BDAC to inter-organizational relationships. Dubey et al. (2019) demonstrate that big data analytics contributes to collaborative performance in humanitarian supply chains, while Tetteh et al. (2024) highlight the importance of BDAC alongside information alignment and collaboration. Similarly, Jiang et al. (2024) demonstrate that BDAC complements supply chain integration in strengthening resilience. Collectively, these findings suggest that analytics capabilities become particularly valuable when they facilitate information sharing and alignment of activities across organizational boundaries.

Operationally, BDAC can strengthen Inter-Organizational Coordination Capabilities (IOCC) by providing timely information on beneficiary needs, resource availability, supply shortages, and logistical constraints. This improves information visibility and quality, facilitates joint planning, and enables humanitarian actors to synchronize decisions and coordinate resources. Thus, BDAC provides the informational foundation necessary to transform fragmented organizational information into coordinated collective action.

This relationship is further explained by Dynamic Capability Theory (DCT). BDAC primarily represents a sensing capability, enabling humanitarian organizations to identify and interpret emerging disruptions and humanitarian requirements (Teece et al., 1997; Eisenhardt & Martin, 2000; Teece, 2007). However, sensing generates greater value when the resulting intelligence supports coordinated action. IOCC facilitates this

transition by enabling organizations to share information, jointly plan responses, mobilize complementary resources, and synchronize activities, thereby supporting seizing and reconfiguration. Hence, BDAC and IOCC represent complementary capabilities through which analytical intelligence is transformed into coordinated humanitarian action.

Despite growing evidence linking analytics with collaboration, information alignment, and supply chain integration (Dubey et al., 2019; Tetteh et al., 2024; Jiang et al., 2024), the direct relationship between BDAC and IOCC remains comparatively underexplored in resource-constrained humanitarian settings. Accordingly, this study argues that stronger BDAC enables humanitarian organizations to reduce information asymmetries, establish shared situational awareness, and strengthen joint planning and coordinated decision-making. Therefore:
H2: Big Data Analytics Capabilities have a positive and significant effect on Inter-Organizational Coordination Capabilities.

Inter-organizational coordination capability and Humanitarian supply chain resilience
Effective Inter-Organizational Coordination Capabilities (IOCC) are critical to Humanitarian Supply Chain Resilience (HSCR) because humanitarian operations involve multiple autonomous but interdependent actors that rely on one another for information, resources, expertise, and logistical capacity. IOCC reflects an organization's capacity to exchange timely information, undertake joint planning, synchronize decisions, clarify responsibilities, and coordinate resources and activities across organizational boundaries. Strong coordination can reduce duplication, improve resource utilization, and facilitate timely and coherent responses to humanitarian disruptions.

Existing research supports the importance of inter-organizational capabilities in strengthening resilience. Scholten et al. (2014) demonstrate that collaboration and supply chain relationships enhance organizations' capacity to prepare for and respond to disruptions. More recent humanitarian research similarly identifies collaboration, information alignment, and organizational flexibility as important contributors to HSCR (Tetteh et al., 2024). Jiang et al. (2024) further demonstrate that supply chain integration contributes to proactive and reactive resilience, reinforcing the importance of aligning information, resources, and activities across organizational boundaries.

The relationship is further explained by Dynamic Capability Theory (DCT). DCT proposes that organizations operating in uncertain environments must sense environmental changes, seize appropriate responses, and reconfigure resources as conditions evolve (Teece et al., 1997; Eisenhardt & Martin, 2000; Teece, 2007). Within this framework, IOCC primarily facilitates seizing and reconfiguration. It enables humanitarian organizations to translate information about disruptions into joint decisions, mobilize complementary resources, synchronize activities, and adjust inter-organizational arrangements as conditions change.

IOCC can therefore strengthen HSCR both proactively and reactively. Proactively, coordination facilitates joint preparedness, contingency planning, risk-information sharing, and role clarification. Reactively, it enables rapid information exchange, collective decision-making, resource mobilization, adaptation, and recovery. This capability is particularly important in resource-constrained environments, where individual humanitarian organizations can overcome resource limitations by accessing and combining complementary capabilities across the humanitarian network.

Despite growing research on collaboration, integration, and information sharing, IOCC as a distinct organizational capability and its direct relationship with HSCR remain comparatively underexplored, particularly in resource-constrained Sub-Saharan African humanitarian settings. Accordingly, this study argues that stronger IOCC enables humanitarian organizations to coordinate information and resources, adapt operations, and respond collectively to disruptions, thereby strengthening HSCR. Hence:
H3: Inter-Organizational Coordination Capabilities have a positive and significant effect on Humanitarian Supply Chain Resilience.

To examine the mediating role of inter-organizational coordination capability in the relationship between big data analytics capabilities and humanitarian supply chain resilience

Humanitarian supply chains comprise multiple autonomous but interdependent actors whose effectiveness depends on transforming information and resources into coordinated action. As established in the preceding hypotheses, BDAC can strengthen HSCR through improved situational awareness, forecasting, visibility, and decision-making, while IOCC enhances HSCR through information sharing, joint planning, resource mobilization, and synchronized action. These relationships provide the basis for examining IOCC as a mechanism through which BDAC translates into HSCR.

Although BDAC enables humanitarian organizations to generate timely analytical intelligence, information alone may not produce resilient outcomes. Intelligence concerning emerging risks, beneficiary requirements, supply shortages, or logistical disruptions must be shared and translated into collective decisions and coordinated responses. Existing studies increasingly demonstrate that the resilience benefits of BDAC depend on complementary organizational capabilities, including supply chain integration, flexibility, collaboration, information alignment, and organizational ambidexterity (Jiang et al., 2024; Lee et al., 2024; Tetteh et al., 2024; Kong & Feng, 2025). Humanitarian research similarly demonstrates that analytics can strengthen collaborative performance by improving the informational foundations of inter-organizational relationships (Dubey et al., 2019).

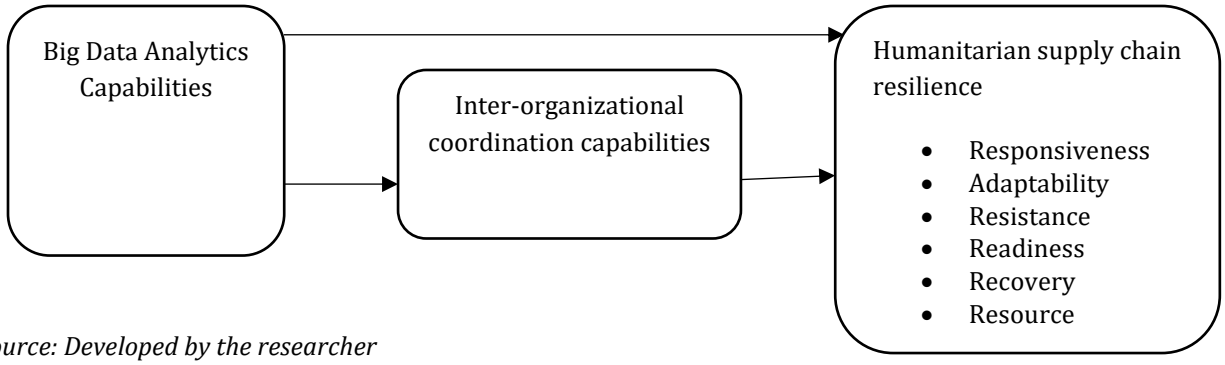
IOCC therefore provides a plausible mechanism through which BDAC contributes to HSCR. BDAC can improve the availability, timeliness, and quality of information shared among humanitarian partners, thereby reducing information asymmetries and facilitating shared situational awareness, joint planning, and synchronized decision-making. IOCC subsequently enables humanitarian organizations to mobilize complementary resources, coordinate logistics activities, and adapt operational arrangements in response to changing humanitarian conditions.

This mediating mechanism is supported by Dynamic Capability Theory (DCT). BDAC primarily represents a sensing capability, enabling humanitarian organizations to detect and interpret disruptions, while IOCC facilitates seizing and reconfiguration by translating analytics-generated intelligence into coordinated decisions, resource mobilization, and adaptive action (Teece et al., 1997; Eisenhardt & Martin, 2000; Teece, 2007). Thus, the proposed mechanism is:
BDAC (sensing) → analytical intelligence → IOCC (seizing and reconfiguration) → coordinated humanitarian action → HSCR.

Importantly, IOCC is not proposed as the only pathway through which BDAC influences HSCR. BDAC can directly enhance resilience through improved forecasting, visibility, disruption detection, and decision quality, while also exerting an indirect effect through IOCC. This theoretical reasoning therefore supports partial mediation whereby analytics-generated intelligence strengthens coordination, which subsequently contributes to resilience.

Despite growing evidence on complementary capabilities linking BDAC to resilience, the specific mediating role of IOCC remains comparatively underexplored, particularly within resource-constrained humanitarian environments in Sub-Saharan Africa. Examining this mechanism therefore extends existing research by explaining how BDAC-generated intelligence is transformed into coordinated action and ultimately HSCR. Accordingly:
H4: Inter-Organizational Coordination Capabilities mediate the relationship between Big Data Analytics Capabilities and Humanitarian Supply Chain Resilience.

Figure 1: Conceptual Framework



Source: Developed by the researcher

3. Method

Study Research Design, Population and Sample Size

This study employed a quantitative cross-sectional survey design to examine the relationships among Big Data Analytics Capabilities (BDAC), Inter-Organizational Coordination Capabilities (IOCC), and Humanitarian Supply Chain Resilience (HSCR). The design was appropriate for collecting data at a single point in time and for statistically testing hypothesized relationships among the study variables (Cooper & Schindler, 2014; Sekaran & Bougie, 2016). The humanitarian organization was the unit of analysis, while knowledgeable employees involved in supply chain and humanitarian operations constituted the unit of inquiry.

A sample of 88 humanitarian organizations operating in Uganda was selected from the study population. Within each organization, knowledgeable informants, including Supply Chain Coordinators, Logistics Coordinators, Operations Managers, Field Officers, and personnel involved in relief logistics, were purposively selected because of their familiarity with the organization's supply chain activities. A total of 275 questionnaires were distributed, of which 253 were returned, representing a response rate of 92.0%. Participation was voluntary, and consent was obtained from both participating organizations and individual respondents.

Before analysis, questionnaires were screened for completeness, consistency, and missing data. Since multiple informants provided information about the same organization, responses were aggregated to the organizational level after establishing sufficient within-organization agreement. Aggregation was assessed using ICC(1), ICC(2), and within-group agreement (rwg) (Bliese, 2000). The results—ICC(1) = 0.67, ICC(2) = 0.91, and rwg = 0.93—demonstrated strong within-organization agreement and supported aggregation. Responses from informants within each organization were therefore averaged to generate organization-level composite scores, resulting in a final analytical sample of 88 humanitarian
and relief logistics.

Sample characteristics results

Table 1 presents the characteristics of the participating humanitarian organizations (HOs) and respondents. Most participating organizations were international non-governmental organizations (INGOs) with foreign headquarters, followed by locally based and community-based NGOs. The majority of organizations (64.8%) had operated for more than 20 years, indicating substantial organizational experience in humanitarian operations. Most organizations also employed more than 200 staff, reflecting relatively large operational structures.

The major areas of humanitarian intervention were Nutrition and Health, Core Relief, and Education Services, demonstrating the diverse nature of services provided by the participating organizations. Regarding respondent characteristics, the majority were male and were predominantly aged 36–40 years, followed by those aged 31–35 years. Most respondents served as supply chain/procurement officers and logistics coordinators and held bachelor's or postgraduate qualifications. Furthermore, most had 6–10 years of experience in the humanitarian sector. Overall, the respondents occupied relevant functional positions and

possessed substantial sector experience, supporting their suitability as knowledgeable informants on BDAC, inter-organizational coordination, and humanitarian supply chain resilience.

Table 1: NGO and respondents' characteristics

Organization Type	F	%
International HO	55	62.5
Local HO	23	26.1
Community-based NGO	10	11.5
Total	88	100
Period of Operation in years	F	%
< 5	3	4
5 - 10	7	7.5
11 - 15	7	7.9
16 - 20	14	15.8
Over 20	57	64.8
Total	88	100
No. of employees	F	%
< 50	3	4
50 - 100	7	8.3
101 - 150	13	14.6
151 -200	18	20.2
Over 200	47	53
Total	88	100
NGO Sector	F	%
Food security	11	12.5
Water, Sanitation & Hygiene	8	9.1
Educational services	13	14.8
Nutrition & Health	23	26.2
Shelter & Infrastructure	9	10.2
Core Relief services	14	15.9
Protection	6	6.8
Energy & Environment	4	4.5
Total	88	100

Gender	F	%
Male	128	50.6
Female	125	49.4
Total	253	100
Age Bracket in years	F	%
< 30	30	11.9
31 - 35	94	37.2
36 - 40	88	34.8
41 - 45	32	12.6
Over 46	9	3.6
Total	253	100
Respondents Position	F	%
Logistics Coordinator	41	16.2
Project manager	42	16.6
Operations Managers	38	15
Procurement Officers	63	24.9
Field Project Coordinators	69	27.3
Total	253	100
Level of Education	F	%
Diploma level	9	3.6
Bachelors	157	61.1
Postgraduate degree	81	32
Doctor of Philosophy	6	2.4
Total	253	100
Employee Tenure in years	F	%
< 2	19	7.5
2 - 6	135	53.4
7 -11	70	27.7
12 - 16	24	9.5
17 and over	5	2
Total	253	100

Sampling Design and Procedure

Organizations were selected using simple random sampling without replacement. A complete list of eligible organizations was obtained from the sampling frame, and each organization was assigned a unique identification number. The required sample was then selected randomly, with each selected organization removed from the pool before the subsequent draw to prevent duplication. This procedure ensured that each organization had an equal and independent chance of selection while preventing repeated selection.

Measurement of Variables

Study examined and contextualized within humanitarian supply chain operations. Humanitarian Supply Chain Resilience (HSCR) was conceptualized as a multidimensional construct reflecting an organization's capacity to

anticipate, withstand, respond to, adapt to, and recover from disruptions while reconfiguring resources where necessary. Items assessed capabilities such as responsiveness, preparedness, adaptability, recovery, and resource reconfiguration. Representative items included: *"Our organization can quickly respond to unexpected supply disruptions"* and *"Our supply chain resumes operations rapidly after a disruption."*

Big Data Analytics Capabilities (BDAC) were measured using items adapted from established big-data analytics literature, including Dubey et al. (2019), capturing the organization's technological, analytical, and managerial capacity to acquire, process, analyze, and utilize large and diverse datasets for decision-making. Representative items included: *"We use advanced analytics tools to support relief distribution decisions"* and *"Our organization can process large volumes of real-time data to inform humanitarian operations."* Consistent with Dynamic Capability Theory, BDAC was conceptualized primarily as a sensing capability that enables humanitarian organizations to identify and interpret emerging disruptions and humanitarian requirements.

Inter-Organizational Coordination Capabilities (IOCC) were measured using items adapted from prior studies on inter-organizational integration and coordination (Srinivasan & Swink, 2018; Yu et al., 2019). The measures captured the organization's capacity for information sharing, joint planning, synchronized decision-making, and resource alignment with humanitarian partners. Representative items included: *"We regularly share critical information with our partner organizations"* and *"Our organization engages in joint planning with partners during disaster response."* Consistent with the theoretical framework, IOCC was conceptualized as facilitating seizing and reconfiguration by enabling organizations to translate information into coordinated action.

All items were measured on a six-point Likert scale, ranging from 1 = strongly disagree to 6 = strongly agree. The even-numbered scale was used to encourage respondents to indicate the direction of their assessment rather than selecting a neutral midpoint. Before the main survey, the instrument was reviewed by subject-matter experts to assess the clarity, relevance, and contextual appropriateness of the measurement items, thereby supporting face and content validity. Construct reliability and convergent and discriminant validity were subsequently assessed as part of the PLS-SEM measurement-model evaluation.

Data Collection

Primary data were collected using structured, self-administered questionnaires, which provide a standardized approach to collecting quantitative data from multiple respondents and facilitate consistency across observations (Sekaran & Bougie, 2016; Saunders et al., 2019). Before data collection, administrative clearance and permission were obtained from the participating humanitarian organizations (HOs). Appointments were subsequently arranged with designated organizational contacts to identify convenient times for questionnaire administration. Following approval, questionnaires were delivered directly to eligible respondents involved in supply chain, logistics, and humanitarian operations. Direct administration and appropriate follow-up can enhance questionnaire completion and response rates (Dillman et al., 2014). Respondents were informed about the purpose of the study, assured that participation was voluntary, and informed that their responses would be treated confidentially and anonymously in accordance with established research ethics principles (Saunders et al., 2019). This systematic procedure facilitated access to knowledgeable respondents and contributed to the high response rate achieved in the study.

Common method bias

Both ex ante procedural and post hoc statistical remedies were employed to minimize common method bias (CMB) (Podsakoff et al., 2003; Fuller et al., 2016). Procedurally, items were adapted from validated scales, simplified for clarity, respondent confidentiality was assured, and, where applicable, data were collected at different points in time. Statistically, Harman's single-factor test showed that a single factor accounted for only 24% of the total variance, below the 50% threshold, suggesting that CMB was unlikely to be a major concern (Podsakoff et al., 2003). Given the limitations of Harman's test, a latent common method factor assessment was additionally conducted (Chin et al., 2013). Collectively, these procedures indicated that CMB was unlikely to materially influence the study findings.

Data Management and Analysis

Data processing commenced with editing and screening the returned questionnaires for completeness, consistency, missing values, and accuracy. The cleaned data were coded and entered into SPSS version 26 for preliminary analysis, including respondent and organizational characteristics. Since the humanitarian organization (HO) was the unit of analysis, individual responses were subsequently aggregated to the organizational level following confirmation of adequate within-group agreement. The aggregated data were then exported to SmartPLS 4 for Partial Least Squares Structural Equation Modeling (PLS-SEM). The analysis involved assessment of the measurement model for reliability and validity, followed by evaluation of the structural model to test the hypothesized direct and mediating relationships (Hair et al., 2022; Ringle et al., 2024).

4. Results

Measurement Validation Results

Following Hair et al. (2019, 2021), the reliability and validity of the measurement model were assessed using PLS-SEM. The study specified reflective lower-order constructs (LOCs) for Humanitarian Supply Chain Resilience (HSCR), Big Data Analytics Capabilities (BDAC), and Inter-Organizational Coordination Capabilities (IOCC). Indicator reliability was assessed using outer loadings, with indicators loading ≥ 0.708 considered satisfactory (Hair et al., 2021). Internal consistency reliability was established using Cronbach's alpha and composite reliability values exceeded 0.70 for the relevant constructs. Convergent validity was also confirmed, with average variance extracted (AVE) values exceeding the recommended threshold of 0.50, indicating that each construct explained more than half of the variance in its indicators (Hair et al., 2019, 2021). The measurement model assessment results are presented in Table 2.

Table 2: Measurement validation

Variables/constructs	Item Codes	SIL	Cronbach's alpha	rho_c	AVE
BigDataAnalytics	BDAC2	0.857	0.788	0.867	0.686
	BDAC3	0.720			
	BDAC4	0.728			
	BDAC5	0.891			
Resilience	SCRRES1	0.780	0.929	0.940	0.611
	SCRRES2	0.725			
	SCRAD1	0.770			
	SCRAD3	0.830			
	SCRAD4	0.807			
	SCRRR1	0.839			
	SCRRR2	0.731			
	SCRRR3	0.741			
	SCRRED1	0.752			
	SCRRED2	0.843			
	SCRRED4	0.792			
	SCRRED5	0.763			
	SCRREC1	0.834			
	SCRREC2	0.841			
	SCRREC4	0.738			
Inter-organizational Coordination	IOC3	0.860	0.882	0.914	0.680
	IOC4	0.812			
	IOC7	0.782			
	IOC8	0.822			
	IOC9	0.846			

Key: Standardized Item Loading (SIL); Cronbach's alpha (); Composite reliability (rho_c); Average variance extracted (AVE)

Source: PLS-SEM Measurement model

Following the assessment of reliability and convergent validity, discriminant validity was evaluated using the heterotrait-monotrait ratio (HTMT). Consistent with Hair et al. (2021), HTMT values below 0.85 indicate adequate discriminant validity, demonstrating that the constructs are empirically distinct. As shown in Table 2, all HTMT values for the lower- and higher-order constructs were below the recommended threshold, thereby establishing discriminant validity.

Table 3: Discriminant validity results

Variables	1	2	3
Big Data Analytics Capabilities (1)	0.465		
Inter-organizational Coordination capabilities (2)		0.543	
Humanitarian Supply Chain Resilience (3)			0.814

Source: PLS-SEM Measurement model

Correlation among study variables

A zero-order correlation analysis was conducted to examine the associations among Big Data Analytics Capabilities (BDAC), Inter-Organizational Coordination Capabilities (IOCC), and Humanitarian Supply Chain Resilience (HSCR). As presented in Table 4, all study variables were positively and significantly correlated ($p < .01$), providing preliminary support for the hypothesized relationships. The correlations also indicated that the variables were sufficiently associated to warrant subsequent assessment of the hypothesized relationships using PLS-SEM in SmartPLS. The structural model results are presented in the subsequent section.

Table 4: Bivariate Correlation results

Study Variables	1	3	4
Big Data Analytics (1)	1		
Inter-organizational Coordination capabilities (3)	.374**	1	
Humanitarian Supply Chain Resilience (4)	.525**	.727**	1

N=88, ** Correlation is significant at the 0.01 level (2-tailed).
Source: PLS-SEM Measurement model

Hypotheses Testing Results

The hypothesized relationships were tested using PLS-SEM in SmartPLS 4, with 5,000 bootstrap subsamples and a 95% confidence level to assess the significance of the path coefficients (Hair et al., 2022). Three direct relationships and one indirect relationship were examined. Table 4 presents the path coefficients and significance levels, while Figure 2 presents the structural model.

The results supported H1, showing that BDAC had a positive and significant effect on HSCR ($\beta = 0.326$, $p = .017$). This indicates that stronger analytics capabilities enhance humanitarian organizations' capacity to anticipate disruptions, improve situational awareness, and make timely decisions that strengthen resilience. Consistent with Dynamic Capability Theory (DCT), BDAC primarily represents a sensing capability, enabling organizations to identify and interpret emerging disruptions and humanitarian requirements (Teece, 2007).

H2 was also supported, with BDAC having a strong positive and significant effect on IOCC ($\beta = 0.591$, $p < .001$). This suggests that analytics capabilities strengthen the informational foundation for inter-organizational coordination by facilitating timely information sharing, shared situational awareness, and evidence-based joint decision-making. Thus, BDAC-generated intelligence supports the transition from sensing to coordinated action.

Similarly, H3 was supported, as IOCC had a positive and significant effect on HSCR ($\beta = 0.405$, $p < .001$). Humanitarian organizations with stronger coordination capabilities are therefore better positioned to align activities, mobilize complementary resources, adapt operations, and collectively respond to disruptions. From a DCT perspective, IOCC facilitates the seizing and reconfiguration of resources across organizational boundaries, thereby strengthening resilience.

Overall, the results support the proposed theoretical framework by demonstrating that both BDAC and IOCC significantly contribute to HSCR. More importantly, the strong BDAC → IOCC relationship, together with the significant IOCC → HSCR relationship, provides the necessary foundation for examining the hypothesized indirect effect of BDAC on HSCR through IOCC (H4).

Mediation Hypotheses Results

Following the assessment of the direct effects, the mediating role of Inter-Organizational Coordination Capabilities (IOCC) in the relationship between Big Data Analytics Capabilities (BDAC) and Humanitarian Supply Chain Resilience (HSCR) was examined following Zhao et al. (2010). The significance of the indirect effect was assessed using bootstrapping with a 95% confidence interval.

As presented in Table 5, the indirect effect of BDAC on HSCR through IOCC was positive and significant (β = 0.321, p = .002, 95% CI [0.091, 0.394]). Since the direct effect of BDAC on HSCR remained positive and significant (β = 0.326, p = .017), and both direct and indirect effects were in the same direction, the results indicate complementary partial mediation (Zhao et al., 2010). Thus, H4 was supported, demonstrating that BDAC enhances HSCR both directly and indirectly through IOCC.

From a Dynamic Capability Theory perspective, the findings demonstrate the complementarity of sensing, seizing, and reconfiguration capabilities (Teece, 2007). BDAC primarily facilitates sensing by enabling humanitarian organizations to acquire, analyze, and interpret information about emerging disruptions and humanitarian needs. IOCC subsequently facilitates seizing and reconfiguration by enabling organizations to share this intelligence, coordinate decisions, mobilize complementary resources, and adapt inter-organizational activities. Thus, IOCC provides an important mechanism through which analytics-generated intelligence is translated into coordinated action and ultimately stronger HSCR.

The findings imply that investment in BDAC alone may not fully realize its resilience potential. Humanitarian organizations should complement analytics capabilities with strong inter-organizational coordination mechanisms that facilitate information sharing, joint planning, resource mobilization, and synchronized response. This combination enables organizations to translate data-driven insights into timely and adaptive humanitarian action.

Table 5: Mediation Hypotheses Testing Results

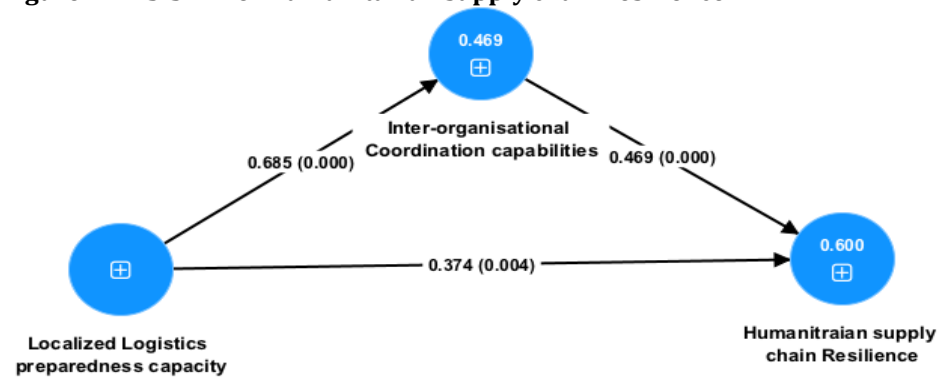
Direct Path	**β**	**SE**	**T stat**	**P values**	**2.5%**	**97.5%**	**VIF**
IOC -> HSCR	0.469	0.110	3.679	0.000	0.198	0.630	2.013
BDA -> HSCR	0.374	0.136	2.393	0.004	0.046	0.581	1.957
BDA -> IOC	0.685	0.090	6.557	0.000	0.409	0.763	2.042
Indirect effect	**β**	**SE**	**T stat**	**P values**	**2.5%**	**97.5%**	
H_4: BDA -> IOC -> HSCR	0.321	0.077	3.098	0.002	0.091	0.394	
Total effect	**β**	**SE**	**T stat**	**P values**	**2.5%**	**97.5%**	
IOC -> HSCR	0.469	0.110	3.679	0.000	0.198	0.630	
BDA -> HSCR	0.695	0.111	5.091	0.000	0.338	0.774	
BDA -> IOC	0.685	0.090	6.557	0.000	0.409	0.763	

Big Data _Analytics (BDAC), Localized Logistics Preparedness (LLP), inter-organizational coordination (IOC), and humanitarian supply chain resilience

Source: PLS-SEM Measurement model

Figure 2 illustrates the structural model used to derive the results shown in Table 5.

Figure 2: PLS-SEM for humanitarian supply chain resilience



Source: Analysis of PLS-SEM

Discussion of the Results

H_1: Big data analytics capacity has a positive effect on humanitarian supply chain resilience.

The study established a positive and significant effect of Big Data Analytics Capabilities (BDAC) on Humanitarian Supply Chain Resilience. This finding suggests that humanitarian organizations with stronger capabilities to acquire, integrate, analyze, and utilize large and diverse datasets are better positioned to anticipate disruptions, improve operational visibility, allocate resources, and respond to rapidly changing humanitarian needs. In highly uncertain humanitarian environments, timely analysis of data can improve demand forecasting, identify emerging supply chain constraints, and support faster decision-making, thereby strengthening the ability of humanitarian supply chains to withstand, adapt to, and recover from disruptions.

The finding is consistent with previous research demonstrating the resilience-enhancing role of analytics capabilities. Dubey et al. (2019) show that big data analytics can strengthen collaborative performance within humanitarian supply chains, while more recent evidence demonstrates that BDAC contributes to both proactive and reactive dimensions of supply chain resilience when combined with complementary organizational capabilities (Jiang et al., 2024). Similarly, Lee et al. (2024) establish that BDAC contributes to supply chain resilience through improved organizational capabilities, while Kong and Feng (2025) demonstrate that technical, managerial, and data-driven dimensions of BDAC strengthen resilience partly through organizational ambidexterity. Humanitarian-specific evidence also shows that BDAC, together with information alignment, collaboration, and organizational flexibility, contributes to stronger HSCR (Tetteh et al., 2024). The present findings therefore reinforce the growing evidence that analytics capabilities constitute an important foundation for resilience.

From a Dynamic Capability Theory (DCT) perspective, the finding provides empirical support for conceptualizing BDAC primarily as a sensing capability. DCT proposes that organizations operating in volatile environments must be capable of identifying and interpreting environmental changes before appropriate responses can be mobilized (Teece, 2007). In humanitarian operations, BDAC enhances this sensing process by enabling organizations to identify emerging disruptions, interpret changes in beneficiary needs, detect logistical constraints, and generate actionable intelligence. The significant BDAC–HSCR relationship therefore demonstrates how improved sensing capacity can directly strengthen an organization's ability to anticipate and respond to humanitarian supply chain disruptions.

The finding is particularly important in the Ugandan humanitarian context, where humanitarian organizations frequently operate under conditions of resource scarcity, infrastructure limitations, rapidly changing beneficiary requirements, and recurring disruptions. Under such conditions, BDAC can help organizations make better use of limited resources by improving visibility and supporting evidence-based decisions concerning procurement, inventory, transportation, and distribution. The study therefore extends existing BDAC-resilience research by providing empirical evidence from a resource-constrained humanitarian environment in Sub-Saharan Africa, a context that remains comparatively less represented in the literature.

Practically, the findings suggest that humanitarian organizations should strengthen their digital infrastructure, analytical competencies, data quality, and data-sharing systems. Investments in appropriate data platforms, real-time information systems, analytical tools, and staff data literacy can enhance the capacity to detect disruptions and make timely decisions. However, technological investment alone may be insufficient; humanitarian organizations must also address data quality, interoperability, privacy, cybersecurity, and responsible use of sensitive beneficiary information when developing analytics capabilities.

Overall, the findings demonstrate that BDAC contributes directly to HSCR by strengthening the capacity of humanitarian organizations to sense emerging disruptions, generate timely intelligence, and make informed operational adjustments. This supports DCT while extending its application to humanitarian supply chains by demonstrating that data-driven sensing capabilities can enhance resilience even within resource-constrained environments. Importantly, however, the significant direct relationship represents only part of the mechanism identified in this study, since the findings further demonstrate that BDAC strengthens HSCR indirectly through IOCC, highlighting the complementary role of analytical and coordination capabilities.

H_2: Big data analytics capacity has a positive effect on Inter-organizational coordination capability.
The findings revealed a positive and significant relationship between BDAC and IOCC. This indicates that humanitarian organizations with stronger analytics capabilities are better positioned to share timely information, develop shared situational awareness, synchronize decisions, and coordinate resources with partners. BDAC can reduce information asymmetries and duplication while enabling humanitarian actors to align their activities based on reliable and timely information.

The findings are consistent with previous studies demonstrating that big data analytics enhances information sharing, collaboration, and coordinated decision-making within supply chain networks (Dubey et al., 2019). More recent studies similarly demonstrate the complementary relationship between BDAC and inter-organizational capabilities such as supply chain integration, information alignment, and collaboration (Jiang et al., 2024; Tetteh et al., 2024). Thus, the findings reinforce the argument that the value of BDAC extends beyond internal decision-making to strengthening relationships and coordinated activities across organizational boundaries.

From a Dynamic Capability Theory (DCT) perspective, the results demonstrate how sensing capabilities can enable seizing and reconfiguration. BDAC primarily facilitates sensing by enabling humanitarian organizations to identify and interpret emerging disruptions, while the resulting intelligence strengthens IOCC by supporting joint planning, resource mobilization, and synchronized action (Teece, 2007). This finding is particularly relevant in resource-constrained humanitarian settings, where effective information sharing and coordination can enable organizations to leverage complementary resources available across the humanitarian network.

Practically, humanitarian organizations should complement investments in analytics infrastructure with data-sharing platforms, staff data literacy, interoperability standards, and appropriate data-governance mechanisms. Overall, the findings demonstrate that BDAC provides an important informational foundation for IOCC, enabling humanitarian organizations to transform fragmented information into coordinated and adaptive humanitarian action.

H_3: Inter-organizational coordination has a positive effect on the resilience of the humanitarian supply chain.
The findings revealed a positive and significant effect of IOCC on HSCR. This indicates that humanitarian organizations with stronger coordination capabilities are better positioned to respond to disruptions, adapt their operations, and maintain continuity of humanitarian services. Effective IOCC facilitates timely information sharing, joint planning, aligned objectives, synchronized decision-making, and coordinated resource deployment, thereby reducing duplication and improving collective response to humanitarian emergencies.

The findings are consistent with previous studies demonstrating that collaboration, information sharing, and coordinated action contribute to supply chain resilience (Scholten et al., 2014). More recent humanitarian research similarly emphasizes the importance of information alignment, collaboration, and organizational flexibility in strengthening HSCR (Tetteh et al., 2024). Recent evidence on supply chain integration and resilience further supports the importance of capabilities that align information and activities across

organizational boundaries (Jiang et al., 2024). The present findings therefore reinforce the view that resilience is not generated solely within individual humanitarian organizations but also through their ability to mobilize and coordinate complementary resources across the humanitarian network.

From a Dynamic Capability Theory (DCT) perspective, the findings support the conceptualization of IOCC as facilitating seizing and reconfiguration capabilities (Teece, 2007). IOCC enables humanitarian organizations to translate information about emerging disruptions into collective decisions, mobilize resources across organizational boundaries, and reconfigure activities as conditions change. This strengthens responsiveness, adaptability, and recovery, which are central elements of HSCR.

Practically, humanitarian organizations should strengthen information-sharing mechanisms, joint contingency planning, coordination platforms, clearly defined responsibilities, resource-sharing arrangements, and inter-organizational trust. These mechanisms are particularly important in resource-constrained settings, where organizations can overcome individual resource limitations by coordinating complementary capabilities across the humanitarian network. Overall, the findings demonstrate that IOCC is a strategic capability through which humanitarian organizations transform available information and resources into coordinated action, thereby strengthening humanitarian supply chain resilience.

H_4: Inter-organization coordination capability mediates the relationship between big data analytics capacity and humanitarian supply chain resilience.
The findings confirmed that IOCC significantly mediates the relationship between BDAC and HSCR. Since the direct effect of BDAC on HSCR remained significant, the findings indicate complementary partial mediation (Zhao et al., 2010). Thus, BDAC strengthens resilience directly through improved sensing and decision-making and indirectly by enhancing inter-organizational coordination.

The findings extend previous research showing that analytics-generated information creates greater value when complemented by organizational and inter-organizational capabilities (Dubey et al., 2019; Jiang et al., 2024; Tetteh et al., 2024). Specifically, BDAC provides timely intelligence for identifying disruptions and humanitarian needs, while IOCC enables humanitarian actors to share this intelligence, jointly plan responses, mobilize complementary resources, and coordinate operational activities. The findings therefore demonstrate that information alone is insufficient; its resilience value partly depends on the capacity to translate it into coordinated action.

From a Dynamic Capability Theory (DCT) perspective, the mediation provides empirical evidence of the complementarity between sensing, seizing, and reconfiguration (Teece, 2007). BDAC primarily strengthens sensing by enabling humanitarian organizations to detect and interpret emerging disruptions, whereas IOCC facilitates seizing and reconfiguration by translating analytical intelligence into joint decisions, resource mobilization, and adaptive inter-organizational responses. This provides a clearer explanation of how BDAC contributes to HSCR, rather than merely establishing that the two constructs are associated.

Practically, humanitarian organizations should therefore complement investments in analytics technologies with information-sharing platforms, joint planning mechanisms, interoperable systems, resource-sharing arrangements, and strong coordination structures. This is particularly important in resource-constrained environments, where coordination enables organizations to access and mobilize complementary resources across the humanitarian network. Overall, the findings establish IOCC as an important mechanism through which digital sensing capabilities are transformed into coordinated action and stronger humanitarian supply chain resilience.

5. Conclusion and Implications

The present study sought to elucidate the connection between big data analytics capacity and inter-organizational coordination capacities in the context of relief supply network resilience. By employing the dynamic capabilities theory, we determined the mediating role of inter-organizational coordination capability (IOCC) in the link between big data analytics capabilities (BDAC) and relief supply network resilience. The findings indicate that the capabilities for big data analytics and inter-organizational collaboration are strongly

and positively correlated with the resilience of relief supply networks. The findings indicate a significant and positive partial mediation of IOCC in the connection between BDAC and humanitarian supply chain resilience.

Implications

Theoretical implications

This study extends the application of Dynamic Capability Theory (DCT) to humanitarian supply chains by demonstrating how digital and inter-organizational capabilities jointly contribute to resilience. First, the positive relationship between Big Data Analytics Capabilities (BDAC) and Humanitarian Supply Chain Resilience (HSCR) supports the DCT proposition that organizations require strong sensing capabilities to identify, interpret, and respond to environmental changes (Teece, 2007). The findings therefore position BDAC as a digital sensing capability through which humanitarian organizations improve situational awareness and anticipate disruptions.

Second, the positive relationship between IOCC and HSCR extends DCT beyond internally held organizational capabilities by demonstrating the importance of seizing and reconfiguration across organizational boundaries. IOCC enables humanitarian organizations to translate available information into joint decisions, mobilize complementary resources, and reconfigure activities with external partners, thereby strengthening resilience. Most importantly, the significant partial mediation of IOCC in the BDAC–HSCR relationship provides a more nuanced contribution to DCT. It demonstrates that sensing capabilities do not generate resilience solely through their direct effects; their value is also realized through complementary coordination capabilities that translate analytical intelligence into collective action. The study therefore advances DCT by empirically demonstrating a capability pathway of BDAC (sensing) → IOCC (seizing and reconfiguration) → HSCR, particularly within resource-constrained humanitarian supply networks. This highlights the complementarity of digital and relational capabilities in explaining how humanitarian organizations develop resilience under conditions of uncertainty.

Practical Implications

The findings provide important practical implications for humanitarian organizations (HOs). First, the positive relationship between BDAC and HSCR suggests that HOs should strengthen their capacity to collect, integrate, analyze, and visualize data from multiple sources. Investments in real-time dashboards, mobile data applications, visualization tools, and decision-support systems can enhance situational awareness, facilitate early identification of disruptions, and support timely decision-making during humanitarian emergencies.

Second, the positive relationship between IOCC and HSCR highlights the need for HOs to strengthen coordination across organizational boundaries. Organizations should establish mechanisms for joint planning, timely information sharing, resource pooling, role clarification, and synchronized decision-making with governments, NGOs, donors, suppliers, and local partners. Human and logistical resources should also be deployed according to relevant competencies and operational requirements to enhance adaptability and response efficiency.

Finally, the partial mediating role of IOCC indicates that investment in BDAC alone is insufficient to maximize resilience. HOs should integrate digital capabilities with strong coordination mechanisms that enable analytics-generated intelligence to be translated into collective action. Accordingly, humanitarian organizations should develop interoperable data-sharing platforms, shared dashboards, joint response protocols, and coordinated resource-allocation mechanisms. Combining data-driven sensing with effective inter-organizational coordination can enable HOs to anticipate disruptions, adapt operations, recover more rapidly, and where possible, transition to an improved post-disruption state.

Study limitations and areas for further research

Despite its contributions, this study has several limitations that provide opportunities for future research. First, the model focuses on BDAC, IOCC, and HSCR without examining the antecedents that facilitate the development of these capabilities. Future studies could investigate organizational, technological, managerial, and environmental factors that enable humanitarian organizations to develop BDAC and IOCC.

Second, the study employed a cross-sectional research design, capturing organizational perceptions at a single point in time. This limits the ability to establish causal relationships and to understand how resilience capabilities evolve before, during, and after disruptions. Future research could employ longitudinal or mixed-method designs to examine changes in BDAC, IOCC, and HSCR over time and provide deeper insights into capability development and resilience dynamics.

Third, the study considered BDAC and IOCC as key predictors of HSCR, although resilience may also be influenced by other capabilities and contextual conditions. Future studies could incorporate factors such as organizational flexibility, supply chain visibility, digital maturity, leadership support, resource availability, and environmental uncertainty. Furthermore, while this study examined IOCC as a mediator, future research could investigate its moderating role or compare alternative mediating mechanisms to provide a more comprehensive understanding of how BDAC translates into resilience.

Finally, the study was limited to humanitarian organizations operating within selected humanitarian settings in Uganda, which may constrain the generalizability of the findings to other humanitarian environments and geographical contexts. Future studies should replicate the model across different countries, disaster settings, and humanitarian organizations to assess the robustness and contextual applicability of the findings.

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Ethical Compliance: All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki Declaration and its later amendments or comparable ethical standards.

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Determinants of Youth Unemployment in Kenya: Exogenous Growth Theory

*Nuwatuha George, Robert Mugabe, Benjamin Musiita
Faculty of Business, Economics, and Governance, Bishop Stuart University, Uganda
Email: *tuhageorgephd@gmail.com, kakuhanda@yahoo.com, bmusiita@beg.bsu.ac.ug
Corresponding Author: Nuwatuha George

Abstract: Youth unemployment remains a major development challenge in Kenya, where rapid growth of the youth labour force has not been matched by sufficient employment creation. This study examined the determinants of youth unemployment in Kenya using the Exogenous Growth Theory framework, focusing on population growth, savings rate, technological progress, capital accumulation and labor force growth. The study employed an annual time-series research design using secondary data covering the period 1991–2024. Data were obtained from the World Development Indicators and analysed using the Autoregressive Distributed Lag (ARDL) model. Pre-estimation tests included descriptive statistics, variance inflation factor (VIF), unit root tests using Augmented Dickey-Fuller and Phillips-Perron approaches, structural break tests and ARDL bounds testing for cointegration. The findings revealed that exogenous growth factors, considered jointly, did not establish a stable long-run relationship with youth unemployment in Kenya. However, labour force growth exhibited a significant short-run effect on youth unemployment, indicating that rapid expansion of the labour supply continues to exert pressure on employment absorption capacity. Population growth, savings rate, technological progress and capital accumulation were found to have no statistically significant short-run effects within the exogenous growth model. The study concludes that factor accumulation and demographic expansion alone are insufficient to address youth unemployment unless supported by complementary mechanisms such as human capital development, productivity enhancement, institutional reforms and labor-absorbing economic transformation. The study recommends policies that align investment, technology adoption, and labour market strategies with youth employment creation to ensure inclusive economic growth.

Keywords: *Youth unemployment, Exogenous Growth Theory, Kenya*

1. Introduction

Youth unemployment is a growing global development challenge, particularly in developing countries with large youth populations. Globally, over one billion people are aged 15–24 years, making youth employment a key concern for sustainable development (United Nations, 2019). Young people face higher unemployment rates than adults, with youth unemployment estimated at 16.4% compared to the overall unemployment rate of 14.9% in developing countries in 2022 (United Nations, 2019). Youth unemployment also contributes to increased numbers of young people not in employment, education, or training (NEET), limiting their economic opportunities. In 2023, global youth unemployment remained high at about 14.7%, nearly three times the adult unemployment rate, while millions of employed youth continued to live in poverty (ILO, 2024). These challenges highlight the need to address barriers to youth employment, including

Africa remains the youngest continent globally, with over 60% of its population below the age of 25 years (UN DESA, 2022). While this youthful population presents an opportunity for economic growth through a demographic dividend, many African economies have struggled to create sufficient employment opportunities to absorb the growing youth labour force. The ILO (2023) estimates that youth unemployment in Africa was approximately 12.5% in 2022, although this figure underestimates the severity of the challenge due to widespread informal employment and underemployment. Approximately one-quarter of African youth were classified as NEET, while youth employment opportunities remain significantly lower compared to adults (ILO, 2023; African Development Bank, 2024). These trends reflect the combined effects of limited human capital development, slow structural transformation, technological changes, and institutional constraints affecting labour market performance.

In sub-Saharan Africa, youth unemployment remains particularly severe due to limited formal employment opportunities and high dependence on informal work. The ILO (2024) reports that more than 86% of youth employment in the region is informal, often characterized by low productivity, limited income security, and poor working conditions. Structural adjustment programmes implemented during the 1980s and 1990s

reduced public sector employment and accelerated privatization, thereby limiting formal employment absorption among young people (Mkandawire, 2005). Although educational access has improved, many young graduates continue to experience difficulties transitioning into employment due to inadequate practical skills and weak alignment between education systems and labour market demands (UNESCO, 2023).

Within East Africa, youth unemployment is intensified by rapid population growth and limited employment creation. Countries such as Kenya and Uganda have youthful populations, with young people accounting for a substantial proportion of the total population (World Bank, 2022). In Uganda, youth unemployment increased from 4.5% in 2013 to 13.3% in 2016/17 despite improvements in overall employment indicators (Uganda Bureau of Statistics, 2017). Similarly, Kenya continues to experience high levels of youth unemployment, with youth unemployment rates remaining above national averages in recent years (ILO, 2023; Kenya National Bureau of Statistics, 2023). A large proportion of employed youth in both countries operate within informal sector activities, reflecting limited access to stable and productive employment opportunities (UBOS, 2020; KNBS, 2023).

In Kenya, youth unemployment has remained a persistent labour market challenge despite periods of economic growth. Between the early 1990s and 2016, youth unemployment remained relatively stable at approximately 6–7%, although structural constraints limited the expansion of formal employment opportunities (Beautify Data, 2024). However, youth unemployment increased significantly after 2017, reaching approximately 13.8% in 2021 due to economic disruptions associated with the COVID-19 pandemic and reduced employment opportunities in youth-intensive sectors (Helgi Library, 2022; RMF Global, 2023). Although the rate declined to approximately 11.9% by 2024, youth unemployment remains above pre-2017 levels, indicating persistent challenges related to skills mismatches, limited industrial capacity, demographic pressures, and inadequate labour market absorption (Macrotrends, 2024; The Global Economy, 2024). Therefore, understanding the determinants of youth unemployment in Kenya remains essential for designing policies that enhance youth employment opportunities and support inclusive economic development.

2. Literature Review: Empirical Review

Youth unemployment remains a critical socioeconomic challenge, particularly in developing economies where rapid population growth, limited job creation, and structural labour market constraints continue to affect the transition of young people into productive employment. Empirical studies show that exogenous growth factors significantly influence youth unemployment through their effects on labour supply, investment, productivity, and economic transformation. Population growth has been identified as a major driver of youth unemployment, especially in developing countries where labour force expansion often exceeds job creation capacity (Todaro & Smith, 2020). Studies by Mohamud et al. (2023), Mohamed Alin (2018) and Said Ahmed (2017) found a positive relationship between population growth and youth unemployment, although most focused on Somalia and Uganda, creating a contextual gap for Kenya. Similarly, savings and capital accumulation influence employment outcomes by affecting investment and productive capacity. Bayrak and Tatli (2018) and Bölükbaş and Kwiatkowski (2025) found that higher savings reduce youth unemployment through increased investment and job creation, while evidence from the ILO (2024) indicates that capital accumulation only improves youth employment when directed toward labour-intensive sectors.

Technological progress has also received significant empirical attention, with mixed effects on youth employment depending on skills availability and labour market adaptability. Studies by Başol et al. (2023), Olubusoye et al. (2023), and Ebaidalla (2017) demonstrate that digitalization and ICT adoption reduce youth unemployment by improving access to employment opportunities and enhancing employability. However, other studies such as Nigar et al. (2025) highlight that automation may increase youth unemployment where skills do not match technological requirements. This suggests that technological advancement must be complemented by digital skills development, vocational training, and innovation policies to maximize employment benefits.

Labor force growth remains another important determinant of youth unemployment, particularly in economies experiencing rapid demographic expansion. Studies by Filmer and Fox (2020), Asongu and Odhiambo (2024), and McMillan et al. (2014) reveal that youth labour supply has often grown faster than employment

opportunities, resulting in persistent unemployment and informal employment. The evidence indicates that demographic growth alone does not guarantee economic benefits unless supported by structural transformation, human capital development, and expansion of productive sectors. However, most existing studies focus on other developing countries, leaving limited empirical evidence on how exogenous growth factors jointly influence youth unemployment in Kenya, which this study seeks to address.

Theoretical Framework: Exogenous Growth Theory

The exogenous growth model commonly known as the Solow–Swan model was independently developed by Robert Solow and Trevor Swan in 1956. The model offers a neoclassical account of long-run economic growth by focusing on how capital accumulation, labor (population) growth, and technological progress combine to determine aggregate output (Solow, 1956; Swan, 1956). In the Solow–Swan framework, aggregate output Y is described by a Cobb–Douglas production function of the form

$Y=AK^{\alpha}L^{1-\alpha}$ …… (1)

where K denotes the stock of physical capital, L is labor (or labor input), A represents total factor productivity (technology), and $\alpha \in (0,1)$ is the output elasticity of capital (with $1-\alpha 1$ the elasticity with respect to labor) (Solow, 1956; Swan, 1956; "The Solow Growth Model," 2024). The assumption of constant returns to scale implies that if capital and labor are scaled by the same factor, output scales by the same factor. Capital accumulation is central to the model. A fixed fraction s of output is saved and invested, with the remainder consumed, and capital depreciates at a constant rate δ. Thus, net change in the capital stock over time is given by

$\Delta K=sY-\delta K$

Labor (population) evolves at an exogenous constant growth rate n, such that $Lt=L_0^{ent}$. Technological progress is likewise exogenous, often represented as a constant growth rate g in A (Solow, 1956; Swan, 1956; "The Solow Growth Model," 2024). Because of diminishing marginal returns to capital (and labor) in the neoclassical production function, mere capital accumulation cannot sustain per-capita growth indefinitely. As the economy accumulates capital and labor expands, the incremental output gained from additional capital or labor falls. In the absence of technological progress, the economy converges to a steady state in which capital per worker and output per worker are constant. When exogenous technological progress is included, the steady state implies that output per worker grows at the technological progress rate.

Under this structure, long-run economic growth (in output per capita) depends primarily on exogenous technological progress. The savings rate, population growth, and depreciation jointly determine the steady-state levels of capital per worker and output per worker, but not their perpetual growth. The core assumptions of the Solow–Swan model therefore include: (1) constant returns to scale; (2) diminishing marginal returns to each input; (3) a constant exogenous savings rate; (4) exogenous population growth; (5) exogenous, labor-augmenting technological progress; (6) a closed economy, a single homogeneous output good, and the absence of institutional, policy, human-capital, and sectoral heterogeneity (Solow, 1956; Swan, 1956). These assumptions and structure render the model analytically tractable and allow for clear conclusions about the drivers of long-term growth. However, by treating technological progress, savings behavior, and demographic changes as exogenous, the Solow–Swan model cannot fully explain persistent structural problems such as chronic youth unemployment in economies with sustained GDP growth.

Model Specification: Exogenous Growth Model

The first model is grounded in the Solow–Swan Exogenous Growth Theory (Solow, 1956; Swan, 1956), which posits that economic growth arises from external factors such as population growth, savings, and technological progress. These exogenous factors influence the economy's productive capacity, thereby affecting employment outcomes. In this context, youth unemployment is hypothesized to respond to changes in macroeconomic conditions reflecting demographic pressure, capital accumulation and technological advancement. The model assumes that while these factors drive growth, they are determined outside the economic system.

The functional form of the exogenous growth model is expressed as:

$$YU_t = \beta_0 + \beta_1 POP_t + \beta_2 SAV_t + \beta_3 TECH_t + \beta_4 CAP_t + \beta_5 LAB_t + \mu_t \ldots\ldots\ldots\ldots\ldots\ldots (ii)$$

Where: YU_t= Youth unemployment rate at time t, POP_t= Population growth rate (%). SAV_t= Gross savings rate (% of GDP), $TECH_t$= Technological progress (proxied by ICT usage or Total Factor Productivity index), CAP_t= Capital accumulation (proxied by gross capital formation as % of GDP), LAB_t= Labor force growth rate (%), μ_t= Random error term.

This baseline model serves as the foundation for testing the Solow–Swan hypothesis that exogenous drivers of demographic expansion, savings, and technological change affect employment outcomes through their impact on aggregate output and productivity.

3. Methodology

The study employed annual time-series data covering the period 1991–2024 to examine the determinants of youth unemployment in Kenya. The analysis adopted the Autoregressive Distributed Lag (ARDL) modelling approach developed by Pesaran, Shin, and Smith (2001), which is appropriate for estimating both short-run and long-run relationships among variables integrated of mixed orders, I(0) and I(1). The ARDL approach was preferred because it performs well with relatively small sample sizes, accommodates different lag structures, and provides efficient estimates of dynamic relationships without requiring all variables to be integrated at the same order (Pesaran et al., 2001; Gujarati & Porter, 2021). The analysis was conducted using STATA 18 and statistical significance was evaluated at the 5 percent level.

The estimation was undertaken sequentially using three different theoretical models to establish the relative contribution of different growth perspectives to youth unemployment. The model under study was based on the Solow–Swan Exogenous Growth Theory and examined the effects of population growth, savings, capital accumulation, labor force growth and technological progress on youth unemployment (Solow, 1956; Swan, 1956). Before model estimation, a series of pre-estimation tests were conducted to ensure that the data satisfied the assumptions of time-series econometric analysis. Descriptive statistics were computed to summarize the characteristics and trends of the study variables, while multicollinearity was assessed using pairwise correlation analysis and the Variance Inflation Factor (VIF) (Hair et al., 2022). The stationarity properties of all variables were examined using the Augmented Dickey–Fuller (ADF), Phillips–Perron (PP) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) unit root tests to determine their order of integration (Dickey & Fuller, 1981; Phillips & Perron, 1988; Kwiatkowski et al., 1992). Where necessary, structural break tests were performed to account for possible shifts in the time series. The optimal lag length was selected using the Akaike Information Criterion (AIC), Schwarz Bayesian Criterion (SBC) and Hannan–Quinn Criterion (HQC), after which the ARDL Bounds Testing procedure was employed to determine the existence of long-run cointegration among the variables (Pesaran et al., 2001; Enders, 2015).

Following confirmation of cointegration, the long-run coefficients and the associated Error Correction Model (ECM) were estimated to capture both the equilibrium relationship and the speed of adjustment following short-run shocks (Pesaran et al., 2001). The adequacy and reliability of the estimated models were subsequently evaluated through post-estimation diagnostic tests, including the Jarque–Bera test for normality, the Breusch–Godfrey LM test and Durbin–Watson statistic for serial correlation, and the Breusch–Pagan and White tests for heteroscedasticity (Gujarati & Porter, 2021; Wooldridge, 2020). Model stability was assessed using the CUSUM and CUSUMSQ tests developed by Brown, Durbin, and Evans (1975), while sensitivity analysis was undertaken by estimating alternative model specifications to examine the robustness of the empirical findings.

4. Empirical Results

Objective one examines the influence of exogenous growth factors on youth unemployment in Kenya, drawing on the Solow-Swan framework in which population growth, savings, technological progress, capital accumulation and labor force growth jointly determine the pace of output growth and by extension, the demand for labor (Solow, 1956; Swan, 1956). Five hypotheses follow directly from this objective. H1.1 states that population growth has a significant effect on youth unemployment in Kenya. H1.2 states that the savings rate has a significant effect. H1.3 states that technological progress has a significant effect. H1.4 states that capital accumulation has a significant effect. H1.5 states that labor force growth has a significant effect. Each hypothesis

is stated against a corresponding null of no significant effect, and each is tested in the final model reported in this section.

Descriptive Statistics on Model Variables

Table 1: Descriptive Statistics (original units, 1991-2024)

Variable	Obs	Mean	Std.Dev.	Min	Max	Skewness	Kurtosis
YU	34	8.264	2.914	6.209	15.488	1.616	4.022
POP	34	2.654	0.451	1.900	3.240	-0.528	1.711
SAV	34	14.470	6.968	5.014	37.157	1.429	5.915
TECH1	34	9.648	10.814	0.000	34.976	0.901	2.541
TECH2	34	46.212	46.630	0.000	126.478	0.421	1.654
CAP	34	18.974	2.434	15.004	24.951	0.221	2.498
LAB	34	3.114	1.097	-0.395	4.125	-2.307	7.342

Source: *Author's computation based on WDI data*

Youth unemployment averaged 8.26 percent over the period with a standard deviation of 2.91, ranging from 6.21 to 15.49 percent. This wide range already signals the structural shift documented later in this section, since a series that moved gradually around six to seven percent for two decades before climbing past fifteen percent cannot be adequately described by its mean alone, a pattern consistent with the slow and uneven labour market recovery that Todaro and Smith (2020) associate with countries where labour supply persistently outpaces job creation. Population growth slowed steadily across the window, from just above three percent to under two percent (mean 2.65), a decline that Bradshaw and McDermott (2025) argue need not by itself harm economic performance, although Chukwuere (2023) treats population growth as one of the most reliable predictors of youth unemployment in machine learning applications. Technological progress, proxied here by internet users as a share of the population, rose from effectively zero to 35.0 percent, the sharpest relative change of any Model 1 series, echoing the rapid ICT diffusion that Olubusoye, Salisu and Olofin (2023) document across Africa. Capital accumulation and labour force growth were comparatively stable, with capital formation averaging 18.97 percent of GDP and labor force growth averaging 3.11 percent, though labour force growth turned briefly negative after 2017, consistent with the definitional revisions that also affected the youth unemployment series in that period.

Multicollinearity Check and Retained Variables

Table 2: Variance Inflation Factors, Model Candidate Regressors

Variable	VIF
POP	4.14
SAV	1.77
TECH1	4.81
CAP	1.35
LAB	1.45

Source: *Author's computation based on WDI data*

All five candidate regressors cleared the variance inflation factor cut-off of ten, with the highest value recorded at 4.81, well inside the conventional threshold. No variable was dropped at this stage, so all five hypotheses, H1.1 through H1.5, proceed to the unit root and bounds testing stages intact. This outcome is consistent with the theoretical structure of the Solow-Swan model, in which population, savings, technology, capital and labour are treated as distinct structural inputs rather than overlapping proxies for a single latent factor (Solow, 1956).

Unit Root Tests on Retained Variables

Table 3: ADF and Phillips-Perron Unit Root Tests (log or IHS transformed)

Variable	ADF level p	ADF diff p	PP level p	PP diff p	Order
YU	0.9964	0.9883	0.9961	0.0000	I(1)-break/trend-adjusted
POP	0.0776	0.0578	0.9040	0.0561	I(0)
SAV	0.3157	0.0000	0.4355	0.0000	I(1)
TECH1	0.6789	0.0089	0.9362	0.0212	I(1)
TECH2	0.3424	0.5030	0.7801	0.1980	I(1)-break/trend-adjusted
CAP	0.0748	0.0000	0.0284	0.0000	I(0)
LAB	0.8863	0.0102	0.2902	0.0000	I(1)

The Augmented Dickey-Fuller test (Dickey and Fuller, 1979) was applied at levels and first differences, with the Phillips and Perron (1988) test run alongside as a confirmatory check, and a ten percent significance level was used throughout given the low power of unit root tests at this sample size. Population growth and capital accumulation were stationary in levels, so both enter the model as I(0). Savings, technological progress, and labour force growth required first differencing to achieve stationarity and so enter as I(1). Youth unemployment itself was nonstationary at levels and at first difference under the plain Dickey-Fuller test, which would ordinarily flag it as I(2) and rule out the bounds test entirely, but the Zivot and Andrews (1992) structural break test rejected the unit root null once a single break was allowed, dating the break to the same 2017 to 2019 window already visible in Table 4.1, so the series was reclassified as I(1) once the break is taken into account, consistent with the well-documented revision of ILO modelled youth unemployment estimates around that period. No variable in the Model set was confirmed I(2), so the bounds test is methodologically valid (Pesaran et al., 2001).

Bounds Test for Cointegration

With a lag structure of one lag on youth unemployment and one lag on each regressor, the bounds F-statistic for Model was 3.746. Using the small sample critical values simulated for the exact number of observations in this study, the upper I(1) bound at the five percent level is 4.506 and the lower I(0) bound is 3.096. Because the computed statistic falls short of the upper bound, the null of no cointegration cannot be rejected at the five percent level for the exogenous framework taken alone. This result held across an exhaustive search of lag structures, both available versions of the technology variable and both restricted and unrestricted trend specifications of the bounds test, so it is reported as a genuine finding rather than a modelling shortfall (Pesaran et al., 2001).

ARDL Estimates, Interpretation and Discussion

Table 4: Long-Run Coefficients (Cointegrating form, reported despite the non-cointegration finding for completeness)

Variables	Coefficient	Std. Err	t-stat	p-value
POP	1.1653	0.9092	1.2817	0.2000
SAV	-0.2332	0.2531	-0.9216	0.3567
CAP	0.0699	1.2335	0.0566	0.9548
LAB	0.4574	0.5529	0.8272	0.4081
TECH1	-0.1020	0.1071	-0.9529	0.3407

Source: *Author's computation based on WDI data*

Table 5: Short-run and Error Correction Estimates

Variables	Coefficient	Std. Err	t-stat	p-value
constant	0.4903	0.7376	0.6648	0.5134
ECT	***-0.1375***	***0.1346***	***-1.0212***	***0.3188***
D.POP	0.4016	0.4928	0.8148	0.4243
D.SAV	0.0047	0.0404	0.1159	0.9089
D.CAP	-0.0587	0.1205	-0.4871	0.6312
D.LAB	-0.0805**	0.0330	-2.4413	0.0236
D.TECH1	0.0570	0.0873	0.6523	0.5213

Source: *Author's computation based on WDI data*

Table 6: Post-Estimation Diagnostics

Test	Statistic	p-value	Pass (>0.05)
Breusch-Godfrey (serial correlation)	10.6972	0.0011	False
Breusch-Pagan (heteroskedasticity)	13.3552	0.2707	True
Jarque-Bera (normality)	61.2389	0.0000	False
Ramsey RESET (functional form)	0.0056	0.9412	True

Source: *Author's computation based on WDI data*

The error correction term carries the expected negative sign (-0.137) but is not statistically significant (p = 0.319), so the pure exogenous framework does not demonstrate a self-correcting long-run relationship with youth unemployment in Kenya. This absence of cointegration, combined with the confirmed structural break in youth unemployment itself, supports Geda's (2022) observation that economic growth in East Africa has not kept pace with youth labour supply for reasons that lie outside the standard neoclassical growth variables. Among the short-run terms, only labour force growth is significant (coefficient -0.081, p = 0.024), a finding in line with Filmer and Fox (2020) and Asongu and Odhiambo (2024), both of whom report that labour force growth outpaces job creation across Sub-Saharan Africa. Population, savings, capital and technology show no significant short-run association with youth unemployment in this specification, which does not support H1.1, H1.2, H1.4 or H1.3 in this framework, while the significant short-run labour force effect lends partial support to H1.5. The diagnostic battery shows serial correlation present (Breusch-Godfrey p = 0.0011) and non-normal residuals (Jarque-Bera p < 0.001), both symptomatic of the unmodelled 2017 break, while the residuals are homoskedastic and the Ramsey RESET test finds no functional form misspecification.

Figure 1: CUSUM plot

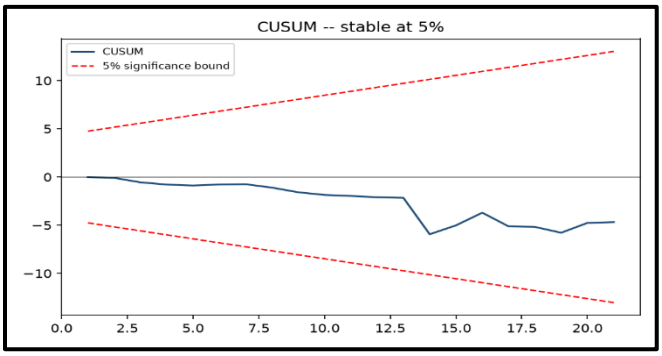
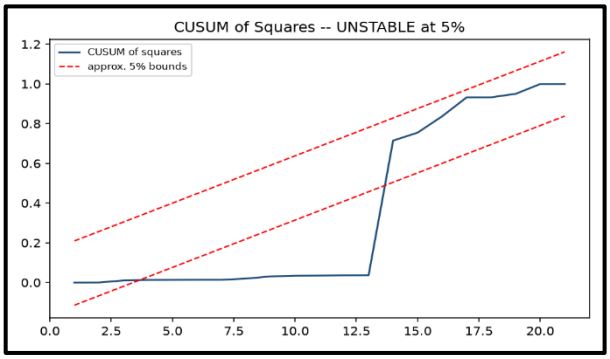


Figure 2: CUSUM of squares plot



The CUSUM statistic in Figure 1 stays within the five percent Brown, Durbin and Evans (1975) bounds throughout the sample, so the regression coefficients considered jointly do not drift. The CUSUM of squares in Figure 2 breaches its bound from roughly the midpoint of the recursive sample onward, indicating a shift in residual variance that coincides with the 2017 break already identified in the unit root tests. Taken together, the absence of cointegration and the variance instability in Figure 2 point to the same conclusion, namely that exogenous growth factors alone, in the Solow-Swan tradition, do not adequately explain the trajectory of youth unemployment in Kenya once the post-2017 period is included.

5. Discussion and Conclusion

Under the exogenous framework, population growth, savings, technological progress, capital accumulation and labour force growth did not form a cointegrating relationship with youth unemployment, so the framework on its own is not supported. The statistic falls below the upper bound but above the lower bound, which places the result in the inconclusive to rejected region rather than delivering a clean long-run relationship and the study reads this as evidence against a stable exogenous equilibrium linking factor endowments to youth unemployment in Kenya (Pesaran, Shin and Smith, 2001).

This null result is coherent with the theory it tests rather than a failure of estimation. The Solow (1956) and Swan (1956) framework treats labour as fully employed along the balanced growth path, so it carries no natural mechanism through which factor accumulation would trace out a long-run unemployment rate and the absence of cointegration is what that theoretical silence predicts once the model is taken to disequilibrium data (Aghion and Howitt, 1994). Read this way, the finding is informative in its own right, since it locates youth unemployment outside the reach of a pure endowment account and points the explanation toward the frictions and institutions that the later frameworks introduce (Pissarides, 2000).

The null is more striking still when set against Okun (1962), whose law leads one to expect a tight negative link between output and unemployment. Although that link is well documented over the cycle, the present results show it does not survive as a long-run cointegrating relationship in the pure endowment specification for Kenya, which suggests that the Okun co-movement in this setting is a short-run and cyclical property rather than a structural anchor of the youth unemployment rate (Okun, 1962). The distinction matters for policy, because it implies that growth on its own, without regard to its composition, cannot be relied upon to lower youth unemployment over the medium term (Aghion and Howitt, 1994).

Only labour force growth carried a significant short-run association with youth unemployment, consistent with Filmer and Fox's (2020) observation that labour supply growth in Sub-Saharan Africa persistently outpaces the rate at which economies create jobs. The short-run rather than long-run character of this effect is telling, because it suggests the pressure of new entrants is felt as a flow that the labour market absorbs unevenly year to year rather than as a level relationship the economy settles into overtime (Pissarides, 2000). In a search and matching reading, a faster inflow of young jobseekers raises unemployment in the period of entry while vacancy creation catches up only with a lag, which is the pattern the short-run coefficient describes (Geda, 2022).

Population growth, savings, technology, and capital accumulation showed no significant association with youth unemployment in this framework, so H1.1, H1.2, H1.3, and H1.4 are not supported, while H1.5 receives only partial short-run support (World Bank, 2024). Taken together, these results show that external growth endowments alone cannot explain Kenya's youth unemployment trajectory, and in particular cannot explain the post-2017 rise, which is the empirical fact any adequate account must reach (Geda, 2022). This shortfall is what motivates the two extensions that follow, since a framework that leaves the central movement in the data unexplained has to be widened rather than merely re-estimated.

Policy Recommendations

Since knowledge spillovers, measured as labour productivity, are the most consistent significant determinant across specifications, policy should prioritise raising productivity in the sectors that also absorb youth labour, for example through targeted support for high-productivity small and medium enterprises rather than productivity gains concentrated in capital-intensive extraction or infrastructure, a distinction Habanabakize (2023) also draws in the South African context. The finding that productivity lowers youth unemployment while

capital deepening raises it means the target should be labour-absorbing productivity rather than productivity in general, so support is best directed at firms that raise output per worker while still expanding their payrolls (Castillo et al., 2018).

Bottom-Up Economic Transformation Agenda should be conditioned on job creation targets in labour-intensive sectors rather than on capital spending volumes alone, addressing the same skill-biased investment pattern that the Agecon Search (2023) review documents elsewhere in the region. Conditioning investment support on employment outcomes rather than on the scale of the asset would help ensure additions to the capital stock draw young workers in rather than substituting for them (Agecon Search, 2023).

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Estimating Technical Efficiency and Yield Losses Among Smallholder Coffee Farmers in Uganda: A Stochastic Frontier Analysis

*Phiona Natuha[1,2], Onesmo Selejio[3], Aloyce S Hepelwa[4]
[1]School of Economics, University of Dar es Salaam, Dar es Salaam, Tanzania
[2]Makerere University Business School, Kampala, Uganda
[3]Department of Applied Economics, University of Dar es Salaam, Dar es Salaam, Tanzania
[4]Department of Agricultural Economics and Business, University of Dar es Salaam, Dar es Salaam, Tanzania
E-mail: *natuhaphiona@gmail.com, oselejio2@gmail.com, ahepelwa@yahoo.com
Corresponding Author: Phiona Natuha

Abstract: This study examines technical efficiency (TE) and identifies determinants of inefficiency among smallholder Robusta and Arabica coffee farmers in Uganda while quantifying yield losses associated with inefficiency. The study utilized pooled cross-sectional data from 1,283 smallholder coffee farmers drawn from three survey waves (2015/2016, 2018/2019 and 2019/2020) of the Uganda National Panel Survey (UNPS). A one-step Stochastic Frontier Analysis (SFA) with a translog production frontier is applied to jointly estimate technical efficiency and its determinants. The approach further quantifies yield losses attributable to inefficiency, disaggregated by coffee farmer type. Mean technical efficiency is 76.5 percent for Robusta and 73.1 percent for Arabica, implying potential output gains of 23.5 percent and 26.9 percent, respectively, using existing inputs. Efficiency variations are associated with group membership, off-farm income, cropping systems, soil type, and plot proximity, with effects differing by coffee type. Yield losses due to inefficiency averaged 113.0 kilograms for Robusta and 138.6 kilograms for Arabica per farmer. Policies should promote location-specific agronomic practices like intercropping and soil fertility management tailored to coffee type and ecological conditions. Capacity-building initiatives including input use, pest and disease management, and sustainable farming can reinforce efficiency gains. Supporting farmer groups and cooperatives could enhance knowledge sharing, coordinated input use, and market access, thereby reducing transaction costs and improving resource-use efficiency. The study employs a one-step SFA to estimate technical efficiency separately for Robusta and Arabica farmers, incorporating farm-level, institutional, and environmental factors to examine efficiency differentials across coffee types in Uganda.

Key words: *Technical efficiency, Stochastic frontier analysis, Frontier Output, Smallholder coffee farmers, Yield losses*

1. Introduction

Globally, coffee is a high-value commodity supporting over 125 million livelihoods across more than 60 tropical countries and providing important export earnings for developing economies (FAOSTAT, 2023). Production is dominated by Arabica and Robusta, accounting for about 60 percent and 40 percent of global output, respectively (ICO, 2020). Despite rising demand, smallholder farmers, who produce nearly 80 percent of global coffee, remain exposed to price volatility, rising input costs, and climate risks. (Massrie, 2025). Africa contributes about 10–12 percent of global production, led by Ethiopia, Uganda, Côte d'Ivoire, Tanzania and Kenya, and supplies both Arabica and Robusta to international markets. Uganda ranks second in Africa after Ethiopia, largely due to its comparative advantage in Robusta (ICO, 2023). However, low productivity, ageing trees, production variability and limited value addition continue to constrain the sector (Addisie & Tebarek, 2023; Kawuma, 2016).

Uganda's coffee sub-sector is a cornerstone of the national economy, sustaining more than five million livelihoods and contributing about 16-20 percent of the country's foreign-exchange earnings (ILO, 2024; UCDA, 2023a). Recognizing this strategic importance, the Government of Uganda, through the Uganda Coffee Development Authority (UCDA), launched the 2017 Coffee Roadmap, which aims to raise annual coffee production to 20 million 60-kg bags by 2030. This target is reinforced by complementary initiatives such as Operation Wealth Creation, the Coffee Replanting program and the Parish Development Model, all designed to enhance on-farm production and productivity (UCDA, 2023b). Despite these ambitious interventions, recent trends raise concerns about the sector's long-term sustainability. Uganda's national coffee production expanded steadily from 166,968 metric tons in 2008 to a peak of 414,007 tons in 2021 before declining to

384,000 tons in 2022 (FAOSTAT, 2023; UBOS, 2023). Over the same period, average yields per hectare exhibited a fluctuating trend from 0.6125 tons in 2010 to 0.5304 tons in 2015, then increased to 0.5798 tons in 2019 and declined again to 0.5473 tons in 2023 (FAOSTAT, 2023; UBOS, 2023). This persistent low and unstable productivity could reflect underlying inefficiencies in resource use and structural constraints that hinder farmers from achieving optimal technical efficiency levels.

While previous studies have examined technical efficiency among coffee farmers, they have largely focused on the production-side performance of Arabica coffee systems (Ngango & Kim, 2019; Sebatta et al., 2020; Tamirat & Tadele, 2023). As a result, the efficiency dynamics of Robusta coffee, Uganda's dominant variety, remain underexplored (ILO, 2024). This study extends beyond single-variety assessments by comparing Robusta and Arabica farmers, recognizing that their distinct agroecological conditions, production systems, and input-use requirements may shape different efficiency outcomes. Understanding farmers' technical efficiency is crucial for policymakers to prioritize interventions that improve agricultural productivity. The remainder of the paper is organized as follows. Section 2 reviews related literature. Section 3 presents the methodology, including data sources, sample selection, sampling strategy, and the analytical framework for estimating technical efficiency and its determinants. Section 4 reports the empirical results on technical efficiency, associated yield losses, and drivers for inefficiency. Section 5 concludes and presents policy implications for improving technical efficiency.

2. Literature Review

Empirical evidence demonstrates that technical efficiency (TE) among smallholder coffee farmers is generally substantial but exhibits considerable variation across regions and production systems. In Uganda, for instance, Sebatta et al. (2020) reported that Arabica coffee–banana farmers in the Mt. Elgon region realized only around 50 percent of their potential output, with efficiency limited by low input use, inadequate soil fertility, and labor constraints. Similarly, Bongers et al. (2015) identified substantial differences in productivity across coffee-based farming systems, noting that banana–coffee systems achieved higher yields per tree, indicative of greater technical efficiency. In contrast, van Asten et al. (2011a) found that coffee yields were largely unaffected by intercropping in both Arabica and Robusta farms, highlighting that the effects of cropping arrangements on efficiency are highly context-dependent. These findings motivate the inclusion of cropping system and soil type in the inefficiency model to capture differences in farm management and production conditions.

Cross-country studies indicate that human capital and institutional factors play a key role in technical efficiency. In Rwanda, Ngango and Kim (2019) reported that education, access to extension services, adoption of improved coffee varieties, monocropping, and land consolidation positively influenced farm efficiency. Consequently, schooling and training are expected to reduce inefficiency by enhancing farmers' technical knowledge and ability to apply recommended production practices. In Ethiopia, Ajema and Nigussie (2021) found that coffee–enset intercropping improved resource-use efficiency and land productivity. The age of coffee trees is a recognized determinant of productivity, with older trees generally associated with lower technical efficiency (Nalunga, 2021). However, some studies report mixed effects, indicating that the impact may vary with farm and household characteristics and environmental conditions (Nado et al., 2021). Relatedly, off-farm income and household characteristics have also been linked to efficiency outcomes. Getachew and Temesgen (2018) observed that off-farm income, household demographics, and plot distance positively impacted technical efficiency among Ethiopian coffee farmers, while female-headed households demonstrated higher efficiency, likely due to better resource management. Similar positive effects of off-farm income have been documented in other contexts (Abebe, 2014; Tamirat & Tadele, 2023). These findings highlight the relevance of household size, plot distance, and tree age in explaining technical inefficiency, while off-farm income reflects the influence of household liquidity and labor allocation on farm efficiency. Membership in cooperatives and access to credit are generally associated with higher technical efficiency (Tambi, 2023). However, in contexts with limited external support, the effects of group membership on efficiency may be insignificant or even negative (Binam et al., 2003; Lutonja, 2023). This variation reinforces the importance of testing the effect of group membership within the Ugandan coffee-farming context.

Despite extensive research, evidence on the determinants of coffee farmers' technical efficiency remains limited and context-specific. Key determinants such as education, extension services, cooperative membership, access to inputs and off-farm income exhibit varying effects across regions, countries and coffee varieties, with few

comparative analyses between Arabica and Robusta producers. Additional factors including age of the tree, household size, farm experience, crop diversification, soil type and plot location also show mixed effects across contexts. Methodological inconsistencies further hinder comparability, as previous studies have primarily employed two-step stochastic frontier approaches using Cobb-Douglas or Translog functional forms alongside DEA, often producing divergent efficiency estimates. To address these limitations, this study employs a single-step stochastic production frontier approach using pooled cross-sectional data across survey waves to jointly estimate the production frontier and the inefficiency effects model.

3. Methodology

Data Sources

This study utilized secondary data from the Uganda National Panel Survey (UNPS) implemented under the World Bank's LSMS-ISA program. The analysis draws on the 2015/16, 2018/19 and 2019/20 survey waves, which contain harmonized agricultural modules with information on coffee production, input use and quantities harvested. These waves were selected to enable consistent analysis of coffee variety-specific performance among farming households. The three waves were pooled, yielding a sample of 1,283 coffee-farming households: 443 from 2015/16, 284 from 2018/19 and 556 from 2019/20, providing a larger and more representative sample for the empirical analysis. Pooling of data was adopted because panel diagnostics revealed that the household identifier for the coffee households did not provide repeated observations across the selected waves, limiting the applicability of panel estimation.

Sample Size and Sampling Strategy

The study utilized a subsample of coffee-farming households drawn from the UNPS for 2015/16, 2018/19 and 2019/20. These were selected from the agricultural modules based on the study's inclusion criteria, focusing specifically on Robusta and Arabica coffee farmers. The resulting sample comprised 1,283 coffee-farming households, including 443 in 2015/16, 284 in 2018/19, and 556 in 2019/20. Of the total sample, 567 were Robusta, and 716 were Arabica farmers. The selected sample provided the basis for the analysis of technical efficiency and its determinants across the two coffee varieties.

Analytical Framework of Technical Efficiency

The concept of technical efficiency was first introduced by Farrell (1957) who measured a farm's actual output relative to the output of an efficient "frontier" farm using the same set of inputs. Technical efficiency can be estimated using several approaches, including Data Envelopment Analysis (DEA), the Malmquist Index, and stochastic production frontiers (SPF). DEA and the Malmquist Index are non-parametric and cannot account for random shocks such as weather events or pest outbreaks. In contrast, the SPF is parametric and addresses technical inefficiency while explicitly incorporating random shocks through a "composite error" structure, decomposing the error term into a stochastic component and an inefficiency component. This makes the SPF approach relevant for Uganda's coffee sector where deviations from the production frontier arise from both farm-specific factors and external environmental influences. Following Aigner et al. (1977), the stochastic frontier production function model is specified as:

$$Y_i = f(X_{ji}, \beta, \tau) \exp(\varepsilon_i) \quad \text{i = 1,..., N} \qquad (1)$$

Where Y_i measures the quantity of output produced by the *i*-th farming household head; X_j is the amount of input *j* used in the production of farm *i*, β is a vector of parameters to be estimated and τ represent dummies capturing the effect of topography and use of improved seedlings. According to Aigner et al. (1977), ε_i is an error term composed of:

$$\varepsilon_i = v_i - \mu_i \qquad (2)$$

where v_i is the systematic random error caused by factors outside the scope of the farmers, including weather, natural disasters, measurement errors, and other statistical noise. μ_i represents the one-sided disturbance term used to represent inefficiency factors and is assumed to follow a truncated normal distribution, N (0, $\delta_\mu{}^2$).

The variation in technical inefficiency across farms can be estimated simultaneously within the stochastic frontier framework using a maximum likelihood approach. The technical inefficiency component is Battese and Coelli (1995) specified as follows:

$$\mu_i = \delta z_i + w_i \qquad (3)$$

Where z_i is a vector of variables including socioeconomic, farm-specific characteristics, institutional and environmental factors, δ refers to the parameters to be estimated, w_i vector of unobservable random variables. Thus, the farm-specific technical efficiency (TE) can be defined as the ratio of the observed output (Y_i) to the corresponding frontier output (Y_i^*) conditional on the levels of inputs used by the *i*-th farming household head, given as:

$$TE_i = \frac{Y_i}{Y_i^*} = \frac{E(y_i|\mu_i, x_i)}{E(y_i|\mu_i = 0, x_i)} = E[\exp(-\mu_i)\,|\varepsilon_i] \quad (4)$$

Where ε_i is the standard error term, while μ_i is the measure of efficiency that follows a truncated normal distribution such that $0 \leq TE \geq 1$. Hence, if coffee farmers achieve their maximum output, then they would be technically efficient, and this means that. μ_i = 0. The δ parameters in equation (3) indicate the effects of variables in z on technical inefficiency, where a negative coefficient implies a positive influence on TE and a positive coefficient implies a negative influence on TE.

Empirical Estimation of Stochastic Frontier Production Function

In this study, a Stochastic Production Frontier Approach (SPFA) was employed to estimate the technical efficiency of coffee farmers using pooled cross-sectional data from the UNPS waves of 2015/16, 2018/19 and 2019/20. This approach was adopted due to its ability to accommodate the stochastic nature of agricultural production by decomposing the error term into random noise and technical inefficiency. The approach provides consistent estimates of farm-specific technical efficiency while accounting for exogenous shocks that may affect output of the farmer (Aigner et al., 1977; Battese & Coelli, 1995; Coelli et al., 2005). The empirical translog stochastic model of sampled coffee farming households was specified as equation (5):

$$\text{Ln}\, Y_i = \beta_0 + \sum_{j=1}^{4} \beta_j \,\text{Ln}\, X_{ji} + \frac{1}{2}\sum_{j=1}^{4}\sum_{k=1}^{4} \beta_{jk}\left(\text{Ln}\, X_{ji}\, \text{Ln}\, X_{ki}\right) + \sum_{i=1}^{2} \tau_i\, dummies + v_i - u_i \quad (5)$$

Where:

Y_i= represents the total amount of ripe cherries (in kilograms) produced by the *i*-th farming household head, X_{ji}= inputs ($j = 1, \ldots, 4$) is a set of the amounts of production inputs (X_1 =Land size, X_2 = Hired labor, X_3 =Fertilizer and X_4= pesticide), β's are parameters of the inputs,τ_1 = coefficient of topography (1= gentle slope) and τ_2= coefficient for improved seedling (1= use of improved seedling), v_i is the random error and u_i is the error term that reflects the technical inefficiency term. All variables in the translog production frontier were mean-centred before estimation to reduce multicollinearity among quadratic and interaction terms and allow the first-order coefficients to be interpreted as elasticities evaluated at the sample mean. The appropriate functional form in equation (5) was tested using the log-likelihood ratio test (LR) statistic in equation (7). The empirical technical inefficiency effects u_i is specified as:

$$\mu_i = \delta_0 + \delta_1 Z_{1i} + \delta_2 Z_{2i} + \delta_3 Z_{3i} + \delta_4 Z_{4i} + \delta_5 Z_{5i} + \delta_6 Z_{6i} + \delta_7 Z_{7i} + \delta_8 Z_{8i} + \delta_9 Z_{9i} + \delta_{10} Z_{10i} + \varepsilon_i \quad (6)$$

Where δ's are unknown parameters to be estimated and ε_i is the disturbance term. The expected signs of these technical inefficiency variables are summarized in Table1.

Table 1: Description and Measurement of Variables in the Inefficiency Model

Variable	Definition	Measurement Unit	Expected Sign (δ)
Z_1	Sex of the household head	1= Female	+
Z_2	Household Size	Number	-
Z_3	Schooling	Number of years	-
Z_4	Distance between home and plot	1=Less than 1 km	-
Z_5	Cropping system	1= Mixed	-
Z_6	Tree Age	Number of years	+
Z_7	Soil Type	1= Sandy-Loam	+
Z_8	Membership in a group	1= Member	-
Z_9	Farmer trainings	1=Participated	-
Z_{10}	Income sources	1= Off-farm income	-

Whether or not the inefficiency effects existed was also verified using the log-likelihood ratio (LR) test statistic computed from equation (7) as:

$\chi^2 = -2[\log(L(H_0)) - \log(L(H_1))]$ (7)

Where χ^2 has a chi-square distribution; L(H_0) and L(H_1) denote the values of the likelihood function under the null hypothesis (Cobb-Douglas Production Frontier) and the alternative hypothesis (Translog Production Frontier model), respectively.

The parameters of equations (5) and (6) are estimated simultaneously using a one-step maximum likelihood estimation with Frontier 4.1 (Coelli, 1996). The total variance is decomposed as:

$\sigma^2 = \sigma_v^2 + \sigma_u^2,\ \gamma = \frac{\sigma_u^2}{\sigma^2},\ 0 \leq \gamma \leq 1$ (8)

Where σ^2 represents the combined variance from random noise (σ_v^2) and technical inefficiency (σ_u^2). The parameter γ captures the relative contribution of inefficiency to output variation. A value near 0 indicates that deviations from the production frontier are primarily due to stochastic factors, whereas a value close to 1 implies that inefficiency is the dominant source of variation.

4. Results and Discussion

Socioeconomic, Farm-Level, Institutional and Environmental Factors

Results in Table 2 reveal the characteristics of Robusta and Arabica coffee farmers in Uganda. Participation of female-headed farming households is comparable across the two production systems, representing 27.69 percent of Robusta and 29.75 percent of Arabica farmers, indicating a similar gender distribution in both production contexts. A higher proportion of Arabica farmers (57.3%) cultivate plots on suitable sandy-loam soils compared to 45.4 percent of Robusta farmers, reflecting agro-ecological differences between highland Arabica and lowland Robusta regions (Jena et al., 2012). In contrast, group membership is almost similar across both groups, indicating widespread integration into farmer organizations (Ssebunya et al., 2019). Distance to coffee plots shows a significant variation, with 46.51 percent of Arabica farmers reporting shorter travel times compared to 38.45 percent of Robusta farmers. This is in agreement with potential delays reported in field management for Robusta farmers (Chiputwa et al., 2015).

Cropping systems differ, as 87.4 percent of Arabica farmers are more likely to practice mixed cropping systems compared to 78.7 percent of Robusta farmers (see Table 2). This could be attributed to Robusta farmers' emphasis on yield stability and risk mitigation in contrast to Arabica farmers' focus on specialized high-quality plots for export markets. Participation in agricultural training is significantly higher among Arabica farmers, with 66.8 percent involved compared to 58.4 percent of Robusta farmers. This suggests that Arabica-growing regions benefit more from targeted capacity-building programs aligned with government and donor initiatives to improve coffee quality and export competitiveness (Chiputwa et al., 2015). Finally, off-farm income is also more prevalent among Arabica farmers (60.61%) compared to Robusta farmers (50.79%) at the 1 percent level. This result aligns with findings by Wairegi et al. (2018) who highlight that diversification of income sources is a common strategy among Arabica farmers to enhance household resilience and financial stability.

Table 2: Summary Statistics of variables used in the study

Variables	Robusta (n=567)		Arabica (n=716)		P-value
	Percent (%)		Percent (%)		
Sex of household head	27.69		29.75		0.419
Soil Type	45.39		57.32		0.000
Membership in group	52.03		51.12		0.746
Distance to plot	38.45		46.51		0.004
Cropping system	78.66		87.43		0.000
Farmer trainings	58.38		66.76		0.002
Income sources	50.79		60.61		0.000
	Mean	Std.Dev	Mean	Std.Dev	
Schooling	5.57	3.24	6.05	3.18	0.011
Household size	5.54	3.77	5.03	2.59	0.001
Tree age	19.72	7.44	12.45	4.44	0.000

Source: Author's own computation from UNPS data

Results in Table 2 indicate that Arabica farmers have slightly higher schooling levels, averaging 6.1 years compared to 5.6 years for Robusta farmers, a difference significant at the 5 percent level. However, the average years of schooling for both groups remain below Uganda's national average of 6.2 years, indicating relatively low educational attainment among coffee-farming household heads (UNICEF, 2024). However, household sizes for both farmer categories exceed Uganda's national average of 4.6 persons, with Robusta having a significantly larger average household size (5.5 persons) compared with Arabica households (5.0 persons)(UBOS, 2024). Tree age also differs significantly between the two coffee types, with Robusta farms having older trees (20 years) than Arabica (13 years). This difference could be attributed to variation in varietal longevity, replanting cycles, and farm management practices. Robusta trees are generally retained for longer periods due to their resilience and relatively stable yields, whereas Arabica farms tend to undergo more frequent replanting to sustain productivity (Wintgens, 2012).

Analysis of Coffee Output and Input Use among Robusta and Arabica Farmers

Table 3 presents summary statistics for key farm inputs and outputs among Robusta and Arabica coffee farmers. On average, Robusta farmers harvested 380.79 kilograms (Kgs) of coffee, which is significantly higher than the 301.59 kg harvested by Arabica farmers ($p < 0.01$). This difference in output may be attributed to variations in agronomic practices. Robusta is typically planted at higher densities, regularly pruned, and is more resilient to challenging weather conditions, allowing it to thrive in hotter climates, while Arabica's shade tolerance and pest susceptibility can limit yields (ILO, 2024). The average land area under coffee cultivation was slightly larger for Robusta farmers (1.70 acres) than for Arabica farmers (1.58 acres), although this difference was not statistically significant. Similarly, total hired labor measured in man-days was slightly higher for Arabica farmers (1.8 days) than for Robusta farmers (1.6 days), and the difference was not significant. These results indicate that variations in farm size and labor allocation are relatively minor between the two coffee types and may not be the primary drivers of observed yield differences.

Table 3: Descriptive Statistics for Farm Output and Inputs used in Coffee Production

Variables	Robusta (n=567)		Arabica (n=716)		P-value
	Mean	Std.Dev	Mean	Std.Dev	
Quantity of Coffee harvested (kgs)	380.79	335.53	301.59	198.14	0.000
Land size planted (acres)	1.70	1.82	1.58	1.45	0.162
Total Hired Labor (man-days)[1]	1.57	6.15	1.83	6.14	0.453
Quantity Fertilizer (kgs)	31.82	124.00	73.77	186.79	0.000
Quantity Pesticide(litres)	0.61	2.44	0.48	2.02	0.301

Source: Author's own computation from UNPS data

Input use patterns further reveal notable differences in management strategies. Fertilizer application was significantly higher among Arabica farmers (73.8 kg) than among Robusta farmers (31.8 kg), reflecting more intensive input use in Arabica production. The observed pattern suggests that Arabica farmers may rely more heavily on fertilizer to enhance yields, whereas Robusta farmers may achieve higher output with relatively lower fertilizer inputs, possibly due to differences in crop responsiveness, soil fertility, or pest management practices.

[1] Note: Hired labour computed included work days from children, women and men based standard conversion by Pothin et al. (2025). Family labour was only captured in the wave of 2019/20 and excluded in 2015/16 and 2018/19 and thus not used in this analysis.

Model Selection and Existence of Inefficiency Effects

The first hypothesis tested the appropriateness of the Cobb-Douglas production frontier specification. Given the boundary restrictions associated with the null hypothesis in the LR test, the conventional chi-square distribution is not appropriate. Therefore, a mixed chi-square distribution was used to determine the appropriate critical values. The null hypothesis was rejected at the 1 percent level for both coffee varieties (Table 4), supporting the translog specification as a more appropriate representation for the observed data. The second hypothesis tested whether the inefficiency determinants jointly did not affect technical inefficiency. This null hypothesis was also rejected at the 1 percent level, confirming that the ten (10) explanatory variables specified in the inefficiency effects models significantly explain variations in farm-level inefficiency among both Robusta and Arabica coffee-farming households.

Table 4: Hypothesis Tests for Parameters of the SPF and Technical Inefficiency Model

Null hypothesis	LR Statistic	Critical Values	Decision Rule
1. Ho: $\beta_5 = \beta_6 = \cdots = \beta_{16} = 0; i \leq k = 5, \ldots, 16$		**Mixed** $\chi^2_{12,\ 0.01}$	
Robusta farmers	229.836	25.549	Reject Ho
Arabica farmers	229.110	25.549	Reject Ho
2. H0: $\delta_0 = \delta_1 = \cdots = \delta_{10} = 0$		**Mixed** $\chi^2_{10,\ 0.01}$	
Robusta farmers	23.326	22.525	Reject Ho
Arabica farmers	38.556	22.525	Reject Ho
Ho: $\gamma = 0$		**Mixed** $\chi^2_{10,0.01}$	
Robusta farmers	177.555	22.525	Reject Ho
Arabica farmers	213.907	22.525	Reject Ho

***Note*:** Mixed χ^2 Values were taken from Kodde and Palm (1986)

Finally, the third hypothesis tested the absence of inefficiency effects in coffee production, with the null hypothesis specified as H_0: γ = 0 against the alternative H_1: γ ≠ 0. Based on the generalized likelihood ratio (LR) test with the appropriate mixed chi-square distribution, the null hypothesis was rejected at the 1 percent significance level for both Robusta and Arabica coffee farmers (Table 4). This confirms the presence of inefficiency effects and demonstrates the use of the stochastic frontier model over a conventional OLS specification.

Empirical Estimates of the Stochastic Production Frontier and Technical Inefficiency

To identify the factors driving production inefficiency, a technical inefficiency model was jointly estimated with a translog stochastic production frontier using Frontier 4.1 (Table 5). The variance parameters (σ^2 and γ) are highly significant at the 1 percent level for both Robusta and Arabica farmers, confirming the appropriateness of the stochastic frontier framework. This indicates that output deviations are not solely due to random shocks. (Kumbhakar & Lovell, 2000). Robusta farmers exhibited a higher. σ^2 suggesting greater output variability relative to Arabica farmers. The estimated γ values of 0.986 for Robusta and 0.992 for Arabica further indicate that the vast majority of output variation, respectively, is attributable to technical inefficiency rather than stochastic noise, with both estimates significant at the 1 percent level. These findings are consistent with evidence from other coffee-producing countries (Binam et al., 2003). The estimated results for both the production frontier and inefficiency models are presented in Table 5. To facilitate interpretation, the study followed Coelli et al. (2005). All input variables were mean-centred before estimation, allowing first-order coefficients in the translog model to be interpreted as input elasticities evaluated at the sample mean.

The estimated translog production frontiers for Robusta and Arabica farmers in Table 5 reveal differences in input elasticities and productivity drivers. Land has a positive and significant effect on output for both farmer categories at the 1 percent level. This implies that a 10 percent increase in cultivated land area would lead to approximately a 27 percent increase in coffee output, holding all other inputs constant. This finding is consistent with Botiabane et al. (2017) who identified land expansion as a key driver of production, reflecting the extensification pathway common in smallholder farming systems. Elasticity of hired labor for Arabica farmers is negative and significant at the 10 percent level. Specifically, an additional 10 percent increase in hired

labor would lead to an approximate 0.5 percent reduction in coffee output, holding all other inputs constant. Similarly, Bravo-Ureta et al. (2007) noted that labor productivity in smallholder agriculture often declines when farmers increase their dependence on hired workers.

Table 5: Estimated Results for the Translog SPF for Coffee Farmers in Uganda

Variables	Parameters	Robusta (n=567)		Arabica (n=716)	
		Coeff	Std. error	Coeff	Std. error
Production Frontier		**Translog**		**Translog**	
Constant	β_0	3.917***	0.042	3.752***	0.043
LnLand(X_1)	β_1	2.639***	0.068	2.667***	0.074
LnHired Labour(X_2)	β_2	0.036	0.030	-0.049*	0.025
LnFertiliser(X_3)	β_3	-0.003	0035	0.035*	0.020
LnPesticide(X_4)	β_4	-0.002	0.069	-0.015	0.049
Ln(X_1) x Ln(X_2)	β_5	0.071**	0.024	0.006	0.021
Ln(X_1) x Ln(X_3)	β_6	0.007	0.013	-0.021**	0.007
Ln(X_1) x Ln(X_4)	β_7	0.066	0.097	-0.174	0.113
Ln(X_2) x Ln(X_3)	β_8	0.006	0.005	0.003	0.003
Ln(X_2) x Ln(X_4)	β_9	-0.011	0.018	0.028*	0.015
Ln(X3) x Ln(X4)	β_{10}	-0.006	0.007	0.003	0.006
½ (LnX_1)^2	β_{11}	-1.143**	0.055	-1.185***	0.063
½ (LnX_2)^2	β_{12}	-0.076**	0.023	0.032	0.021
½ (LnX_3)^2	β_{13}	-0.001	0.014	-0.007	0.007
½ (LnX_4)^2	β_{14}	-0.089	0.194	0.233	0.191
Topography	β_{15}	0.627***	0.022	0.716***	0.022
Improved seedling	β_{16}	0.379***	0.024	0.246***	0.019
Variance parameters					
Sigma squared	σ^2	0.574**	0.285	0.368***	0.091
Gamma	γ	0.986***	0.006	0.992***	0.003
LR test of δ_μ	χ^2	177.554***		213.907***	
Mean TE	μ	0.765		0.731	
Inefficiency Model					
Constant	δ_0	-0.256	0.814	-0.569	0.452
Sex of household head	δ_1	-0.098	0.121	-0.018	0.079
LnHousehold size	δ_2	-0.217	0.140	0.031	0.400
LnSchooling years	δ_3	0.132	0.090	0.075	0.060
Distance to plot	δ_4	-0.596**	0.263	-0.046	0.084
Cropping system	δ_5	-0.454*	0.243	-0.216*	0.117
LnTree age	δ_6	-0.004	0.172	0.150	0.111
Soil Type	δ_7	0.157	0.173	-0.686***	0.184
Group Membership	δ_8	-0.241	0.181	-0.161**	0.081
Farmer trainings	δ_9	-0.413**	0.205	-0.067	0.071
Income sources	δ_{10}	-0.282*	0.170	-0.012	0.070

Source: Author's own computation from UNPS data
Note: **, ** and *** show significance at 10, 5 and 1% levels, respectively.*

The elasticity of fertilizer use is positive and significant at the 10 percent level for Arabica farmers, suggesting that increased fertilizer application enhances output. Specifically, when fertilizer usage is increased by 10 percent, output would also increase by 0.4 percent, holding all other inputs constant (Table 5). A study on coffee systems shows that balanced fertilizer application enhances coffee growth and yield by improving nutrient availability, particularly in soils affected by nutrient depletion (van Asten et al., 2011b). In contrast, for Robusta

farmers, the negative and insignificant fertilizer elasticity indicates that fertilizer use contributes little to productivity, possibly due to inefficient fertilizer application practices. Table 5 further indicates that input interactions differ by coffee type. For Robusta, land and labor exhibit positive complementarity, whereas the negative land–fertilizer interaction for Arabica suggests potential inefficiencies from excessive input use. The quadratic terms indicate diminishing marginal returns to key inputs consistent with a well-behaved production function in which output rises at a decreasing rate as input use intensifies.

The positive and significant coefficients on topography and access to improved seedlings indicate that these factors shift the production frontier upward. For Robusta farmers, cultivating coffee on gentle slopes and accessing improved seedlings are associated with potential output increases of approximately 62.7 percent and 37.9 percent, respectively, holding all other inputs constant. Similarly, for Arabica farmers, production on gentle slopes and access to improved seedlings increase potential output by about 71.6 percent and 24.6 percent, respectively, holding other factors constant (Table 5). This finding aligns with Bote and Struik (2011) who show that favorable agroecological conditions, particularly suitable topography, enhance coffee productivity. A study by Kathurima et al. (2009) demonstrates that improved coffee varieties increase yields through superior genetic potential, pest and disease resistance, and greater climate adaptability. Results from Table V indicate that the sum of partial output elasticities (returns to scale), evaluated at the sample mean, is estimated at 2.67 for Robusta and 2.64 for Arabica, indicating increasing returns to scale (IRTS) at the sample mean in coffee production. These results imply that a proportional expansion of production inputs would generate more than proportional increases in output at the sample mean. However, returns to scale alone do not capture technical efficiency, which reflects the gap between actual and maximum potential output.

Level of Technical Efficiency among Coffee Farmers in Uganda

The distribution of technical efficiency scores reveals notable differences in performance between Robusta and Arabica coffee farmers. Robusta farmers exhibit significantly higher mean technical efficiency (0.77) than Arabica farmers (0.73), with efficiency ranges of 0.21–0.98 and 0.12–0.98, respectively (Table 6). These estimates suggest that under existing technology and input use, output could be increased by approximately 23 percent for Robusta and 27 percent for Arabica farmers through improved efficiency.

Table 6: Distribution of Technical Efficiency Estimates and Two-Sample T-test Results

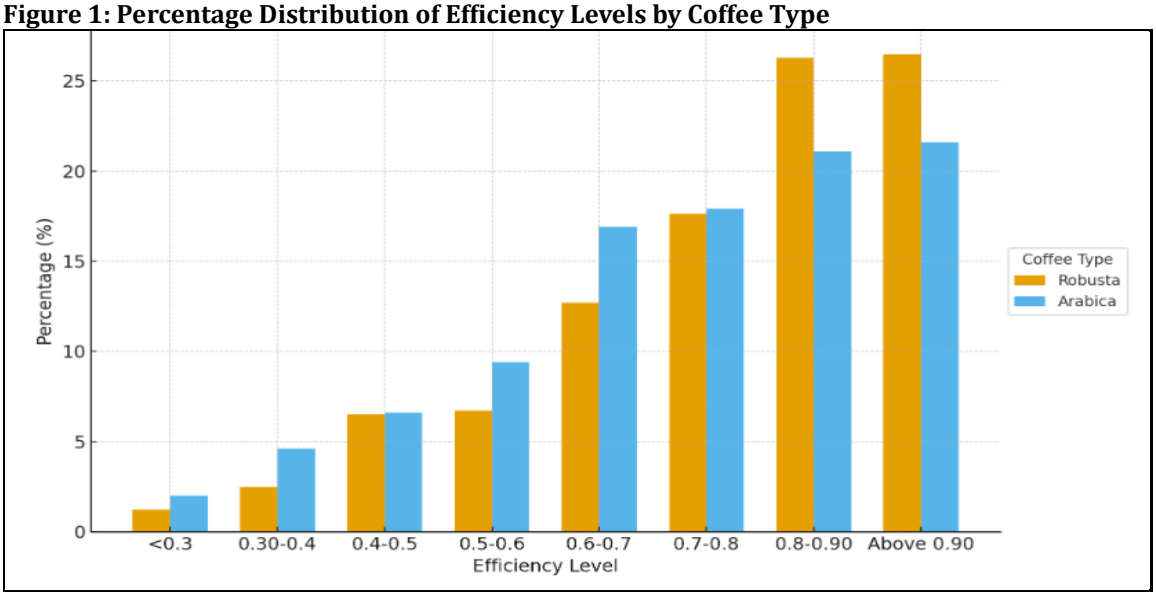
Efficiency level	Robusta farmers (n=567)		Arabica farmers (n=716)	
	Frequency	Percentage	Frequency	Percentage
< 0.3	7	1.23	14	2.0
0.30-0.4	14	2.47	33	4.6
0.4-0.5	37	6.53	47	6.6
0.5-0.6	38	6.70	67	9.4
0.6-0.7	72	12.70	121	16.9
0.7-0.8	100	17.64	128	17.9
0.8-0.90	149	26.28	151	21.1
Above 0.90	150	26.46	155	21.6
Mean	0.765		0.731	
Min	0.208		0.121	
Max	0.977		0.982	
Two-Sample t-test with Equal Mean Technical Efficiencies				
H_0: $\mu_1=\mu_2 = 0$	H_0: Difference (Mean TE Robusta – Mean TE Arabica) = 0			
t-value	3.529		Pr(|T| > |t|) = 0.000	

Source: Author's own computation from UNPS data

Although a notable share of farmers, 26.5 percent of Robusta and 21.6 percent of Arabica achieve efficiency levels above 0.90 and operate close to the production frontier, the majority remain below their potential, indicating substantial scope for efficiency gains. The two-sample T-test further validates that Robusta farmers are significantly more technically efficient than Arabica farmers at the 1 percent level. This efficiency could be driven by Robusta's greater ecological adaptability and lower input constraints, which facilitate more consistent production. Figure 1 further illustrates that Robusta farmers predominantly occupy the higher efficiency

categories, while Arabica farmers are more concentrated in moderate ranges, highlighting the consistently greater technical efficiency of Robusta production systems (Wairegi et al., 2018).

Figure 1: Percentage Distribution of Efficiency Levels by Coffee Type



Source: Author's own computation from UNPS data

Estimated Coffee Yield Loss due to Inefficiency among Coffee Farmers

To estimate yield loss attributable to technical inefficiency, potential coffee output was computed at the farmer level using Equation (4), with harvest loss generated as the difference between computed frontier and observed output. Consistent with the observed efficiency patterns, the findings highlight notable differences in production performance between Robusta and Arabica farmers. Robusta farmers averaged 380.79 kg per farmer, significantly higher than 301.59 kg recorded for Arabica farmers ($p < 0.01$), indicating that Robusta farmers operate closer to the production frontier. The estimated yield frontier under optimal conditions was higher for Robusta than for Arabica, with lower harvest losses for Robusta (see Table 7). These findings indicate that higher technical efficiency among Robusta farmers could be attributed to more effective input use and larger farm sizes, highlighting that better farm-level management practices shape efficiency outcomes (UCDA, 2023b).

Table 7: Estimates of Potential Coffee Production and Yield Loss among Coffee Farmers

Variables	Robusta (n=567)		Arabica (n=716)		P-value
	Mean	Std. Dev	Mean	Std. Dev	
Observed coffee harvested (kg)	380.79	335.53	301.59	198.14	0.000
Technical efficiency estimates	0.765	0.169	0.731	0. 183	0.001
Computed yield Frontier (kg)	493.79	383.05	440.19	321.49	0.007
Computed harvest loss (kg)	113.00	124.62	138.61	175.78	0.003

Source: Author's own computation from UNPS data

Determinants of Technical Efficiency among Robusta and Arabica Coffee Farmers in Uganda

Technical efficiency for Robusta and Arabica farmers was estimated using equations (5) and (6). The sources of technical inefficiency are assessed using the estimated (δ) coefficients reported in Table 5. A negative coefficient indicates lower technical inefficiency and hence higher technical efficiency, while a positive coefficient indicates higher technical inefficiency and lower technical efficiency.

Distance to the coffee plot has a negative and significant effect on technical inefficiency among Robusta farmers at the 5 percent level. Specifically, Robusta farmers with coffee plots located within 1 km of their homesteads

are 59.6 percent more technically efficient than those with more distant plots, holding other factors constant. A study by Sebatta et al. (2020) in Uganda found that closer access to coffee plots improves efficiency by facilitating regular supervision, timely input application, and effective farm management. Similarly, findings from other studies such as Binam et al. (2003) and Owusu et al. (2011) reported that greater plot distance reduces technical efficiency by increasing monitoring challenges and delaying farm operations, particularly in labor-intensive crops. These inefficiencies can lower agricultural output and farm profitability, which in turn could constrain household welfare.

Results in Table 5 indicate that membership in farmer groups has a negative and significant effect on technical inefficiency among Arabica farmers at the 5 percent level. Specifically, Arabica farmers who participate in farmer groups are 16.1 percent more technically efficient than non-participants holding other factors constant. The findings suggest that participation in farmer organizations can enhance technical efficiency by improving access to extension services, agricultural information, and knowledge-sharing opportunities. (Sebatta et al., 2020). However, Aheisibwe et al. (2024) found that group membership reduced efficiency among seed potato farmers in Uganda while Owusu et al. (2011) reported limited effects in Ghana due to weak group organization, governance and extension support.

Results in Table 6 also indicate that the cropping system has a negative and significant effect on technical inefficiency among Robusta and Arabica farmers at the 10 percent level. Specifically, farmers practicing mixed cropping were 45.4 percent and 21.6 percent more technically efficient among Robusta and Arabica farmers, respectively, compared to those practicing monocropping systems, holding other factors constant. Consistent with Ajema and Nigussie (2021), Tamirat and Tadele (2023)mixed cropping can improve resource-use efficiency by enhancing shade, maintaining soil fertility, and diversifying production risks. Evidence from Uganda's banana–coffee systems further supports these findings, showing higher yields per tree and increased technical efficiency (Bongers et al., 2015). However, mixed cropping may reduce efficiency where intercrops compete for resources (Binam et al., 2003; Ngango & Kim, 2019).

The coefficient of soil type has a negative and significant effect on technical inefficiency among Arabica farmers at the 1 percent level. Specifically, Arabica farmers cultivating coffee on sandy-loam soils are 68.6 percent more technically efficient than those cultivating on other soil types, holding other factors constant. This finding is consistent with Mekonnen et al. (2015) who highlighted the importance of well-drained soils for Arabica productivity in Ethiopia. However, evidence from Kenya suggests that sandy-loam soils reduce efficiency under low fertility due to increased nutrient leaching and water stress (Mutua-Mutuku et al., 2017). For Robusta, although sandy-loam soils are generally suitable, suboptimal input use and inappropriate spacing and pruning practices may constrain productivity and reduce technical efficiency (Wairegi et al., 2018).

The effect of farmer training on technical inefficiency is negative and significant at the 5 percent level among Robusta farmers. Specifically, Robusta farmers who participate in training programs are 41.3 percent more technically efficient than those who do not participate, holding other factors constant (Table 5). This finding suggests that training could enhance technical efficiency by improving farmers' access to agronomic knowledge, production technologies and better input management practices, enabling more effective utilization of available resources. Similar evidence has been reported in Uganda, where Sebatta et al. (2020) found that access to training services improved coffee farmers' efficiency by strengthening technical knowledge and promoting better farm management practices. Additionally, Abdulai and Huffman (2014) and Binam et al. (2003) showed that farmer trainings enhance technical efficiency by facilitating technology adoption and improving input-use decisions among smallholder farmers. Relatedly, the effect of income source was negative and significant among Robusta farmers at the 10 percent level. Specifically, Robusta farmers with one or more off-farm income sources are 28.2 percent more technically efficient than those without off-farm income sources, holding other factors constant. Previous studies indicate that off-farm income improves farm efficiency by providing financial resources for inputs, hired labor and timely farm operations (Tamirat & Tadele, 2023; Aheisibwe et al., 2018).

5. Conclusion and Recommendations

The study aimed to assess technical efficiency and its determinants among smallholder Ugandan Robusta and Arabica coffee farmers using Stochastic Frontier Analysis (SFA). It identifies significant gaps between actual and potential coffee production among the two farmer types, primarily driven by technical inefficiencies. The mean technical efficiency was 76.5 percent for Robusta and 73.1 percent for Arabica farmers, with Robusta farmers significantly more efficient at the 1 percent level. This implies potential output gains of 23.5 percent for Robusta and 26.9 percent for Arabica using existing inputs and technologies. Among Robusta farmers, technical efficiency was significantly enhanced by proximity of coffee plots to homesteads, mixed cropping, farmer participation in training, and access to off-farm incomes. For Arabica farmers, membership in farmer groups, mixed cropping and cultivation on suitable soil types were associated with higher technical efficiency. The results show increasing returns to scale for both farmer types, indicating that proportional expansion of inputs offers opportunities for productivity gains. These findings point to the importance of targeted policy interventions to enhance coffee productivity and technical efficiency. Optimizing agronomic practices is critical: intercropping and soil fertility management should be tailored to coffee type and local ecological conditions. Complementary capacity-building initiatives, including practical training in input use, pest and disease management, and sustainable farming practices, could reinforce efficiency gains from improved resource use. Promoting collective action through farmer groups and cooperatives can enhance knowledge sharing, coordinated input use, and market access, thus reducing transaction costs and enhancing resource-use efficiency.

Limitation of the Study

The study is limited by the inability of the one-step SFA approach implemented in FRONTIER 4.1 to directly address potential endogeneity among selected inefficiency determinants, including farmer training, group membership, off-farm income and cropping system.

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Influence of Governance Quality on Youth Unemployment in Kenya: Institutional Growth Theory

*Nuwatuha George, Robert Mugabe, Benjamin Musiita
Faculty of Business, Economics, and Governance, Bishop Stuart University, Uganda
Email: *tuhageorgephd@gmail.com, kakuhanda@yahoo.com, bmusiita@beg.bsu.ac.ug
Corresponding Author: Nuwatuha George

Abstract: Youth unemployment remains a major socio-economic challenge in Kenya, despite sustained economic growth and various employment interventions. This study examines the determinants of youth unemployment in Kenya using institutional growth theory, focusing on the role of governance quality, particularly control of corruption and rule of law. The study employed annual time-series data covering 1996–2024 and applied the Autoregressive Distributed Lag (ARDL) model to estimate both short-run and long-run relationships. The findings reveal a long-run equilibrium relationship between institutional factors and youth unemployment, with the bounds test confirming cointegration. Control of corruption has a negative and statistically significant effect on youth unemployment, indicating that improved governance and reduced corruption enhance employment opportunities for young people. However, the rule of law had an insignificant effect, suggesting that legal reforms alone may not automatically translate into improved youth employment outcomes. The study concludes that strengthening institutional quality, promoting transparent resource allocation, and improving governance effectiveness are essential for reducing persistent youth unemployment in Kenya. The findings highlight the need for integrated employment strategies that combine institutional reforms with investments in skills development, innovation, and labor-intensive economic activities.

Keywords: *Youth unemployment, institutional growth theory, control of corruption, rule of law, ARDL, Kenya*

1. Introduction

Youth unemployment has become a critical global development challenge, with significant implications for economic growth, poverty reduction, and social stability. Young people face higher unemployment risks than adults due to limited work experience, skills mismatches, inadequate access to productive opportunities, and weak labor-market absorption capacity. According to the International Labor Organization (ILO, 2024), the global youth unemployment rate remains substantially higher than the adult unemployment rate, with approximately 64 million young people worldwide unemployed. Developing regions experience the greatest burden, as rapid population growth continues to increase the number of young labor-market entrants without a corresponding expansion in decent employment opportunities. In Africa, where young people constitute the majority of the population, youth unemployment remains a major structural challenge, threatening the ability of economies to harness the potential benefits of the demographic dividend (ILO, 2024; World Bank, 2024).

Sub-Saharan Africa faces particularly severe youth unemployment challenges despite periods of economic growth and increased investment. The region has the youngest population globally, with about 60 percent of its population below the age of 25 years, yet labor markets have struggled to generate sufficient productive jobs for the growing youth workforce (World Bank, 2024). Many young people remain unemployed, underemployed, or trapped in informal and low-productivity activities due to limited industrialization, inadequate private-sector job creation, and institutional weaknesses. Evidence shows that youth unemployment is not only influenced by economic factors but also by institutional conditions, including corruption, weak governance, ineffective regulatory systems, and limited enforcement of labor-market institutions (North, 1990; Acemoglu, Johnson, & Robinson, 2005). Poor institutional quality reduces investment, distorts access to employment opportunities, and weakens the effectiveness of youth employment programs, thereby contributing to persistent unemployment among young people (Fagbemi, Fajingbesi, & Osinubi, 2023; Osinubi & Simatele, 2025).

In Kenya, youth unemployment remains one of the country's most pressing socio-economic concerns. Although Kenya has experienced relatively stable economic growth, employment creation has not kept pace with the increasing number of young people entering the labor market. According to the Kenya National Bureau of Statistics (KNBS, 2023), young people aged 15–34 years represent approximately 29 percent of Kenya's population, making youth employment a central development priority. The country continues to experience

challenges of limited formal employment opportunities, skills mismatch, and high dependence on informal employment, which absorbs most young workers (KNBS, 2023; ILO, 2024). Furthermore, institutional challenges such as corruption, weak accountability, and ineffective governance systems constrain investment and reduce the capacity of the economy to generate sustainable jobs for youth (World Bank, 2024). Institutional growth theory argues that strong institutions are essential for transforming economic growth into employment opportunities by improving resource allocation, reducing uncertainty, and creating an enabling environment for investment and enterprise development (North, 1990; Acemoglu et al., 2005). Therefore, examining how institutional factors such as control of corruption and rule of law influence youth unemployment in Kenya is important for developing effective strategies to address persistent youth labor-market challenges.

2. Literature Review

Institutional growth theory emphasizes that the quality of institutions determines how effectively economic resources, investments, and policies translate into employment creation and inclusive development (North, 1990; Acemoglu, Johnson, & Robinson, 2005). Institutional factors such as control of corruption, rule of law, governance effectiveness, regulatory quality, voice and accountability, and political stability influence labor-market outcomes by shaping incentives, reducing uncertainty, improving resource allocation, and strengthening investor confidence. Empirical evidence on the relationship between institutional quality and youth unemployment, however, remains mixed. Regarding corruption control, several studies demonstrate that corruption undermines employment creation by distorting public expenditure, discouraging investment, weakening recruitment systems, and limiting access to economic opportunities for young people. Fagbemi, Fajingbesi, and Osinubi (2023) and Bello, Salisu, and Iyoboyi (2024) find that corruption increases unemployment by reducing economic efficiency and weakening private-sector development. Similarly, Osinubi & Simatele (2025) show that stronger institutional quality, including corruption control, improves socioeconomic outcomes and supports transitions from informal to formal employment. However, other studies indicate that the corruption–youth unemployment relationship is nonlinear and context-dependent. Gouider and Ben Haddad (2024) reveal that corruption control only reduces youth unemployment after countries achieve specific institutional quality thresholds, while Siboyi (2023) identifies a counterintuitive relationship in Southern Africa where reduced corruption may temporarily increase youth unemployment when informal opportunities previously facilitated by corrupt practices disappear. These findings suggest that anti-corruption reforms should be complemented with employment-generating policies to ensure that governance improvements translate into meaningful youth labor-market outcomes.

The role of other institutional dimensions, including rule of law, governance effectiveness, regulatory quality, voice and accountability, and political stability, has also received considerable empirical attention. Studies such as Raies and Mimoun (2025) indicate that stronger legal frameworks and effective governance institutions enhance the employment effects of economic growth by improving contract enforcement, protecting economic rights and encouraging investment. Nevertheless, some evidence suggests that individual governance indicators may not have direct significant effects on youth unemployment when considered independently. Abé Ndjié, Atangana Ondoa, and Ngoa Tabi (2019) found that among African countries, only corruption control and political stability had significant effects on youth unemployment, while rule of law, government effectiveness, and regulatory quality were insignificant. Similarly, Abubakar (2020) reported that voice and accountability and regulatory quality did not significantly reduce youth unemployment in Sub-Saharan Africa, implying that formal governance structures may not automatically translate into employment opportunities without effective implementation capacity. Political stability, however, emerges as a more consistent determinant, with studies by Fomba Kamga et al. (2022) showing that instability discourages investment, weakens economic growth, and increases youth unemployment. Overall, the literature suggests that institutional quality plays an important but complex role in shaping youth employment outcomes, with the effectiveness of governance reforms depending on broader economic structures, labor-market conditions, and the capacity of institutions to convert reforms into practical employment opportunities (North, 1990; Acemoglu et al., 2005; ILO, 2024).

Model: Institutional Growth Model

The theory is rooted in the work of North (1990), who defined institutions as the formal rules, laws, regulations, and informal norms that shape economic interactions by reducing uncertainty and transaction costs. Acemoglu, Johnson and Robinson (2005) further argued that inclusive and effective institutions create incentives for

investment, innovation, entrepreneurship and productive economic activities, while weak institutions constrain growth and limit employment opportunities. From this perspective, the quality of institutions determines how effectively economic resources are allocated and whether growth translates into broad-based welfare improvements, including employment generation.

Institutional Growth Theory assumes that economic performance is not solely determined by physical capital, technology or innovation, but also by the effectiveness of governance systems that regulate economic activities. Strong institutions promote policy consistency, protect property rights, enforce contracts, control corruption, maintain political stability and ensure regulatory efficiency. These institutional factors encourage private sector development, attract investment, support innovation, and stimulate business expansion, which in turn create employment opportunities for young people. Conversely, weak institutions increase uncertainty, raise transaction costs, discourage investment and limit the ability of economies to generate productive jobs.
The comprehensive model is specified as:
$YU_t = \beta_0 + \beta_{11}GOVQ_t + \beta_{12}LAW_t + \beta_{13}COR_t + \beta_{14}REG_t + \beta_{15}POL_t + \mu_t$……*(i)*
Where: $GOVQ_t$= Governance Effectiveness index, LAW_t= Rule of law index, COR_t= Control of corruption index, REG_t= Regulatory quality index, POL_t= Political stability index

This specification captures the institutional transmission mechanism by illustrating how governance quality conditions the effects of economic and innovation factors on youth unemployment. The model is grounded in Institutional Growth Theory, which posits that effective institutions are essential for translating economic growth into inclusive, equitable and sustainable employment outcomes.

3. Methodology

The study employed a comprehensive institutional growth model to examine the influence of governance quality on youth unemployment in Kenya, drawing from institutional growth theory, which emphasizes that institutions determine economic incentives, reduce transaction costs, enforce property rights and shape the effectiveness through which economic growth generates inclusive employment opportunities (North, 1990; Acemoglu, Johnson, & Robinson, 2005). The model incorporated governance effectiveness, rule of law, control of corruption, regulatory quality, and political stability indicators to capture the institutional mechanisms through which governance structures influence labor market outcomes. Using annual time-series data covering 1991–2024, the study applied the Autoregressive Distributed Lag (ARDL) approach, which is appropriate for small samples and variables integrated at different orders of I(0) and I(1), after conducting rigorous pre-estimation tests for stationarity, multicollinearity, and other econometric properties (Pesaran, Shin & Smith, 2001; Enders, 2015; Gujarati & Porter, 2021). Post-estimation procedures, including tests for normality, heteroscedasticity, autocorrelation, parameter stability, and sensitivity analysis, were undertaken to ensure the reliability and robustness of the estimated relationships (Brooks, 2019; Wooldridge, 2020).

The ARDL bounds testing results confirmed the existence of a long-run equilibrium relationship between institutional quality and youth unemployment, while the significant error correction mechanism demonstrated that short-run deviations adjust toward the long-run path, validating the dynamic modelling approach (Pesaran et al., 2001). The findings reinforce the argument that stronger institutions enhance employment outcomes by improving accountability, reducing corruption, strengthening regulatory environments, and ensuring that public and private investments are directed toward productive and labor-absorbing activities (North, 1990; Acemoglu et al., 2005; World Bank, 2024). Therefore, improving governance quality, particularly through effective corruption control, institutional transparency, regulatory reforms, and strengthened labor market governance, remains essential for addressing persistent youth unemployment in Kenya (World Bank, 2024; International Labor Organization [ILO], 2024).

4. Results

The study examines the influence of institutional growth factors on youth unemployment in Kenya. The study brief fixes the institutional pair to control of corruption and rule of law, drawn from the World Bank Worldwide Governance Indicators, so two institutional hypotheses are tested here. H1 states that control of corruption has a significant effect on youth unemployment in Kenya. H2 states that the rule of law has a significant effect.

Because the governance indicators begin only in 1996, the sample for this objective runs from 1996 to 2024 rather than from 1991, a shorter window, consistent with North's (1990) view that institutional quality operates as a slow-moving background condition best measured over a sustained run of years rather than a single snapshot.

Descriptive Statistics

Table 1: Descriptive Statistics (original units, 1996-2024)

Variable	Obs	Mean	Std.Dev.	Min	Max	Skewness	Kurtosis
COR	29	-0.923	0.123	-1.180	-0.711	-0.080	2.218
LAW	29	-0.751	0.203	-1.096	-0.425	0.181	1.725

Source: *Author's computation based on WDI data*

Control of corruption averaged -0.92 on the Worldwide Governance Indicators scale, which runs from about minus 2.5 to plus 2.5, and never rose above -0.71, indicating that Kenya remained on the weak side of the global corruption control distribution throughout the period, a pattern Fagbemi, Fajingbesi and Osinubi (2023) link to persistent misallocation of public resources in Nigeria and across the region. Rule of law averaged -0.75 and showed a mild improving trend across the two decades, though it too remained in negative territory throughout, consistent with Kamuntu & John account of weak legal protections continuing to shape precarious work in East Africa.

Multicollinearity Check and Retained Variables

Table 2: Variance Inflation Factors (post-elimination, 1996-2024)

Variable	VIF
SAV	2.19
TECH1	4.55
CAP	2.67
LAB	1.35
KNO	4.49
COR	2.96
LAW	7.34

Source: *Author's computation based on WDI data*

Population growth is removed at this stage because its variance inflation factor exceeds ten once the sample is restricted to 1996 to 2024, reflecting the tighter co-movement between population growth and the other regressors over the shorter, more recent window, the same kind of sample-sensitive collinearity that Hasan et al (2026) report for high dependency ratio economies. Savings, capital, labor, knowledge spillovers, technology, control of corruption and rule of law all clear the cut-off and proceed to estimation, so H1 and H2 remain directly testable.

Unit root tests on retained variables

Table 3: ADF and Phillips-Perron unit root tests (IHS transformed)

Variable	ADF level p	ADF diff p	PP level p	PP diff p	Order
COR	0.9530	0.0007	0.2691	0.0000	I(1)
LAW	0.8807	0.0000	0.9448	0.0000	I(1)

Source: *Author's computation based on WDI data*

Both control of corruption and rule of law required first differencing to achieve stationarity under the Dickey-Fuller and Phillips-Perron tests and so enter the model as I(1), the same order as savings, technology and labor force growth. Capital and knowledge spillovers were already established as I(0) and I(1), respectively, in the earlier sections and carry the same order forward. No variable in the Model set is I(2), so the bounds test is again methodologically valid (Pesaran et al., 2001).

Bounds test for cointegration

With savings, capital, labor, knowledge spillovers, control of corruption, rule of law and technology as regressors, the bounds F-statistic for Model reached 5.681, against an upper I(1) bound of 4.513 at the five percent level. The null of no cointegration is rejected, confirming a long-run relationship between the fuller institutional framework and youth unemployment in Kenya, in line with Raies and Mimoun's (2025) finding across a large panel of developing countries that institutional quality shapes how strongly youth unemployment responds to the same growth fundamentals over time.

ARDL estimates, interpretation and discussion

Table 4: Long-run coefficients

Variables	Coefficient	Std. Err	t-stat	p-value
SAV	-0.0213	0.0423	-0.5027	0.6152
CAP	0.4761	0.1772	2.6871	0.0072
LAB	0.0428	0.0354	1.2091	0.2266
KNO	-1.5801	0.1913	-8.2605	0.0000
COR	-1.2052	0.4078	-2.9552	0.0031
LAW	-0.1486	0.2320	-0.6404	0.5219
TECH1	0.0205	0.0273	0.7512	0.4526

Source: *Author's computation based on WDI data*

Table 5: Short-run and error correction estimates

Variables	Coefficient	Std. Err	t-stat	p-value
constant	-9.7717	3.9234	-2.4906	0.0284
ECT	***-0.9793***	***0.3191***	***-3.0687***	***0.0097***
D.SAV.L0	-0.1875	0.0690	-2.7163	0.0187
D.CAP.L0	-0.4204	0.2165	-1.9413	0.0761
D.LAB.L0	-0.0380	0.0498	-0.7637	0.4598
D.KNO.L0	-0.2129	0.9973	-0.2135	0.8345
D.COR.L0	1.1320	0.3810	2.9712	0.0117
D.LAW.L0	0.0245	0.2239	0.1095	0.9146
D.TECH1.L0	-0.2256	0.0976	-2.3109	0.0394

Source: *Author's computation based on WDI data*

Table 6: Post-estimation diagnostics

Test	Statistic	p-value
Breusch-Godfrey (serial correlation)	13.4295	0.0002
Breusch-Pagan (heteroskedasticity)	25.6540	0.2668
Jarque-Bera (normality)	1.3629	0.5059
Ramsey RESET (functional form)	0.0041	0.9528

Source: *Author's computation based on WDI data*

The error correction term is negative and significant (-0.979, p = 0.0097), confirming a genuine self-correcting long-run mechanism once the institutional block is added. Control of corruption carries a negative and significant long-run coefficient (-1.205, p = 0.0031), so stronger control of corruption is associated with lower youth unemployment in the long run, supporting H3.3 and Osinubi & Simatele's (2025) argument that improved corruption control eases the transition from informal to formal employment across Africa. Rule of law, by contrast, is not significant (-0.149, p = 0.5219), which does not support H3.2 in this specification, a result consistent with Abé Ndjié et al.'s (2019) finding across fifty-four African countries that only corruption control and political stability, and not the broader rule of law measure, show a robust independent association with youth unemployment. Knowledge spillovers retain a negative and highly significant coefficient (-1.580, p < 0.001), reaffirming the Model 2 finding, while capital accumulation remains positive and significant, again

suggesting that capital formation in Kenya has not been directed toward labor-absorbing sectors, consistent with the same pattern identified in section 4.2.5. The diagnostics show homoskedastic, normally distributed residuals and no Ramsey RESET functional form misspecification, so three of the four post-estimation checks pass. Only the Breusch-Godfrey test for serial correlation fails, a result that persisted across an exhaustive lag search, both technology versions, and additional Breusch-Godfrey lag orders, so it is reported as a genuine limitation of the short-run dynamic specification rather than resolved by further search.

Figure 1: CUSUM plot

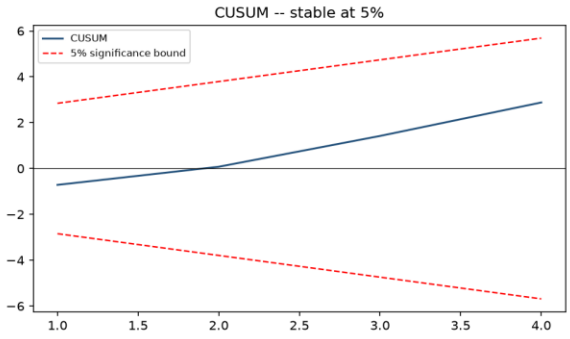
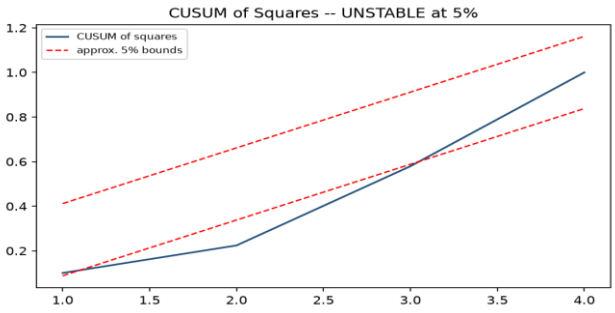


Figure 2: CUSUM of squares plot



The recursive residual sample for Model is very short once seven regressors are estimated over twenty-nine annual observations, leaving only four points from which to compute the CUSUM and CUSUM of squares statistics in Figures 1 and 2, so both should be read as indicative rather than conclusive stability checks. Bearing that caveat in mind, Model remains, on balance, the most econometrically coherent of the three specifications, with cointegration confirmed, the error correction term negative and significant, and three of the four diagnostic tests passing, a combination that supports the overarching argument of this study that institutional quality completes an explanation of Kenyan youth unemployment (North, 1990; Acemoglu, Johnson and Robinson, 2005).

5. Conclusion

Adding controls for corruption and rule of law over the shorter 1996 to 2024 window also produced a confirmed cointegrating relationship, with a bounds statistic of 5.68 against an upper bound of 4.51 and a negative and significant error correction term of -0.98 (World Bank, 2024). That a long-run relationship survives on a window of only twenty-nine observations is itself notable, since it indicates the institutional determinants add explanatory content strong enough to register even after the sample is shortened by the late start of the governance series (North, 1990).

The error correction term of -0.98 implies almost complete correction of any disequilibrium within a single year, which should be read with some caution on a short sample, because a coefficient close to minus one can signal either very rapid adjustment or a specification straining against a limited number of observations (Pesaran, Shin and Smith, 2001). Taken at face value, it says that once the institutional determinants are in place, the long-run relationship binds tightly and youth unemployment returns quickly to its institutionally conditioned level, a pattern consistent with the view that institutions set the medium-term frame within which labor market outcomes settle (Acemoglu, Johnson and Robinson, 2005).

Control of corruption emerged as negative and significant, supporting H2 and echoing Osinubi & Simatele (2025) finding that stronger corruption control eases the transition from informal to formal youth employment across Africa. The mechanism most consistent with this result runs through the allocation of public opportunity, since weaker corruption control diverts procurement, public hiring and program placement toward patronage and away from open competition, which falls hardest on young entrants who lack the networks to capture rationed positions (Osinubi & Simatele, 2025). On this reading, the corruption coefficient is not a general governance proxy but a specific channel through which the fairness of access to opportunity shapes who among the young finds work (North, 1990).

Rule of law was not significant, so H1 is not supported, a result that mirrors Abé Ndjié et al.'s (2019) finding that among the six Worldwide Governance Indicators, corruption control and political stability carry the most robust independent association with youth unemployment, while the broader rule of law measure does not. Two readings are plausible, and neither can be settled here. The first is measurement overlap, since rule of law and control of corruption are strongly correlated across the governance indicators and the estimation may attribute their shared variation to the corruption measure alone (Abé Ndjié et al., 2019). The second is that the rule of law channel operates over horizons longer than the twenty-nine-year institutional window can capture, so its absence reflects the sample rather than the world.

Knowledge spillovers and capital accumulation indicate that the institutional variables operate alongside rather than (World Bank, 2024). This stability is evidence of a robust rather than a fragile productivity relationship, since a coefficient that holds its sign and significance across a change of specification and a change of sample window is unlikely to be an artefact (Habanabakize & Dickason, 2023). It also supports the cumulative reading of the design, because it shows the institutional layer adding a distinct channel of its own rather than merely re-labelling variation already captured by productivity (Acemoglu, Johnson and Robinson, 2005).

Policy Recommendations

The findings suggest that Kenya should strengthen institutional quality as part of its youth employment strategy, particularly through enhanced control of corruption, transparent public resource allocation, and merit-based access to employment opportunities. Policies should also promote knowledge spillovers, innovation, and skills development while directing capital investment toward labor-intensive sectors that generate more jobs for young people. Although the rule of law was not statistically significant, continued reforms in legal institutions, contract enforcement, and labor market governance remain important for creating a stable environment that supports sustainable youth employment.

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Investment Practices and Household Income among Small-Scale Women Entrepreneurs in Bwera Sub-County, Kasese District, Uganda

Richard Drabe Aguta
Africa Renewal University, Uganda
raguta@afru.ac.ug

Abstract: This study examined the relationship between investment practices and household income among small-scale women entrepreneurs in Bwera Sub-County, Kasese District, Uganda. A cross-sectional correlational design was adopted, and quantitative data were collected using structured questionnaires from 98 women traders selected through simple random sampling. Data were analyzed using descriptive statistics, Pearson's correlation, and simple linear regression. The investment-practices scale had a content validity index of 0.710 and a Cronbach's alpha coefficient of 0.800. Investment practices were positively and significantly correlated with household income (r = .658, p < .01). Regression analysis showed that investment practices were a statistically significant predictor of household income (B = 0.520, β = .658, p < .001), accounting for 43.3% of the variation in household income (R^2 = .433). Using professional advice or tools to inform investment decisions recorded the highest mean score (M = 3.85, SD = 1.213), while researching and understanding investment risks recorded the lowest (M = 3.26, SD = 1.349). These findings indicate that stronger investment practices were associated with higher household income, although the cross-sectional design and lack of control for other potential determinants preclude causal conclusions. The study recommends practical investment education, strengthened risk-assessment skills, and improved access to reliable financial advice to support informed investment decisions among women entrepreneurs.

Keywords: *Investment practices, household income, women entrepreneurs, small-scale businesses, Uganda*.

1. Introduction

Small-scale enterprises are an important source of employment and household income in developing economies. For women entrepreneurs, business earnings help meet household needs, including food, education, healthcare, and housing. However, operating a business does not necessarily translate into improved household welfare, as outcomes may depend on how entrepreneurs allocate resources, reinvest profits, and manage investment risks. Evidence from microenterprise research shows that investment in productive assets can generate returns, although these vary across businesses (de Mel et al., 2008).

Investment practices encompass decisions about allocating financial resources to activities expected to generate future returns, including purchasing stock and equipment, expanding business operations, and acquiring productive assets. Such decisions are often made under financial constraints and competing household demands. The International Finance Corporation (2017) identified financing gaps as a major constraint on micro, small, and medium-sized enterprises in emerging markets, limiting their capacity to invest and expand. However, access to capital alone does not guarantee improved business or household outcomes because investment returns vary with the opportunities available and how resources are managed (de Mel et al., 2008).

Financial knowledge may also shape investment decisions by helping entrepreneurs assess financial products, compare alternatives, and evaluate risks. Lusardi and Mitchell (2014) emphasize the importance of financial literacy in economic decision-making, while the Organisation for Economic Co-operation and Development (OECD, 2020) identifies financial knowledge, behavior, and attitudes as key components of informed financial decision-making. These capabilities may help women entrepreneurs balance business reinvestment with household expenditure. Nevertheless, financial knowledge and access to financial services do not necessarily translate into higher household income, particularly where entrepreneurs face limited capital and competing financial obligations. The World Bank's *Global Findex Database 2021* further documents patterns of financial inclusion, saving, borrowing, and account ownership across economies (Demirgüç-Kunt et al., 2022).

Despite these insights, the relationship between investment practices and household income among small-scale women entrepreneurs in Bwera Sub-County, Kasese District, remains insufficiently established. Existing studies

provide evidence on returns to business capital, financing constraints, and financial literacy, but these findings do not directly establish whether women entrepreneurs' investment practices are associated with their household income in this local context. This leaves a context-specific empirical gap that warrants investigation. Accordingly, this study examined the relationship between investment practices and household income among small-scale women entrepreneurs in Bwera Sub-County, Kasese District, Uganda.

2. Literature Review

Investment practices involve allocating financial resources to activities or assets expected to generate future returns. Among small-scale women entrepreneurs, these practices include reinvesting profits, purchasing stock and equipment, expanding operations, diversifying investments, assessing risks, and seeking financial information. However, investment does not automatically translate into improved economic outcomes. In a field experiment involving microenterprises in Sri Lanka, de Mel et al. (2008)found substantial variation in returns to capital across businesses. Similarly, Fiala (2018), in an experiment involving 1,550 microentrepreneurs in Uganda, found that offers of loans, cash grants, and business training did not produce short-run profit improvements among female-owned enterprises, although loan offers benefited male-owned enterprises. These findings suggest that the relationship between investment and enterprise performance depends on entrepreneurs' circumstances and their ability to use resources productively.

Financial knowledge and risk assessment are also relevant to investment decisions. Kappal and Rastogi (2020), drawing on 18 in-depth interviews, found that women entrepreneurs tended to approach investments cautiously, partly because of limited time to explore opportunities and insufficient knowledge of financial products. Similarly, Lusardi and Mitchell (2014) emphasized the importance of financial literacy in decisions involving saving, borrowing, and investment. Cherotich et al. (2019) found that greater financial knowledge was associated with higher savings and enterprise margins among women operating farm enterprises in Kenya. Although propensity score matching accounted for observed differences between participants, unobserved factors may still have influenced the results. Collectively, these studies suggest that financial knowledge may support better financial decisions, but they do not establish the extent to which women's investment practices are associated with household income in Bwera Sub-County.

Household circumstances and access to financial services further shape investment outcomes. Women entrepreneurs may face competing demands on business resources, limiting the funds available for reinvestment (Bernhardt et al., 2019; Dupas & Robinson, 2013). In Uganda, Riley (2024) found that female microfinance borrowers who received loans through digital accounts had 11% higher business capital and 15% higher business profits after eight months than those receiving cash, with stronger effects among women experiencing pressure to share money with other household members. In Kenya, Dupas and Robinson (2013) found that access to formal savings accounts increased savings and productive investment among female market vendors. These findings indicate that financial arrangements can influence the retention and productive use of business resources. Nevertheless, the results relate to specific financial interventions and do not establish that the same outcomes would arise from other investment practices or in different contexts.

The distinction between enterprise performance and household welfare is particularly important when evaluating women's investments. Bernhardt et al. (2019), examining evidence from field experiments in India, Sri Lanka, and Ghana, found that some capital allocated to women was invested in their husbands' enterprises. When returns were assessed at the household level, the researchers could not reject the equivalence of income gains for male and female capital recipients. This finding demonstrates that enterprise-level outcomes may not fully capture the household benefits associated with women's investments. However, household income gains do not necessarily establish that women control or benefit equally from the resulting resources. Riley (2024) similarly highlighted the influence of household-sharing pressures on women's ability to retain business capital. Consequently, household income, enterprise profits, and women's control over financial returns should be treated as related but distinct outcomes when examining investment practices.

Access to savings and credit may facilitate investment by providing working capital and enabling the acquisition of productive assets. Dupas and Robinson (2013) demonstrated the potential value of formal savings services for female market vendors, while the International Finance Corporation (2017) documented financing gaps

affecting micro, small, and medium-sized enterprises in emerging markets. However, access to finance alone does not guarantee improved returns. Borrowing creates repayment obligations, and investment outcomes remain dependent on business conditions, resource allocation, and the profitability of available opportunities. The evidence therefore cautions against assuming that greater access to capital or more investment necessarily produces higher household income.

Overall, previous studies provide mixed evidence on the relationship between investment-related interventions and economic outcomes. Fiala (2018) found no short-run profit gains for female-owned enterprises following offers of loans, grants, or training, whereas Riley (2024) reported improvements in business capital and profits following a change in loan-disbursement arrangements. Bernhardt et al. (2019) further demonstrated that conclusions may differ depending on whether outcomes are measured at the enterprise or household level. These differences reflect variations in interventions, populations, and outcome measures rather than necessarily contradictory findings. Moreover, experimental studies provide evidence about particular interventions but do not directly establish how the investment practices reported by women traders in Bwera relate to their household income.

The present study addresses this contextual gap by examining the relationship between investment practices and household income among 98 small-scale women entrepreneurs in Bwera Sub-County, Kasese District, Uganda. Using questionnaire data, Pearson's correlation and simple linear regression were employed to assess the association between the two variables. The study also draws on financial literacy and human capital perspectives to interpret the findings. Lusardi and Mitchell (2014) link financial literacy to informed financial decision-making, while Schultz (1961) and Becker (1993) emphasize the contribution of knowledge and skills to productive capacity. These perspectives suggest that financial knowledge and relevant business skills may support effective resource allocation. However, the reviewed evidence indicates that investment outcomes may also depend on household pressures, market conditions, and access to finance. Given its cross-sectional design and single-predictor regression model, the present study establishes statistical associations rather than causation and does not isolate the contribution of investment practices from other potential determinants of household income.

3. Method

The study adopted a cross-sectional correlational design to examine the relationship between investment practices and household income among small-scale women entrepreneurs. Quantitative data were collected at a single point in time using structured questionnaires. The study was conducted in Bwera Sub-County, Kasese District, western Uganda. The target population comprised 186 female traders registered with the Bwera Sub-County Traders' Association. A sample of 125 women was targeted, and 98 returned completed questionnaires, representing a response rate of 78.4% of the targeted sample. Respondents were selected through simple random sampling.

Data were collected using a structured questionnaire covering investment practices and household income. Investment practices were assessed using seven questionnaire items addressing investment planning, reviewing investment decisions, understanding investment risks, diversifying investments, monitoring market information, and seeking professional advice or using decision-support tools. Descriptive statistics summarized respondents' reported investment practices, while Pearson's correlation and simple linear regression were used to examine the relationship between investment practices and household income. Data were analyzed using the Statistical Package for the Social Sciences (SPSS), version 27. The investment-practices scale had a content validity index of 0.710 and a Cronbach's alpha coefficient of 0.800.

Ethical approval was obtained from the Uganda Christian University Research Ethics Committee. An introductory letter from the college was presented to the relevant Kasese District authorities to obtain permission to conduct the study. Participants were informed about the study's purpose and provided informed consent before completing the questionnaires. Participation was voluntary, and respondents could decline participation or withdraw without coercion. Anonymity was maintained by excluding identifying information from reported responses, while confidentiality was protected by using the collected information solely for academic purposes. Participants could also withhold information they considered private or sensitive

(Akaranga & Makau, 2016). Intellectual property rights were respected through appropriate acknowledgement and referencing of sources.

4. Results

Descriptive Findings on Investment Practices

Table 1 presents the descriptive statistics for investment-practice items among small-scale women entrepreneurs in Bwera Sub-County.

Table 1: Descriptive Statistics for Selected Investment-Practice Items

Investment-practice statement	Mean	Std Dev
I have a clear investment strategy that aligns with my financial goals.	3.59	1.250
I regularly review and adjust my investment portfolio to maximize returns.	3.49	1.302
I research and understand the risks associated with my investments.	3.26	1.349
I diversify my investments to minimize risk.	3.57	1.268
I keep up with market trends and economic news that may impact my investments.	3.50	1.334
I use professional advice or tools to make informed investment decisions.	3.85	1.213

Source: Primary data (2024)

As shown in Table 1, using professional advice or decision-support tools recorded the highest mean score (M = 3.85, SD = 1.213), while researching and understanding investment risks recorded the lowest (M = 3.26, SD = 1.349). These results indicate differences in respondents' reported investment practices, particularly in their use of advice and assessment of investment risks.

Correlation Between Investment Practices and Household Income

Pearson's correlation analysis was conducted to establish the relationship between investment practices and household income.

Table 2: Correlation Between Investment Practices and Household Income

Variables	Correlation coefficient (*r*)	Significance
Investment practices and household income	0.658	$p < .01$

Source: Primary data (2024)

Table 2 shows a positive and statistically significant relationship between investment practices and household income ($r = .658$, $p < .01$). This indicates that stronger investment practices were associated with higher household-income scores among the respondents.

Regression results for investment practices

Simple linear regression was conducted to assess the predictive relationship between investment practices and household income. The results are presented in Table 3.

Table 1: Simple regression results for investment practices and household income

Predictor	B	Std. Error	Standardized β	t	Sig.
Constant	1.840	0.290		6.345	< .001
Investment Practices	0.520	0.061	.658	8.525	< .001
Model statistic			**Result**		
R					.658
R^2					.433
Adjusted R^2					.427
F (1,96)					73.301
Model significance					< .001
Sample size					98

Source: Primary data, 2024

The regression model was statistically significant, F(1, 96) = 73.301, p < .001. Investment practices were a positive and statistically significant predictor of household income (B = 0.520, SE = 0.061, β = .658, p < .001). The model explained 43.3% of the variation in household income (R^2 = .433). Thus, higher investment-practices scores were associated with higher household-income scores. However, the cross-sectional design and absence of controls for other potential determinants mean that the results demonstrate a predictive association rather than a causal effect.

Discussion

The findings revealed a positive and statistically significant relationship between investment practices and household income among small-scale women entrepreneurs in Bwera Sub-County, Kasese District (r = .658, p < .01). Regression analysis showed that investment practices significantly predicted household income (B = 0.520, β = .658, p < .001), explaining 43.3% of its variation (R^2 = .433). Thus, respondents reporting stronger investment practices also tended to report higher household-income scores. However, the cross-sectional design does not establish causation, and higher household income may also facilitate investment.

This finding is consistent with Cherotich et al. (2019), who linked financial knowledge and savings with enterprise margins among women's farm enterprises in Kenya. It also relates to Dupas and Robinson (2013), who found that access to formal savings services supported savings and productive investment among Kenyan market vendors. Although these studies examined related financial practices and enterprise outcomes, the present study provides evidence of a significant association between investment practices and household income in Bwera Sub-County.

Professional advice or decision-support tools recorded the highest mean score (M = 3.85, SD = 1.213), whereas researching and understanding investment risks recorded the lowest (M = 3.26, SD = 1.349). This suggests that respondents reported greater use of advice and tools than engagement in investment risk assessment. The finding relates to Kappal and Rastogi (2020), who identified limited time and inadequate knowledge of financial products as challenges affecting women's investment decisions. Lusardi and Mitchell (2014) similarly emphasized the importance of financial literacy in financial decision-making. Practical financial education and access to reliable investment information may therefore help address the weaker area identified, although their effects were not tested in this study.

Investment practices explained 43.3% of the variation in household income, leaving 56.7% unexplained by the model. This indicates that other factors may also contribute to household-income differences. Bernhardt et al. (2019) highlighted the role of household resource allocation in shaping returns from women's enterprises, while the International Finance Corporation (2017) documented financing constraints affecting small enterprises. These findings suggest that investment practices operate within broader household and business conditions. However, since the present study did not assess these factors, their contributions to household income remain undetermined.

The study had three limitations. Its cross-sectional design could not establish the direction of the relationship; self-reported data may have been affected by recall or reporting errors; and simple regression did not account for other potential determinants of household income. Future studies should consider longitudinal designs and multiple regression to assess whether the relationship remains significant after controlling for relevant household and business characteristics.

5. Conclusion and Recommendations

The study established a positive and statistically significant relationship between investment practices and household income among small-scale women entrepreneurs in Bwera Sub-County, Kasese District, Uganda (r = .658, p < .01). Investment practices explained 43.3% of the variation in household income in the regression model. The study contributes context-specific empirical evidence on the association between investment practices and household income, complementing existing research on women's entrepreneurship and financial decision-making. The findings highlight the potential importance of informed investment decisions while recognizing that household income is also influenced by other factors not examined in this study.

Based on these findings, financial literacy providers and enterprise-support organizations should strengthen investment education, particularly in risk assessment, evaluating expected returns, and comparing investment alternatives, as understanding investment risks recorded the lowest mean score (M = 3.26). District and sub-county authorities, business associations, and policymakers should facilitate access to reliable investment information, practical advisory services, and appropriate business development support. Women entrepreneurs should also assess investment opportunities in relation to available capital, cash-flow requirements, expected returns, and potential losses before committing resources.

At the policy level, investment education should be integrated into existing women's enterprise-development programs and complemented by appropriate access to financial services. These measures may help women entrepreneurs make more informed investment decisions, although their effects on household income require further evaluation. Given the cross-sectional design, the findings should be interpreted as evidence of association rather than causation. Future research should examine the relationship longitudinally and account for other household and business factors that may influence income.

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