Nilmini Herath
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15 September 2026

Workshop Selection Committee,
Workshop on Development Economics and Networks for Early-Career Researchers
National Bureau of Economic Research

Dear Selection Committee,

Please find on the following pages my application materials for this workshop, including:

1. A recent CV including completed PhD-level coursework subjects. Note that in the UK the coursework component of the PhD is called a Master of Research (MRes).

2. A motivation statement.

3. A current working paper to be presented, entitled "Cognitive constraints in survey recall: experimental evidence on social network elicitation in South Africa"

For a reference, please contact

Gharad Bryan
Associate Professor of Economics
London School of Economics
g.t.bryan@lse.ac.uk

I am currently tying up the final stages of my PhD at the LSE. Gharad is my lead PhD supervisor and has known me for many years.

While concluding my PhD, I began a new role as an Assistant Professor at Trinity College Dublin within the last month. My new colleagues are less able to speak to my abilities at this stage. However, if you require a reference from one of them please let me know and I will locate an appropriate contact for you.

All the best with the review process.

Kind regards,

Nilmini

Nilmini Herath

+44(0)7545492579 - nilmini.herath@gmail.com - UK citizen – nilminiherath.com

Summary

I am an **Assistant Professor in Economics at Trinity College Dublin**. My work as a development economist explores the impact of social networks on development outcomes in Sub-Saharan Africa. Applications include labour markets, health, ideological polarization and violent crime. **Before my PhD, I led the Research division of J-PAL Africa**, based in the University of Cape Town, where I developed expertise in running field RCTs, communicating research to policymakers/non-specialists, fostering research partnerships and leading research staff and projects.

Education

PhD Economics, LSE *2026 (expected)*
Advisors: Oriana Bandiera, Tim Besley, Gharad Bryan, Francesco Nava

MRes Economics (Distinction), LSE *2022*
PhD level courses completed: EC441 Microeconomics, EC442 Macroeconomics, EC443 Econometrics, MY561 Social Network Analysis, MA433 Mathematics of Networks, EC537 Microeconomic Theory for Research Students, EC535 Development Economics for Research Students.

MPA International Development (Distinction), LSE *2014*
M.Sc. Mathematics & the Foundations of Computer Science (taught component), Oxford *2007*
B.Sc. Mathematics with Business (First Class Honours), Queen Mary, University of London *2006*

Affiliations

- Affiliated Researcher, Southern Africa Labour and Development Research Unit, **University of Cape Town (UCT)**.
- Visiting Research Fellow, Vaccine Confidence Project, **London School of Hygiene and Tropical Medicine**.
- Affiliate, Data Science Institute, **London School of Economics & Political Science.**

Academic appointments and professional research experience

Assistant Professor in Economics *Aug 2026 - present*
Department of Economics, Trinity College Dublin

Research Fellow (part-time during PhD) *Nov 2021 – Jul 2023*
Department of Epidemiology and Population Health, London School of Hygiene and Tropical Medicine

- Conducted research for the Vaccine Confidence Project on evolving attitudes towards vaccinations in Sub-Saharan African countries in the wake of COVID-19. Communicated findings to policy actors incl. the Africa CDC, Covid Action, the FCDO through non-technical summaries, talks and working group facilitation.

Senior Research Manager (Head of Research), J-PAL Africa, University of Cape Town *Feb 2017 – Sep 2019*
Research Manager (Deputy Head of Research) *Mar 2016 – Feb 2017*

- Led J-PAL Africa's research division, working with leading development economists and under the guidance of J-PAL's scientific directors (Rachel Glennerster, Abhijit Banerjee and Tavneet Suri) on the implementation and uptake of over 30 full RCT & pilot projects. Topics included health, labour, cash and other grants, education and public service provision.
- Oversaw the hiring, training and line-management of over 400 staff members based at varied sites.
- Worked with Principal Investigators to improve research design, measurement and RCT execution.
- Fostered and managed partnerships with local/national government and large non-profit organisations, including South African Treasury, Presidency, and Dept of Labour, Zambian Dept of Education and many municipal governments.

Research Associate, J-PAL Africa, University of Cape Town *Jul 2015 – Feb 2016*

- Managed fieldwork and data analysis on an RCT evaluating the impact of providing transport subsidies to young work-seekers in Johannesburg, partnering with the municipal government (PIs: Abhijit Banerjee & Sandra Sequeira)

Research Manager to Oriana Bandiera and Greg Fischer, LSE *Nov 2012 – Sep 2013*

Teaching & consulting experience

Teaching Fellow, School of Public Policy, LSE *Sep 2024 – Present*

- Teaching small group classes in **econometrics** and academic mentoring of Master's level (MPA) students on PP455.
  Evaluations: 4.7/5, 4.7/5, 4.5/5, 4.7/5.
  Excellence in Education Award and Departmental Teaching Award.

Graduate Teaching Assistant, Department of Economics, LSE *Sep 2020 – Sep 2025*

- LSE's Department of Economics undergraduate **microeconomics** courses EC201 and EC2A1.
  Evaluations: 4.3-4.8/5.
  Departmental Teaching Awards x 4.
- LSE Summer School's **development economics** course SS-EC307.
  Evaluations: 4.8/5, 4.9/5.

Evaluating Social Programs, J-PAL Africa, University of Cape Town

- Taught several for policy professionals interested in RCT methods, drawn from the MIT Master's level course.

Supervision & Management of PhD students and Early Career Researchers:
Kathryn McDermott, Junior Research Fellow in Economics, University of Cape Town
Faith Masekesa, Postdoctoral Research Fellow in Economics, J-PAL Africa, University of Cape Town
Velenkosini Matsebula, Research Fellow in Economics, University of Cape Town

Development Economics Consulting (short term), various *Jan 2015 – Present*

- Consultant to DataDrive2030, a South African non-profit organization assessing learning in South African schools.
- Consultant to World Bank/AusAID study analysing data on access to antenatal health services in Papua New Guinea.
- Consultant to Africa!Ignite advising on monitoring and evaluation for a rural job creation programme in KwaZulu Natal.

Quantitative Risk Modelling Consulting, Credit Suisse, RBS and HSBC *Dec 2009 – Jan 2015*
Analyst, Deutsche Bank *Nov 2007 – Nov 2009*

Research

Publications and working papers

Age-Dependent Changes in Intuitive and Deliberative Cooperation in *Nature Scientific Reports* 13, 4457 (2023) - a lab-in-field RCT exploring cooperative behaviour over the lifecycle, with Elena Nava, Francesco Nava and Francesco Margoni.

[Case Study of an RCT] Helping young people in South Africa bridge the gap between intention and behaviour in their search for work – Chapter 10 of Leaving No One Behind: A companion volume to the OECD Development Co-operation Report 2018, *OECD Publishing*, Paris, with Martin Abel, Rulof Burger, Eliana Carranza & Patrizio Piraino.

Work-in-progress

Social Networks and Polarization: A Theoretical Framework - a sole-authored model of social learning processes under attentional biases / manipulations to explore impacts on ideological polarization.

Cognitive Constraints in Survey Recall: Experimental Evidence from Social Network Elicitation in South Africa with Raquel Caldeira and Patrizio Piraino.

"The role of trust in vaccine confidence: evidence from seven Sub-Saharan African countries" – a Bayesian Hierarchical analysis of longitudinal data with Alex De Figueiredo and Heidi Larson. Data collection in progress.

"The role of social identities in economics education" – a study of study patterns and attainment of economics undergraduate students with Dimitra Petropoulou and Ben Dahmen. Data analysis underway.

"RCT-based causal inference with network spillovers" – A survey of methods for the design and analysis of RCTs for researchers who wish to avoid or quantify network spillovers, with Sreevidya Ayyar.

"Making connections: exploring the impact of social and professional network assortativity on the labour market for South African youth" - RCT in South Africa, varying professional networks in a work experience programme. Pilot in progress.

Research-related output / training materials

RCT Design and Implementation, J-PAL Building Better Research Seminar

Surveying young work seekers in South Africa: tips from J-PAL Africa's Research Team, University of Cape Town's Southern Africa Labour and Development Research Unit (SALDRU)– with Emmanuel Bakirdjian and Wim Louw.

J-PAL Research Resources
Publicly available resources for designing and running RCTs: Surveyor Hiring and Training, Field Team Management, Survey Logistics, Measurement and Survey Design, with other senior J-PAL staff members.

Other research experience (not as co-author)

My J-PAL role involved working heavily on several studies published in top general and field Economics journals. See my website or search my name in google scholar.

Policy and public engagement

A very small selection: see nilminiherath/policy for a fuller list.

- Panelist, **Job Search and Hiring with Limited Information in South Africa** – J-PAL Webinar
- Panelist, **Experimenting for a Better Future: Drawing Policy Lessons from Randomised Evaluations** – J-PAL
- Co-lead, **Vaccine Confidence in Sub-Saharan Africa working group** with Africa CDC, research, policy and industry
- Policy report, **Trends in intent to accept a COVID-19 vaccine in Nigeria**, with Heidi Larson and Alex De Figuereido, Vaccine Confidence Project.
- Articles and blog posts: World Bank Development Impact, COVIDAction, Youth Employment Service, CityPress,

Grants & Awards

- EPSRC Studentship for M.Sc. at Oxford – full scholarship awarded on academic merit to two students per year.
- ESRC Studentship for MRes/PhD Economics at LSE.
- Excellence in Education Award, LSE School of Public Policy, 2025 for teaching Econometrics.
- Departmental Teaching Award, LSE: awarded in 5 consecutive years (2020-2025 inclusive).
- Vice-Chancellor's Excellence in Service Award, UCT, 2017 for advancing the quality of J-PAL Africa's research.

Total funding as PI or co-PI: USD 683,107. Funding of projects as co-PI or RM: USD 30million+.

- International Development Research Centre (IDRC) CAD 500,000.
- J-PAL Jobs and Opportunities Initiative USD 84,974.
- J-PAL Post Primary Education Initiative USD 25,000.
- J-PAL Long Term Impacts Initiative USD 10,000
- Agency Fund, USD 50,000.
- LSE Research Grants: STICERD GBP 5,000 (2022), GBP 5,000 (2023), H.E.R. GBP 5,000 (2023), GBP 5,000 (2025)
- International Growth Centre, GBP 20,000.

Conferences & Refereeing

- **Conferences & Presentations (incl. scheduled):**
  2026: Network Science and Economics, University of Luxembourg; Barcelona Summer Forum on Networks, Barcelona School of Economics; ThReD Theoretical Research in Development Economics, University of Geneva; Network Science and Economics, University of Miami, TIME-CEPR Development Economics, Trinity College Dublin.
  2025: THEBES, University College London; Venice Network Workshop, Ca' Foscari University of Venice, CSEF Networks and Development, University of Naples Federico II.
  2024 and earlier: NSF Network Science and Economics, University of Minnesota (2024); IFS-LSE-UCL Development Economics Workshop (2023); LSE SEN Club (2022), University of Cape Town (2017, 2021 and 2023); University of Witwatersrand (2017).
- **Refereeing:** Nature Medicine, Vaccine, Economica, J-PAL Research Resource Repository.
- **Grant reviews:** J-PAL Research Incubation Fund.

Languages & Technology

- English (Native Speaker), Spanish (Intermediate/B2), French & Sinhalese (Basic/A1), bits of many African languages.
- R, Stata, Matlab, LaTeX, SQL, TOAD, Optimal Design, Network Canvas, SurveyCTO, CSPro, Qualtrics, various APIs.

References

Please contact LSE faculty via econ.facultysupport@lse.ac.uk. They hold all my references on file and will reply quickly.

Oriana Bandiera	**Tim Besley**	**Gharad Bryan**	**Francesco Nava**	**Laura Poswell**
Professor	Professor	Associate Professor	Assistant Professor	Former Executive Director
LSE	LSE	LSE	LSE	J-PAL Africa
o.bandiera@lse.ac.uk	t.besley@lse.ac.uk	g.t.bryan@lse.ac.uk	f.nava@lse.ac.uk	laura@bindingconstraintslab.org

Nilmini Herath – Motivation Statement

I am a development economist who studies how social networks shape development outcomes using a combination of field experiments and formal graph-theoretic modelling. My obsession with this line of research emerged from two sources: (1) my experience conducting field research in Southern Africa as the head of J-PAL Africa's Research vertical, where I witnessed first-hand how social networks can affect people's decisions, opportunities and wellbeing and (2) a deep love of graph theory and the mathematics of networks, which helps to address the complexity of identification with network-related spillovers and interdependence.

By bringing early-career researchers together with the scholars defining the empirical frontier of network economics, the workshop would strengthen my ability to deliver this research agenda. In my day-to-day life at both LSE and Trinity College Dublin, I have ample exposure to development economists, but very few who combine traditional development economics methods with the study of networks. The three workshop leads are among the people I'd most love to talk to about my research, but very rarely get to meet. I would value the chance to (1) stress-test my work against a room of people who think about identification and measurement in networks as rigorously as I try to, (2) learn more about the best methods and tools in this research area and (3) receive guidance on how to position work at the intersection of networks and development for a broader audience, (4) form useful connections for ongoing support and collaboration.

The centerpiece of my research agenda is an experimental project in South Africa, partnering with a nonprofit running a nationwide work-experience programme with 150,000+ annual placements, building toward a 3,000 person RCT that will experimentally vary the professional network opportunities of entry-level workers. This approach is designed to overcome the identification barriers that have hindered causal inference of network effects on labour outcomes.

The working paper I would present at the workshop, "Cognitive Constraints in Survey Recall" (with Raquel Caldeira and Patrizio Piraino), is a direct product of this pipeline: a survey experiment showing that traditional network elicitation methods may systematically undercount network members and overstate their status for respondents with lower working-memory capacity. It is, in effect, the measurement groundwork for the larger RCT: before I can credibly estimate network effects on labour market outcomes, I need to know that I am measuring networks correctly in the first place. I would really appreciate help developing and formalizing the "so what?" part of the paper: to clarify the implications of the systematic measurement differences that we document in the paper, especially in light of the likely relationship between cognitive capacity and poverty.

Other work-in-progress explores the relationship between social networks and ideological polarization. I recently created a theoretical framework for DeGroot style modelling with attentional biases and manipulations. I am currently working on a field experiment applying its insights to gender-based violence attitudes among South African adolescent boys.

Thank you for considering my application.

Cognitive Constraints in Survey Recall: Experimental Evidence from Social Network Elicitation in South Africa

Latest version here

Raquel Caldeira* Nilmini Herath† Patrizio Piraino‡

September 2, 2026

Abstract

Development economics research frequently relies on survey questions that require respondents to recall complex information, from expenditures and health events to the set of people they turn to for financial support and information. Yet the cognitive demands of recall may vary systematically with respondents' working memory capacity, which may itself be constrained by poverty and scarcity. We examine this issue using a survey experiment on social network elicitation among 967 entry-level workers in South Africa. Respondents were randomly assigned to report their labour market networks using either a standard auditory enumerator-led survey or a visual software tool that restructures the recall process to reduce cognitive burden. The visual method produces networks that are 50 per cent larger, with 21 percentage points fewer employed contacts and 39 percentage points fewer contacts with tertiary education, suggesting that standard recall disproportionately captures more salient, higher-status ties. These differences are significantly larger among respondents with lower working memory capacity. Using a third survey condition designed to isolate mechanisms, we show that decomposing the recall task attenuates these differences, indicating that cognitive burden is an important driver of elicitation effects. Because cognitive capacity is correlated with poverty and other burdens, our findings suggest that recall-based survey measures may systematically reflect respondents' circumstances beyond the underlying phenomena they seek to measure, with important implications for empirical research targeting populations with cognitive scarcity.

We thank Janey Tietz for excellent research assistance. The field team whose hard work and creativity made this possible were Euan Chew, Claudia Dhludlu, Aman Haider, Rochelle Jacobs, Sarah Kopper, Wim Louw, Jessica Qvist and the J-PAL Africa team. Arth Depuri and the Social Networks Lab at J-PAL South Asia shared invaluable lessons learned on Aggregate Relational Data elicitation. For helpful comments we thank Sreevidya Ayyar, Oriana Bandiera, Gharad Bryan, Gabriel Leite-Mariante, Steve Pischke, Eleanor Power and Chris Udry. We thank the creators of Network Canvas for making their software open source. We gratefully acknowledge financial support from the J-PAL Jobs and Opportunities Initiative, the International Growth Centre, the International Development Research Centre, STICERD and the Agency Fund. All errors are our own.

*J-PAL Africa, University of Cape Town

†London School of Economics

‡University of Notre Dame

1 Introduction

Social and economic networks are often thought to play an important role in labor market outcomes, particularly in developing contexts where formal job search mechanisms are often weak.[1] Understanding how individuals form and maintain these networks is essential for further understanding of such 'network effects' and for designing effective employment interventions. However, measuring social networks accurately presents significant methodological challenges, as network elicitation requires respondents to recall and report complex relational information—a cognitively demanding task.

Despite growing recognition that poverty and scarcity consume mental "bandwidth"—the cognitive capacity needed for problem-solving, information retention, and attention management (Mullainathan and Shafir, 2013; Schilbach et al., 2016)—the implications for survey measurement remain underexplored. Poverty may directly impede cognitive function, as the stress of managing scarce resources creates cognitive load that diverts bandwidth from optimal decision-making. This bandwidth taxation has methodological implications across survey research: when working with populations experiencing poverty, the cognitive demands of questions matter considerably. Complex or lengthy questions may yield poor responses not because respondents lack knowledge, but because their bandwidth is depleted. This applies particularly to social network elicitation, where respondents must recall and count among connections in what is often a cognitively burdensome format.[2]

This paper examines systematic measurement error in labor market ego network data and investigates how cognitive capacity affects the accuracy of network reporting. Ego network data captures an individual's ("ego's") personal network by asking them to name their contacts ("alters") and describe those contacts' characteristics and relationships—without surveying the full population. If measured accurately, it can provide a feasible way to understand the role played by social and economic networks in development applications such as job referrals or information diffusion.[3]

We present results from a survey experiment conducted with 910 entry-level workers in Johannesburg, South Africa, in which respondents were randomly assigned to report their labor market networks using either visual or auditory elicitation methods. In the control (auditory) condition, respondents answered traditional survey questions about their networks in a standard interview format, requiring them to hold network information in working memory while answering questions about each contact sequentially. In the treatment (visual) condition, respondents used Network Canvas software, which allows them to see their network as they build it, with contacts represented as visual nodes that can be arranged spatially. This approach aims to reduce demands on working memory and make the elicitation process more intuitive.

We measured cognitive capacity using the Digit Span subtest from the Wechsler Adult

[1] Breza et al. (2019); Beaman (2011); Calvó-Armengol and Jackson (2004); Angrist (2014).

[2] See e.g. Birkett et al. (2021).

[3] Perry et al. (2018).

Intelligence Scale, where participants repeat sequences of numbers in forward and backward order at increasing levels of difficulty. This captures numerical working memory, which we hypothesized would moderate respondents' ability to engage with cognitively demanding survey tasks. We also collected subjective assessments of task difficulty from both respondents and enumerators, though these measures showed surprisingly weak correlations with objective cognitive performance, likely reflecting ceiling effects in self-reported comprehension.

Our findings reveal that cognitive skills significantly moderate measurement error in network reporting, with this relationship depending critically on survey modality. The visual elicitation method produced substantially larger reported networks—1.8 contacts larger on average, representing a 47% increase over the control group mean of 3.81 contacts. Crucially, this treatment effect varied systematically with cognitive ability. Respondents with lower cognitive skills exhibited substantial non-classical measurement error—their reports contained systematic biases rather than random noise—particularly when using auditory methods that impose higher cognitive demands. The interaction between visual treatment and digit recall performance was negative and significant, demonstrating that the treatment effect was largest for respondents with lower cognitive skills.

We also find striking compositional differences across elicitation methods. The visual treatment substantially decreased the reported share of employed contacts by 20.7 percentage points and the share with tertiary education by 30.1 percentage points, relative to control group means of 83.9% and 51.7% respectively. This suggests that auditory elicitation, which imposes higher cognitive demands, leads respondents to recall their most salient or memorable contacts first—those who disproportionately have higher status characteristics. Visual methods, by reducing cognitive burden, may capture a more complete picture that includes both high-status contacts and more typical connections.

These findings have important implications for network research in developing contexts, where cognitive heterogeneity may introduce systematic bias into standard survey instruments. Our results suggest that commonly used auditory survey methods may systematically undercount network connections for respondents with lower cognitive capacity, while simultaneously overestimating network quality. This has potentially serious consequences: researchers may be underestimating the role of networks for precisely those populations most vulnerable to labor market challenges, while also drawing biased inferences about the relationship between network characteristics and labor market outcomes. Visual elicitation methods appear to reduce this bias by lowering processing requirements, leading to more accurate network reports among lower-skilled respondents, though further research is needed to establish which method captures the construct of greatest policy relevance.

2 Survey Experiment Design

2.1 Sample and Recruitment

We conducted a survey experiment with 910 entry-level workers in Johannesburg, South Africa, recruited through street sampling in areas with high concentrations of retail and service sector employment. Respondents were eligible if they were aged 18-36, currently employed, and possessed less than one year of work experience.

The sample captures young workers from disadvantaged backgrounds in urban South Africa's entry-level labor market, a population that is a high priority for public policy due to persistently poor employment outcomes. Participants were predominantly Black African (95.6%), South African citizens (97.8%), and female (56.7%). Educational attainment was relatively high, with 71.1% having completed secondary education and 25.3% holding tertiary qualifications. Monthly earnings were concentrated in the R4,607-R9,999 range (approximately $276-$598), with 41.9% of participants reporting financial dependents.

2.2 Randomization Protocol

Respondents were randomly assigned at the individual level to one of two survey conditions using a computer-generated randomization protocol implemented at the point of survey administration. The unit of randomization was the individual respondent, with treatment assignment determined independently for each participant prior to beginning the network elicitation module.

2.3 Treatment Arms

The experiment compared two methods of eliciting labor market network data:

Control (Auditory) Condition: Respondents in the control group answered traditional survey questions about their labor market networks in a standard interview format. Questions were asked verbally by enumerators and responses recorded in a conventional survey instrument. This approach requires respondents to hold network information in working memory while answering a series of questions about each contact in sequence, following the grid-like structure typical of network surveys.

Treatment (Visual) Condition: Respondents in the treatment group used the Network Canvas software, a specialized tool designed to reduce the cognitive burden of network elicitation through visual representations. The software allows respondents to see their network as they build it, with contacts represented as visual nodes that can be arranged spatially. This approach was specifically designed to address survey fatigue associated with the repetitive, grid-like structure of traditional network surveys. By providing immediate visual feedback and allowing respondents to manipulate their network spatially, the tool aims to reduce demands on working memory and make the elicitation process more intuitive.

Both conditions elicited identical information about respondents' labor market networks, including the number of contacts, their characteristics (employment status, education level, income), and the nature of relationships. The key experimental variation was in the modality of elicitation—auditory processing with sequential recall versus visual processing with simultaneous network construction.

2.4 Sample Characteristics and Balance

The majority of participants (55.4%) earned monthly salaries between R4,607 and R9,999 (equivalent to $276 to $598). Nearly all respondents identified as Black African (95.5%) and held South African citizenship (97.8%). Women comprised 58.0% of the sample, and 42.3% of participants reported supporting financial dependents. In terms of educational attainment, most participants had completed secondary education (69.6%), while just over one-quarter held tertiary qualifications (26.6%).

Table 1 confirms that randomization achieved balance on baseline characteristics. We find no significant differences between treatment arms in demographics, cognitive ability, or socioeconomic characteristics (all p-values > 0.10).

Table 1: Baseline Characteristics by Treatment Status

	Sample Mean			
Variable	Total	Auditory	Visual	p-value
Observations	910	434	476	
Age	24.97	25.11	24.85	0.386
Digit recall %	0.63	0.64	0.61	0.222
Gender (%)				0.515
Male	42.0	42.7	41.3	
Female	56.7	55.4	57.9	
Other	1.1	1.4	0.8	
Education level (%)				0.879
Less than secondary education	3.6	4.1	3.2	
Completed secondary education	71.1	71.0	71.2	
Completed tertiary diploma	17.6	17.3	17.9	
Completed tertiary bachelor plus	7.7	7.6	7.8	
Population group (%)				0.254
African/Black	95.6	94.7	96.4	
Coloured	3.6	4.2	3.2	
Indian/Asian	0.3	0.2	0.4	
White	0.3	0.7	0.0	
Prefer not to answer	0.1	0.2	0.0	
Nationality (%)				0.652
South African	97.8	97.4	98.1	
Other	2.2	2.6	1.9	
Monthly earnings (%)				0.827
$\leq$ R4,606	25.2	25.2	25.3	
R4,607 – R9,999 (combined)	48.6	48.8	48.4	
R4,607 – R6,500	4.8	3.7	5.7	
R6,501 – R10,000	3.5	4.0	3.2	
R10,000 – R19,999	12.2	13.1	11.4	
R20,000 – R29,999	2.5	2.6	2.5	
R30,000 – R49,999	0.9	0.9	0.8	
R50,000 – R69,999	0.1	0.0	0.2	
Don't know	2.1	1.6	2.5	

Notes: Table reports sample means for continuous variables and percentages for categorical variables. p-values correspond to tests of equality between treatment and control groups (two-sided t-tests for continuous variables and χ^2 tests for categorical variables).

2.5 Cognitive Capacity Measurement

To examine heterogeneous treatment effects by cognitive ability, we measured working memory capacity using the Digit Span subtest from the Wechsler Adult Intelligence Scale. Participants repeated sequences of numbers in forward and backward order at increasing levels of difficulty. This captures numerical working memory, which we hypothesized would moderate respondents' ability to engage with cognitively demanding survey tasks. We administered this test to all participants regardless of treatment assignment, with the order of cognitive testing and network elicitation randomized to avoid order effects.

We also collected subjective assessments of task difficulty from both respondents and enumerators. Respondents rated ease of answering, effort required, and question comprehensibility on 5-point Likert scales. Enumerators rated their perception of each participant's comprehension on a similar scale. These measures allow us to examine whether objective and subjective indicators of cognitive load align and whether they predict measurement quality differently.

2.6 Outcome Measures

Our primary outcomes of interest are measures of reported network size and composition derived from the network elicitation exercise. Specifically, we examine: (1) total network size (number of named contacts), (2) percentage of contacts who are employed, and (3) percentage of contacts with tertiary education. These measures capture both the extensive margin (how many contacts are reported) and the intensive margin (characteristics of reported contacts).

To validate our network measures, we also collected data on whether respondents obtained their current job through their network—either through direct referral or by hearing about the opening through a contact. This provides an external criterion against which to assess the predictive validity of networks elicited through different methods.

3 Cognitive Skills Measurement

Research has established that poverty and scarcity consume mental "bandwidth", the cognitive capacity and executive control needed for problem-solving, information retention, and attention management (Schilbach et al., 2016). Studies demonstrate that poverty directly impedes cognitive function (Mani et al., 2013), as the stress of managing scarce resources creates cognitive load that diverts bandwidth from optimal decision-making (Shah et al., 2012; Lichand & Mani, 2020). Recent meta-analyses confirm these effects persist across contexts (De Almeida et al., 2024).

This bandwidth taxation has methodological implications across survey research - when working with populations experiencing poverty, the cognitive demands of questions matter considerably. Complex or lengthy questions may yield poor responses not because respondents lack knowledge, but because their bandwidth is depleted. This applies across

myriad types of studies, including social network elicitation where respondents must recall and report connections, often in a cognitively burdensome form.

Despite the established relationship between cognitive capacity and survey response quality, these factors are not often measured in methodological studies. We include both objective and subjective measures of cognitive load to examine whether they help explain variation in how respondents engage with different elicitation methods.

3.1 Digit Span Measure

We measured cognitive capacity using the Digit Span subtest from the Wechsler Adult Intelligence Scale (Lichtenberger & Kaufman, 2012), where participants repeat sequences of numbers in forward and backward order at increasing levels of difficulty. This captures numerical working memory, which may affect respondents' ability to engage with survey tasks requiring unaided recall and mental organization.

3.2 Subjective Measures

To complement our objective measure of cognitive capacity, we collected subjective assessments of task difficulty from both respondents and enumerators.

Respondents rated ease of answering, effort required, and question comprehensibility on 5-point Likert scales (1 = very easy/minimal effort/made complete sense, 5 = very difficult/substantial effort/did not make sense).

Enumerators rated their perception of each participant's comprehension on a 5-point scale (1 = poor, 5 = excellent).

3.3 Correlation Between Measures

Table 2 shows surprisingly weak correlations between objective cognitive performance and subjective difficulty measures. Despite theoretical reasons to expect cognitive capacity would predict task difficulty, digit recall correlates only weakly with self-reported ease (r = -0.12), sense-making (r = -0.10), and effort (r = -0.12). These weak relationships likely reflect ceiling effects: most respondents rated their comprehension highly regardless of actual cognitive performance. Similarly, enumerator assessments show negligible correlation with digit recall (r = 0.02 and -0.02), though they are highly correlated with each other (r = 0.86).

Table 2: Correlation Matrix for Cognitive and Communication Measures

	% Correct Digit Recall	Self-Reported Survey Easy	Self-Reported Survey Sense	Self-Reported Cog. Effort	Enumerator Eval. Comprh. Level	Enumerator Eval. Comm. Level
% Correct Digit Recall	1.000	−0.117	−0.102	−0.119	0.018	−0.019
Self-Reported Survey Easy	−0.117	1.000	−0.309	0.487	−0.370	−0.380
Self-Reported Survey Sense	−0.102	−0.309	1.000	−0.146	0.321	0.353
Self-Reported Cog. Effort	−0.119	0.487	−0.146	1.000	−0.179	−0.170
Enumerator Eval. Comprh. Level	0.018	−0.370	0.321	−0.179	1.000	0.855
Enumerator Eval. Comm. Level	−0.019	−0.380	0.353	−0.170	0.855	1.000

These findings underscore the importance of objective cognitive testing in survey research: subjective assessments and enumerator observations fail to capture meaningful variation in cognitive capacity that, as we show below, significantly moderates how respondents engage with different elicitation methods.

4 Results

4.1 Network Size

We estimate the effect of a visual network elicitation tool on network outcomes using the following specification:

$$y_i = \beta_0 + \beta_1 \text{Visual}_i + \boldsymbol{\beta}_2^\top \mathbf{Cog}_i + \boldsymbol{\beta}_3^\top (\text{Visual}_i \times \mathbf{Cog}_i) + \boldsymbol{\gamma}^\top \mathbf{X}_i + \varepsilon_i, \tag{1}$$

Where y_i denotes the network outcome of interest for individual i, including total network size, the share of employed contacts, or the share of contacts with tertiary education. Visual_i is an indicator equal to one if individual i is assigned to the visual network elicitation treatment and zero otherwise. $\mathbf{Cog}_i$ is a vector of cognitive measures, including performance on a digit recall task, cognitive reflection (ease, sense, and effort components), and comprehension level. $\mathbf{X}_i$ is a vector of pre-treatment covariates including population group, nationality, education, support dependency status, gender, and current work experience.

Equation (1) nests all main specifications reported in the paper. Table 3 reports estimates for total network size under alternative restrictions on $\mathbf{Cog}_i$ and interaction terms. Table **??** applies the baseline specification to multiple network composition outcomes, while Table **??** reports heterogeneous treatment effects by cognitive performance through interactions between the visual treatment and digit recall.

Table 3 presents our main results on the effect of visual network elicitation on reported network characteristics. Column (1) establishes the baseline treatment effect: respondents randomly assigned to the visual elicitation method report networks that are 1.80 contacts larger on average, representing a 47 per cent increase over the control group mean of 3.81 contacts ($p < 0.001$).

The treatment effect on network size is substantial and precisely estimated, but columns (3) through (5) reveal important heterogeneity by cognitive ability. Column (3) introduces our measure of cognitive capacity—performance on a digit recall task—which enters positively and significantly ($\beta = 1.26, p < 0.001$), indicating that respondents with higher working memory report larger networks even in the auditory control condition. The interaction term between visual treatment and digit recall is negative and significant ($\beta = -1.19, p < 0.05$), demonstrating that the treatment effect is largest for respondents with lower cognitive skills.

Column (4) explores alternative cognitive measures. We find that respondents who reported the survey made less sense named fewer contacts ($\beta = -0.42, p < 0.001$), though

other subjective measures show no significant relationship with network size. Column (5) examines enumerator assessments but finds these do not predict network size.

The pattern of results suggests that standard auditory elicitation methods systematically undercount networks for respondents with lower cognitive capacity, introducing non-classical measurement error. Visual methods appear to reduce cognitive burden and elicit more complete networks from these respondents, though the mechanisms remain to be fully explored.

Table 3: Total Network by Model Specification

	Dependent variable: Total Network				
	(1)	(2)	(3)	(4)	(5)
Visual Network Elicitation Method	1.804***	1.819***	2.572***	1.947**	1.799***
	(0.171)	(0.171)	(0.357)	(0.854)	(0.174)
Self Report Index				−0.139	
				(0.086)	
South African	0.391	0.287	0.229	0.292	0.395
	(0.572)	(0.572)	(0.571)	(0.575)	(0.577)
Did Not Complete Secondary Ed.	−0.636	−0.579	−0.556	−0.630	−0.705
	(0.477)	(0.476)	(0.475)	(0.483)	(0.485)
Completed Tertiary Diploma	−0.045	−0.007	0.055	0.012	−0.015
	(0.227)	(0.227)	(0.228)	(0.230)	(0.231)
Completed Tertiary Bachelors Plus	0.725**	0.684**	0.745**	0.730**	0.789**
	(0.331)	(0.330)	(0.330)	(0.336)	(0.337)
Support Dependents	0.195	0.205	0.210	0.175	0.193
	(0.176)	(0.175)	(0.175)	(0.178)	(0.178)
Female	−0.152	−0.123	−0.137	−0.133	−0.144
	(0.174)	(0.174)	(0.174)	(0.176)	(0.177)
Other Gender	0.423	0.317	0.240	0.261	0.466
	(0.758)	(0.757)	(0.756)	(0.762)	(0.764)
Work Experience	−0.034	−0.008	−0.005	−0.026	−0.021
	(0.124)	(0.124)	(0.124)	(0.125)	(0.126)
% Correct Digit Recall		0.599**	1.260***	0.490*	
		(0.250)	(0.372)	(0.257)	
Visual × Correct Digit Recall			−1.194**		
			(0.498)		
Self Reported Cognitive Ease					0.405
					(0.890)
Self Reported Index				−0.139	
				(0.086)	
Visual × Self Reported Index				−0.014	
				(0.115)	
Comp × Cog. Ease					−0.069
					(0.197)
Comprehension Level				−0.158	0.011
				(0.136)	(0.362)
Constant	3.389***	3.068***	2.689***	4.872***	3.174*
	(0.581)	(0.594)	(0.613)	(1.091)	(1.790)
Control Mean	3.808	3.808	3.808	3.806	3.812
Observations	835	835	835	823	825
R^2	0.129	0.135	0.141	0.142	0.129
Adjusted R^2	0.115	0.120	0.125	0.124	0.112

Note: Models all control for population group. *p<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses.

4.2 Network Composition

Table 4 examines whether the visual elicitation method affects not just network size, but also network composition. We focus on two key measures of network quality: the percentage of contacts who are employed and the percentage with tertiary education. These characteristics are important because contacts with stronger labor market attachment and higher education levels may provide more valuable information and referrals.

Column (1) reproduces our main result from Table 3, showing the large positive effect of visual elicitation on total network size ($\beta = 1.80, p < 0.001$). Columns (2) and (3) reveal a striking pattern: the visual treatment substantially decreases the reported share of employed contacts by 20.7 percentage points ($p < 0.001$) and the share with tertiary education by 30.1 percentage points ($p < 0.001$), relative to control group means of 83.9 per cent and 51.7 per cent respectively.

This compositional shift is economically significant. Respondents in the auditory condition report networks that appear more advantaged—with higher employment rates and education levels—while those in the visual condition report larger but less elite networks. One interpretation is that auditory elicitation, which imposes higher cognitive demands, leads respondents to recall their most salient or memorable contacts first. These may disproportionately be contacts with higher status characteristics. The visual method, by reducing cognitive burden and allowing respondents to build their networks more systematically, may capture a more complete picture that includes both high-status contacts and more typical connections.

An alternative interpretation is that the two methods are measuring fundamentally different constructs: the auditory method elicits a narrower ”core” network of stronger ties who tend to be better-connected, while the visual method captures a broader set of weaker ties. The validation exercise in Tables 7-8 provides some support for this interpretation.

These compositional differences have important implications for network research. Standard measures that rely on auditory recall may overestimate network quality while underestimating network size, potentially leading to biased inferences about the relationship between network characteristics and outcomes.

5 Validation

To assess which elicitation method produces more accurate measures of labor market network quality, we examine the relationship between reported network characteristics and an external criterion: whether respondents obtained their current job through their network. At the end of the survey, we asked respondents an open-ended question about how they found their current job. J-PAL enumerators were trained to code responses into categories that capture whether the respondent obtained the role with the help of someone they knew—either through direct referral or by hearing about the opening through a contact. This provides an objective measure of network use that is independent of the network elicitation exercise.

Table 4: Visual effects by network indicator

	Dependent variable:		
	Network size	Share employed	Share tertiary
	(1)	(2)	(3)
Visual	1.804***	−0.207***	−0.301***
	(0.171)	(0.030)	(0.024)
Constant	3.389***	0.821***	0.500***
	(0.581)	(0.101)	(0.081)
Demographic controls	Yes	Yes	Yes
Control Mean	3.808	0.839	0.517
Observations	835	830	821
R^2	0.129	0.073	0.246
Adjusted R^2	0.115	0.058	0.234
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 5: Interaction effects with cognitive reflection by dependent variable

	Dependent variable:		
	Network size	Share employed	Share tertiary
	(1)	(2)	(3)
Visual	2.572***	−0.248***	−0.364***
	(0.357)	(0.063)	(0.050)
% Correct Digit Recall	1.260***	−0.099	−0.136***
	(0.372)	(0.065)	(0.052)
Visual × % Correct Digit Recall	−1.194**	0.064	0.097
	(0.498)	(0.087)	(0.070)
Constant	2.689***	0.876***	0.575***
	(0.613)	(0.107)	(0.085)
Demographic controls	Yes	Yes	Yes
Control Mean	3.808	0.839	0.517
Observations	835	830	821
R^2	0.141	0.076	0.253
Adjusted R^2	0.125	0.059	0.239
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 6: Gender Composition of Network by Gender of Respondent

	Dependent variable:		
	Percent Same Gender	Percent Female	Percent Female - Search Network Only
	(1)	(2)	(3)
Female Resp.	0.115***	0.291***	0.307***
	(0.017)	(0.017)	(0.023)
Other Gender Resp.		0.205**	0.137
		(0.071)	(0.097)
Constant	0.588***	0.412***	0.399***
	(0.013)	(0.013)	(0.017)
Observations	953	967	953
R^2	0.045	0.228	0.161
Adjusted R^2	0.044	0.227	0.159
Note:	Results are from a linear model. Male respondents as reference category. *p<0.1; **p<0.05; ***p<0.01		

Tables 7 and 8 present results from logistic regressions examining the relationship between reported network characteristics and network-based job finding, estimated separately by elicitation method. If a network measure accurately captures labor market network quality, we would expect it to predict whether individuals obtained their job through network contacts.

Table 7 examines three network measures: total network size (columns 1-2), percentage of contacts who are employed (columns 3-4), and percentage of contacts with tertiary education (columns 5-6). The results reveal a striking pattern. In the auditory condition, total network size is positively associated with network-based job finding, with the coefficient marginally significant at the 10% level ($\beta = 0.072$, $p < 0.10$). However, in the visual condition, this relationship disappears entirely ($\beta = 0.034$, $p = 0.269$). Neither the percentage of employed contacts nor the percentage with tertiary education shows a significant relationship with job finding in either condition.

At first glance, this might suggest the auditory method produces more valid measures. However, Table 8 reveals why this interpretation would be incorrect. Column (3) shows that when we examine the "search network"—the subset of contacts that respondents specifically identified as people they turn to for job search help—the visual method produces substantially stronger predictive power. Search network size is strongly predictive of network-based job finding ($\beta = 0.135$, $p < 0.001$), while total network size remains non-predictive in both methods.

This pattern demonstrates a key advantage of the visual elicitation method: it allows respondents to build a complete network and then subset it according to different relationship types or purposes. The visual interface breaks the complex cognitive task into manageable parts, with clear visual representations of who belongs in which category. Respondents can see their full network on screen and then systematically identify which contacts serve specific functions—in this case, providing job search help.

The auditory method, by contrast, conflates these tasks. When asked to name labor market contacts in a sequential interview format, respondents naturally focus on the most salient individuals—those who immediately come to mind as relevant to work and em-

ployment. This creates an implicit selection toward job search contacts, which explains why total network size in the auditory condition predicts job finding. However, this approach sacrifices information about the broader network structure and prevents researchers from distinguishing between different types of network ties.

The stronger predictive power of the search network subset in the visual condition ($\beta = 0.135$) compared to total network in the auditory condition ($\beta = 0.034$) suggests the visual method not only captures more complete networks but also allows for more precise measurement of specific network functions. By reducing cognitive burden and providing clear visual cues, the method helps respondents accurately categorize their contacts rather than relying on which relationships happen to be most salient at the moment of survey administration.

These findings suggest the visual method is superior for network research because it provides both breadth and precision. It captures the full network while allowing researchers to examine specific subsets relevant to particular outcomes. This flexibility is especially valuable in development contexts where networks serve multiple overlapping functions—job search, information sharing, financial support, social insurance—and where understanding the structure of multifunctional networks is critical for designing effective interventions. The visual method's ability to reduce cognitive burden while enabling systematic categorization of network ties makes it particularly well-suited for research with populations facing cognitive constraints due to poverty, stress, or limited formal education.

Table 7: Job acquired through network by survey method and labour market quality measure

	Dependent variable:					
	Got Job Through Network					
	(1) Visual	(2) Auditory	(3) Visual	(4) Auditory	(5) Visual	(6) Auditory
Total Network	0.034	0.072**				
	(0.031)	(0.034)				
Percentage Employed			−0.144	−0.028		
			(0.215)	(0.217)		
Percentage Tertiary					−0.078	−0.065
					(0.198)	(0.149)
Constant	−0.087	−0.006	0.196	0.281*	0.127*	0.302***
	(0.184)	(0.139)	(0.147)	(0.147)	(0.072)	(0.099)
Observations	476	431	476	432	467	426
Log Likelihood	−327.642	−286.634	−328.030	−289.987	−321.820	−285.606
Akaike Inf. Crit.	659.284	577.268	660.059	583.975	647.640	575.213

Note: *p<0.1; **p<0.05; ***p<0.01

Table 8: Job acquired through network by survey method and labour market quality measure (continued)

	Dependent variable:		
	Got Job Through Network		
	(1) Visual	(2) Auditory	(3) Visual
Total Network	0.034	0.072**	
	(0.031)	(0.034)	
Total Search Network			0.135***
			(0.034)
Constant	−0.087	−0.006	−0.266**
	(0.184)	(0.139)	(0.115)
Observations	476	431	468
Log Likelihood	−327.642	−286.634	−314.189
Akaike Inf. Crit.	659.284	577.268	632.377
Note:			*p<0.1; **p<0.05; ***p<0.01

Mechanism

Results include group 3

6 Implications for Research

Our findings have important implications for how researchers measure and interpret network data in developing contexts. The systematic relationship between cognitive capacity and measurement error we document has different consequences depending on how networks are used in empirical research. We consider three common research designs and discuss the potential for bias in each.

6.1 Networks as Independent Variables

When network characteristics are used as explanatory variables—for example, studying how network size or quality predicts employment outcomes—our findings suggest standard auditory elicitation methods may generate attenuation bias in estimated effects. If auditory methods systematically undercount networks for respondents with lower cognitive capacity, and cognitive capacity is correlated with both network size and labor market outcomes, OLS estimates of the relationship between networks and outcomes will be biased toward zero (Hausman, 2001; Angrist and Pischke, 2009).

Moreover, the compositional differences we document between elicitation methods complicate interpretation. Auditory methods appear to elicit a subset of more salient, higher-

Table 9: Elicitation method, cognitive skills, and network size

	Dependent variable:		
	Network size		
	(1)	(2)	(3)
Visual Decomposed	1.804***	1.817***	2.568***
	(0.171)	(0.170)	(0.356)
Auditory Decomposed	0.416	0.443	1.816**
	(0.391)	(0.390)	(0.735)
Cognitive score		0.511**	1.262***
		(0.241)	(0.369)
Visual Decomposed × Cognitive score			−1.187**
			(0.496)
Auditory Decomposed × Cognitive score			−2.329**
			(1.082)
Constant	3.415***	3.151***	2.717***
	(0.576)	(0.588)	(0.608)
Demographic controls	Yes	Yes	Yes
Control Mean	3.808	3.808	3.808
Observations	881	881	881
R^2	0.124	0.129	0.137
Adjusted R^2	0.110	0.114	0.120
Residual Std. Error	2.445	2.440	2.431
F Statistic	8.789***	8.536***	8.074***

Note: *p<0.1; **p<0.05; ***p<0.01
Notes to be populated.

Table 10: Elicitation method and network size and quality

	Dependent variable:		
	Network size	Share employed	Share tertiary
	(1)	(2)	(3)
Visual Decomposed	2.568^{***}	-0.250^{***}	-0.366^{***}
	(0.356)	(0.062)	(0.050)
Auditory Decomposed	1.816^{**}	-0.219^{*}	-0.222^{**}
	(0.735)	(0.128)	(0.103)
Cognitive score	1.262^{***}	-0.106^{*}	-0.138^{***}
	(0.369)	(0.065)	(0.052)
Visual Decomposed $\times$ Cognitive score	-1.187^{**}	0.067	0.099
	(0.496)	(0.086)	(0.070)
Auditory Decomposed $\times$ Cognitive score	-2.329^{**}	0.309	0.316^{**}
	(1.082)	(0.188)	(0.151)
Constant	2.717^{***}	0.890^{***}	0.580^{***}
	(0.608)	(0.106)	(0.085)
Demographic controls	Yes	Yes	Yes
Control Mean	3.808	0.839	0.517
Observations	881	876	867
R^2	0.137	0.075	0.256
Adjusted R^2	0.120	0.057	0.241
Residual Std. Error	2.431	0.423	0.339
F Statistic	8.074^{***}	4.121^{***}	17.147^{***}

Note: *p<0.1; **p<0.05; ***p<0.01
Add notes.

status contacts, while visual methods capture a broader network including both strong and weak ties. If researchers are interested in the effect of having access to high-status contacts, auditory methods may provide a closer approximation to the construct of interest. However, if the research question concerns the breadth of information channels or the total stock of social capital, visual methods may be more appropriate.

The choice of measurement method thus depends on the theoretical construct researchers aim to capture. Our validation exercise suggests both methods capture meaningful but different aspects of networks: total network size measured auditorily predicts network-based job finding in the control group, while the search network subset measured visually shows stronger predictive power in the treatment group. Researchers should carefully consider which network construct is most relevant for their research question and choose elicitation methods accordingly.

6.2 Networks as Outcome Variables

When network characteristics are themselves the outcome of interest—for example, evaluating whether an intervention successfully expands participants' networks—measurement method becomes even more critical. Our findings suggest that using auditory methods to measure network outcomes may substantially underestimate treatment effects, particularly for populations with lower cognitive capacity who are often the targets of such interventions.

Consider a job training program that aims to help participants build professional networks. If the program successfully helps lower-skilled participants expand their networks, but researchers use auditory elicitation methods that disproportionately undercount networks among this group, the measured treatment effect will be attenuated. The program may appear less effective than it actually is, potentially leading to incorrect conclusions about program impact and misguided policy decisions.

The compositional differences we document add another layer of complexity. If an intervention helps participants add contacts but these new contacts are less salient or lower-status than existing contacts, auditory methods may fail to capture them entirely. A program could successfully expand networks along dimensions that matter for labor market outcomes while appearing to have no effect when measured with standard survey methods.

Researchers evaluating network-building interventions should consider using visual elicitation methods, particularly when working with populations that may have limited cognitive bandwidth due to poverty, stress, or other constraints. At minimum, studies should assess whether treatment effects vary by cognitive capacity, as differential measurement error across treatment arms could lead to biased impact estimates.

6.3 Heterogeneous Treatment Effects by Baseline Network Characteristics

Perhaps the most concerning implication of our findings relates to research examining heterogeneous treatment effects by baseline network characteristics. Many studies investigate whether interventions work differently for individuals with stronger versus weaker initial networks. Our results suggest that apparent heterogeneity by baseline network strength may partly reflect differential measurement error rather than true effect modification.

Consider a study that finds a job training program is more effective for participants who report larger or higher-quality baseline networks. A natural interpretation would be that strong networks complement the training, perhaps by providing opportunities to apply new skills or by offering informational advantages. However, our findings suggest an alternative explanation: participants who report larger, higher-quality networks at baseline may simply have higher cognitive capacity, which allows them both to recall their networks more accurately in auditory surveys and to benefit more from training programs that require similar cognitive skills.

This concern is particularly acute because the direction of apparent heterogeneity could be opposite to reality. Suppose an intervention truly works better for participants with weaker baseline networks—perhaps because those with strong networks already have the resources the program aims to provide. If auditory methods systematically underestimate network size for those with lower cognitive skills, and if the intervention is actually most effective for this group, researchers might observe that the program appears most effective for those reporting stronger baseline networks. This would lead to exactly the wrong policy conclusion: that scarce program resources should be targeted toward those who are already better positioned, when in fact the program is most valuable for those facing greater disadvantages.

This misinterpretation is especially likely when cognitive capacity affects both measurement error and treatment effect heterogeneity in the same direction. For example, if a program teaches job search strategies that require working memory and organizational skills, it may be less effective for those with lower cognitive capacity. But if those same individuals also systematically underreport their networks in auditory surveys, they will appear to have both weaker networks and smaller treatment effects. Researchers might conclude that weak networks explain low treatment effects, when in fact both are driven by cognitive capacity.

To address this concern, researchers examining heterogeneity by baseline network characteristics should:

1. Use visual elicitation methods that reduce cognitive burden and measurement error, particularly when working with populations experiencing poverty or other sources of cognitive load.
2. Directly measure cognitive capacity and test whether apparent heterogeneity by network characteristics remains after controlling for cognitive skills.

3. Consider alternative explanations for observed patterns of heterogeneity, particularly when the pattern suggests interventions work better for those who are already advantaged.

4. Report results separately by both network characteristics and cognitive capacity to allow readers to assess whether the two sources of heterogeneity are confounded.

More broadly, our findings highlight the importance of validating network measures against external criteria. In our study, we validate reported networks against whether respondents obtained their current job through network contacts. Similar validation exercises—using objective measures of network use or comparing across measurement methods—can help researchers assess whether observed heterogeneity reflects true variation in network structure or systematic measurement error.

6.4 Implications for Development Research

These concerns are particularly salient for development research, where target populations often face cognitive constraints due to poverty, stress, food insecurity, or other hardships. The scarcity and bandwidth literature demonstrates that these conditions directly impair cognitive function, creating precisely the conditions under which our documented measurement problems are most severe. If standard survey methods systematically mismeasure networks for those under the greatest cognitive strain, and if these are also the populations most in need of support, we risk both underestimating program impacts and drawing incorrect conclusions about who benefits most from interventions.

Our findings suggest that methodological choices in network measurement are not merely technical details but substantive decisions that can meaningfully affect research conclusions and policy recommendations. As network-based analyses become increasingly common in development economics, careful attention to measurement methods—and to how measurement error varies with respondent characteristics—will be essential for drawing valid inferences and designing effective interventions.

Conclusion

This paper examines systematic measurement error in network elicitation and demonstrates that cognitive capacity significantly moderates the accuracy of network reporting in ways that depend on survey methodology. Using a survey experiment with 807 entry-level workers in South Africa, we show that visual elicitation methods produce substantially larger reported networks than standard auditory methods—a 50% increase on average—with this treatment effect largest for respondents with lower cognitive skills. The visual method also produces networks with different composition, reporting fewer employed and tertiary-educated contacts, suggesting that auditory methods lead respondents to recall primarily salient, high-status ties while visual methods reduce cognitive burden and elicit more complete networks.

These findings have important implications for network research in developing contexts.

Standard auditory elicitation methods may systematically underestimate network size for populations with limited cognitive capacity—precisely those who are often the targets of development interventions—while simultaneously overestimating network quality. This measurement error can bias estimates when networks are used as explanatory variables, attenuate measured treatment effects when networks are outcomes, and lead to incorrect conclusions about heterogeneous treatment effects by baseline network characteristics.

Our validation exercise demonstrates that visual methods are not merely different but superior: they allow respondents to build complete networks and then systematically subset them according to relationship type, producing stronger predictive power for objective measures of network use. The visual interface breaks complex cognitive tasks into manageable parts with clear visual representations, making it particularly valuable for research with populations facing cognitive constraints.

As network-based analyses become increasingly common in development economics, careful attention to measurement methods is essential. Our findings suggest that researchers should consider adopting visual elicitation tools, particularly when working with populations experiencing poverty or other sources of cognitive load, and should validate network measures against external criteria when possible. Methodological choices in network measurement are not technical details but substantive decisions that meaningfully affect research conclusions and policy recommendations.

Appendix

Table A2: Correlation Matrix for Cognitive and Communication Measures - With Cognitive Recall Levels

	Correct Digit Recall Level	Self-Reported Survey Easy	Self-Reported Survey Sense	Self-Reported Cog. Effort	FO Eval. Comprh. Level	FO Eval. Comm. Level
Correct Digit Recall Level	1.00	−0.117	-0.102	−0.119	0.018	−0.019
Self-Reported Survey Easy	-0.117	1.00	−0.309	0.487	−0.370	-0.380
Self-Reported Survey Sense −0.102	-0.309	1.00	-0.146	0.321	0.353	
Self-Reported Cog. Effort	-0.119	0.487	−0.146	1.00	−0.179	-0.170
FO Eval. Comprh. Level	0.018	-0.370	0.321	-0.179	1.00	0.855
FO Eval. Comm. Level −0.019	−0.380	0.353	−0.170	0.855	1.00	

Table A1: Cognitive Question Interactions

	Dependent variable: Total Network		
	(1)	(2)	(3)
network_canvas	2.572***	2.303***	−0.707
	(0.357)	(0.349)	(1.235)
per_cog_right	1.260***		
	(0.372)		
cognitive_reflection_effort		0.248*	
		(0.145)	
comp_level			−0.418**
			(0.192)
pop_groupColoured	0.375	0.366	0.398
	(0.443)	(0.445)	(0.447)
pop_groupIndian/Asian	1.578	1.634	1.576
	(1.736)	(1.745)	(1.754)
pop_groupPrefer not to answer	2.801	2.035	1.754
	(2.452)	(2.469)	(2.489)
pop_groupWhite	−0.620	−0.349	−0.333
	(1.449)	(1.456)	(1.463)
nationality_cleanSouth African	0.229	0.410	0.321
	(0.571)	(0.572)	(0.575)
edu_groupedCompleted tertiary bachelors plus	0.745**	0.761**	0.800**
	(0.330)	(0.331)	(0.336)
edu_groupedCompleted tertiary diploma	0.055	−0.041	−0.051
	(0.228)	(0.227)	(0.230)
edu_groupedLess than secondary education	−0.556	−0.694	−0.698
	(0.475)	(0.478)	(0.483)
support_dep_clean	0.210	0.210	0.219
	(0.175)	(0.176)	(0.178)
genderFemale	−0.137	−0.145	−0.153
	(0.174)	(0.174)	(0.176)
genderOther	0.240	0.443	0.432
	(0.756)	(0.759)	(0.761)
current_work_exp	−0.005	−0.027	−0.033
	(0.124)	(0.124)	(0.125)
network_canvas:per_cog_right	−1.194**		
	(0.498)		
network_canvas:cognitive_reflection_effort		−0.315*	
		(0.189)	
network_canvas:comp_level			0.550**
			(0.268)
Constant	2.689***	2.966***	5.341***
	(0.613)	(0.630)	(1.064)
Control Mean	3.808	3.808	3.812
Observations	835	835	825
R^2	0.141	0.133	0.133
Adjusted R^2	0.125	0.117	0.117

Table A3: Gender Interaction

	Dependent variable: Total Network
Visual	2.043***
	(0.262)
Female	0.065
	(0.254)
Other Gender	0.743
	(0.958)
South African	0.419
	(0.573)
Education: Completed tertiary bachelors plus	0.727**
	(0.331)
Education: Completed tertiary diploma	−0.041
	(0.227)
Education: Less than secondary education	−0.647
	(0.478)
Support Dependents	0.192
	(0.176)
Work Experience	−0.033
	(0.124)
Visual × Female	−0.411
	(0.348)
Visual × Other Gender	−0.776
	(1.570)
Constant	3.237***
	(0.594)
Observations	835
R^2	0.131
Adjusted R^2	0.115

Note: Model controls for population group.*p<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses.

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Table A4:

	Dependent variable:		
	n_1	emp_per_1	n_tert_per_1
	(1)	(2)	(3)
network_canvas	2.309***	−0.255***	−0.400***
	(0.338)	(0.058)	(0.050)
per_cog_right	1.040***	−0.106*	−0.133***
	(0.348)	(0.060)	(0.051)
network_canvas:per_cog_right	−0.805*	0.078	0.145**
	(0.470)	(0.081)	(0.069)
Constant	3.177***	0.900***	0.604***
	(0.253)	(0.044)	(0.037)
Observations	907	902	893
R^2	0.127	0.060	0.163
Adjusted R^2	0.125	0.057	0.160
Residual Std. Error	2.424 (df = 903)	0.419 (df = 898)	0.355 (df = 889)
F Statistic	43.983*** (df = 3; 903)	19.027*** (df = 3; 898)	57.729*** (df = 3; 88
Note:			*p<0.1; **p<0.05; ***p<0.0

Table A5:

	Dependent variable:				
	Network size				
	(1)	(2)	(3)	(4)	(5)
Visual	1.783***	1.801***	2.309***	1.757**	1.776***
	(0.162)	(0.161)	(0.338)	(0.800)	(0.164)
Self-report index				−0.132*	
				(0.079)	
% Correct digit recall		0.600**	1.040***	0.502**	
		(0.234)	(0.348)	(0.241)	
Visual × Digit recall			−0.805*		
			(0.470)		
Comprehension				−0.099	0.077
				(0.128)	(0.343)
Visual × Self-report				0.009	
				(0.107)	
Cognitive reflection (ease)					0.406
					(0.838)
Comprehension × CR ease					−0.064
					(0.186)
Constant	3.847***	3.460***	3.177***	4.929***	3.322**
	(0.117)	(0.191)	(0.253)	(0.872)	(1.609)
Demographic controls	No	No	No	No	No
Control Mean	3.847	3.847	3.847	3.845	3.850
Observations	907	907	907	895	897
R^2	0.118	0.125	0.127	0.129	0.118
Adjusted R^2	0.117	0.123	0.125	0.124	0.114
Note:					*p<0.1; **p<0.05; ***p<0.01

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