# Structural embeddedness and innovation commercialization in Tanzanian universities: The moderating role of network embeddedness

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**Recommended Citation:** John, M., Pasape, L., & Sassi, A. L. (2026). Structural embeddedness and innovation commercialization in Tanzanian universities: The moderating role of network embeddedness. *African Quarterly Social Science Review, 3*(3), 528–546. https://doi.org/10.51867/AQSSR.3.3.44

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## ABSTRACT

This study examines the relationship between structural embeddedness and innovation commercialization among researchers across five Tanzanian public universities, drawing on Granovetter's theory of social embeddedness. It tests three hypotheses: the direct influence of structural embeddedness on commercialization ($H0_1$), the moderating role of network embeddedness on this relationship ($H0_2$), and the direct effect of network embeddedness on commercialization ($H0_3$). Data were collected from 274 academic staff across five public universities and analysed using partial least squares structural equation modelling with 5,000 bootstrap subsamples. The measurement model satisfied all convergent and discriminant validity criteria. Structural embeddedness positively and significantly influenced innovation commercialization (beta = 0.314, $p < 0.001$), supporting H1, and network embeddedness exerted a significant positive direct effect (beta = 0.362, $p < 0.001$), confirming H3. The moderation analysis yielded a significant negative interaction (beta = -0.100, p = 0.013): the positive influence of structural embeddedness weakened as network embeddedness intensified, suggesting a substitution effect in which researchers already deeply embedded in their networks derive diminishing returns from additional structural positioning. The model explained 46.1% of variance in innovation commercialization. We conclude that structural and network embeddedness are not simply additive but interact in ways that redistribute the returns to positional advantage, extending network theory by showing its dimensions can function as partial substitutes rather than complements in a developing-country university context. We recommend that Tanzanian universities and research administrators prioritise strengthening the overall quality and density of academic-industry networks, through shared infrastructure, cross-institutional platforms and industry engagement programmes, over interventions that target only individually well-positioned researchers, since the observed substitution effect implies that network-level investment yields broader and more equitable commercialization gains.

**Keywords:** Innovation Commercialization, Network Embeddedness, Network Theory, PLS-SEM, Structural Embeddedness, Tanzanian Universities

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## I. INTRODUCTION

Universities in sub-Saharan Africa occupy a distinctive position in the innovation ecosystem. They generate research outputs, train human capital, and house specialized laboratories, yet the commercial translation of their discoveries remains strikingly low compared to universities in developed economies (Nsanzumuhire et al., 2023). This is not simply a matter of limited research capacity; it is a structural problem of translation, where the pathway from knowledge production to commercial application is blocked in ways that resources and capacity alone cannot explain. Tanzanian universities share this challenge and, in several respects, represent one of its more acute manifestations. Despite national policy frameworks that explicitly call for universities to serve as engines of knowledge-based economic growth, Tanzania's universities convert only a negligible fraction of their intellectual property into marketable products, patents, or licensing agreements (Mashoto, 2022).

The gap between policy commitment and commercial outcome in Tanzania is well documented. National research and innovation policy frameworks call on universities to establish formal linkages with industry and to raise research and development investment substantially above current levels, yet actual spending and output remain well below these stated targets (Kadikilo et al., 2024). More telling than the funding gap itself is what the existing investment has produced: the conversion of university research into patents, licences, spin-off companies and lasting industry partnerships remains far below what national policy targets would lead one to expect (Maziku, 2021). Tanzania has the policy framework; what it has not yet built is the bridge between that framework and commercial outcomes.

Empirical evidence from within Tanzania confirms that this failure is systemic rather than incidental. Kadikilo et al.,(2024), drawing on interviews with university leaders, regulators and academics across Tanzania's four largest public institutions, found that weak inter-institutional collaboration, fragmented research policy and thin mentorship structures continue to constrain research productivity and its translation into practical application. Maziku (2021), in a scientometric analysis of Tanzania's national science system, similarly identifies chronic barriers to research productivity, including negligible industry engagement and limited institutional incentives for commercialization, across the country's major public universities. Mashoto (2022) reports that only a minority of Tanzanian universities and research institutions in the health and allied sciences had a functioning Intellectual Property Management Office at the time of study, and that formal employment-to-invent contracts, where they existed, were often poorly understood by the researchers they were meant to govern. Together, these studies establish that the commercialization problem is not located at the level of individual researchers but runs through the institutional and relational fabric of the university system itself.

Scholars have begun to ask why this gap persists. Most existing work approaches the problem from a narrow angle, focusing on institutional obstacles, inadequate funding, weak technology transfer offices, poor regulation, or on individual researcher traits such as entrepreneurial orientation and prior industry experience (Perkmann et al., 2021; Cunningham et al., 2019). These factors matter but explain only part of the picture: a well-funded researcher with institutional support can still fail to commercialize, while one in a resource-constrained setting can succeed. What both explanations tend to leave out is the social environment in which researchers operate, the professional relationships and innovation networks that give them access to the knowledge, contacts and opportunities commercialization requires. Recent reviews of the university-industry relations literature make precisely this point, calling for research on how academic social networks shape commercialization outcomes outside the Western contexts where most existing evidence has been gathered (Perkmann et al., 2021; Cunningham et al., 2019).

Network theory, as articulated by Granovetter (1985), provides a compelling lens for examining these social-structural conditions. Granovetter argued that economic action is embedded in concrete social relations rather than atomistic individual decisions. Applied to university settings, a researcher's position within collaborative networks, whether that commercialization measured through co-authorship, joint projects, or formal institutional linkages, shapes access to the resources and opportunities requires. A professor active across inter-university committees, co-authorship ties and industry advisory boards occupies a structurally different position than an equally productive but relatively isolated colleague, and network theory predicts this difference will yield different commercial outcomes even when talent and research quality are held constant.

Two analytically distinct dimensions of embeddedness are examined here. Structural embeddedness refers to the position an academic occupies within the innovation network, the number, diversity and configuration of connections, and whether they bridge otherwise disconnected clusters of actors (Burt, 1992; Owen-Smith & Powell, 2004). Network embeddedness operates at the ecosystem level: it captures the academic's perception of the overall network environment as cohesive, resource-rich and conducive to knowledge exchange, reflecting the collective properties of the innovation system rather than the academic's individual position within it (Uzzi, 1997; Nsanzumuhire et al., 2023). Where structural embeddedness is positional, network embeddedness is contextual, and the two dimensions need not move in tandem: a researcher may occupy a structurally central position yet perceive the surrounding network as fragmented and unsupportive, or hold a peripheral structural position within an ecosystem that is dense and resource-rich. It is this potential divergence that raises the question at the heart of this study. A third dimension, relational embeddedness, the quality and depth of specific dyadic ties, is examined in a companion study using the same sample and is not tested directly here.

If each dimension of embeddedness independently influences commercialization outcomes, an important further question arises: do they also interact? Specifically, does the degree to which a researcher perceives the surrounding network as dense and facilitative amplify or dampen the effect of their own structural positioning on commercialization? Prior literature has largely treated these dimensions separately or conflated them, leaving the interaction mechanism underexplored (Zhou, 2022). The few studies that have tested interaction effects between embeddedness dimensions have focused on firm-level outcomes in developed-country manufacturing and technology sectors, leaving university contexts in the developing world largely unexamined. This study fills that gap by testing whether network embeddedness moderates the relationship between structural embeddedness and innovation commercialization in a context where both institutional support and network infrastructure are comparatively underdeveloped.

Scholarly attention to embeddedness and innovation has grown considerably in developed and some emerging-economy contexts, yet empirical tests of the embeddedness-commercialization relationship within Tanzanian or East African university settings are virtually absent from the literature. To the authors' knowledge, this is among the first quantitative attempts to do so. Its findings are best understood as a foundational contribution that opens this line of inquiry for Sub-Saharan African innovation scholarship, one that invites replication and extension in comparable institutional settings rather than a final word on the question.

Three objectives guide this investigation. First, to determine the extent to which structural embeddedness influences innovation commercialization among academic researchers in Tanzanian universities. Second, to assess whether network embeddedness moderates the relationship between structural embeddedness and commercialization. Third, to evaluate the direct effect of network embeddedness on commercialization outcomes. These objectives are tested through partial least squares structural equation modelling (PLS-SEM) on data from 274 respondents drawn from five public universities: The University of Dar es Salaam (UDSM), Sokoine University of Agriculture (SUA), Dar es Salaam Institute of Technology (DIT), the University of Dodoma (UDOM), and the Open University of Tanzania (OUT).

Three contributions follow from this work. First, it extends Granovetter's network embeddedness theory to a developing-country higher education context, where most tests of the theory have relied on firm-level data from North American, European or East Asian settings. Second, it disentangles the structural and network dimensions of embeddedness and tests their interaction, revealing a substitution effect that contrasts with the complementarity assumption implicit in much prior work. Third, it offers evidence-based guidance for university administrators and policymakers seeking to strengthen the conditions under which academic research reaches commercial application, moving the policy discussion beyond the individual-researcher focus that currently dominates.

### 1.1 Statement of the Problem

Despite growing policy attention to university-based innovation across Tanzania, the translation of academic research into commercially viable products, licences and spin-off ventures remains rare relative to the volume of research now being produced (Kadikilo et al., 2024). This gap persists even as individual academics report engaging in the collaborative activity that network theory identifies as a precursor to commercialization. What is missing is empirical clarity on which dimension of an academic's network position actually drives this translation, and whether these dimensions work together or against one another. Existing accounts of the Tanzanian innovation ecosystem document institutional barriers such as weak intellectual property infrastructure, but say little about network mechanisms at the level of the individual researcher: whether structural position enables commercialization, whether perception of the broader network environment matters more, or whether the two interact (Ndege et al., 2021). Without this clarity, universities risk designing interventions that target the wrong lever, or that assume dimensions of embeddedness behave identically when they may not. This study addresses that gap by testing, in a single integrated model, whether structural embeddedness predicts innovation commercialization among Tanzanian academic researchers, and whether network embeddedness conditions that relationship.

### 1.2 Research Hypothesis

*$Ho_1$*: Structural embeddedness positively and significantly influences the commercialization of innovation among academic researchers in Tanzanian universities.

*$Ho_2$*: Network embeddedness significantly moderates the relationship between structural embeddedness and innovation commercialization among academic researchers in Tanzanian universities.

*$Ho_3$*: Network embeddedness positively and significantly influences the commercialization of innovation among academic researchers in Tanzanian universities.

## II. LITERATURE REVIEW

### 2.1 Theoretical Foundation: Network Theory

Network theory, developed by Granovetter (1973), holds that economic behaviour cannot be understood apart from the social structures in which it is situated. Granovetter's concept of embeddedness challenged both the under-socialised view of neoclassical economics, which treats actors as atomistic decision-makers responding to price signals, and the over-socialised view of classical sociology, which reduces behaviour to internalised norms. Instead, economic action is embedded in ongoing systems of social relations that constrain and enable individual choice (Granovetter, 1985): the pattern of social connections in which an actor is situated shapes the information, resources and normative pressures available to that actor, and through these mechanisms influences outcomes that individual attributes alone would not predict.

Subsequent scholarship has extended this foundational insight in ways this study draws on directly. Burt (1992) proposed that actors bridging structural holes gain non-redundant informational advantages that dense network closure cannot provide. Uzzi (1997) identified a paradox: while deeply embedded ties facilitate fine-grained information transfer, excessive density can produce insularity and rigidity, an embeddedness trap that impedes rather than facilitates innovation. Moran (2005) resolved some of this tension empirically, showing that structural and relational embeddedness exerts independent effects on performance, each contributing unique explanatory value beyond the other. More recently, Radko, Belitski and Kalyuzhnova (2023) reconceptualised the entrepreneurial university through a stakeholder lens, arguing that embeddedness-based advantages are filtered through the competing interests of internal and external stakeholders, a refinement particularly relevant to resource-constrained settings such as Tanzania. Guerrero and Siegel (2024) similarly called for a more prosocial framing of technology transfer that accounts for developmental outcomes alongside commercial ones. These developments justify this study's treatment of embeddedness as a multidimensional construct whose separate dimensions are theorised to exert distinct, and potentially interactive, effects on commercialization.

The theory distinguishes relational embeddedness, the quality and depth of dyadic ties between pairs of actors, from structural embeddedness, the position an actor occupies within the overall network architecture. A third dimension, network embeddedness, describes the network's global properties, its density, cohesion, reach and overall resource availability (Moran, 2005). These dimensions are analytically separable: two actors may share a strong tie while occupying very different structural positions or an actor may occupy a central position within a sparse, resource-poor network. Recognising that these dimensions can exert both independent and interactive effects has driven much subsequent work across management, sociology and innovation studies (Nahapiet & Ghoshal, 1998; Phelps et al., 2012; Zhou, 2022).

In university contexts, network theory applies directly because academic research is inherently collaborative and knowledge-intensive. Information about industry needs, funding sources and regulatory pathways is distributed unevenly across the academic network, and its diffusion follows network pathways: researchers learn about industry problems through colleagues on advisory boards, discover funding through co-authors at other institutions, and find commercialization partners through introductions brokered by mutual connections. Researchers who occupy structurally advantaged positions gain disproportionate access to these resources (Phelps et al., 2012), leading network theory to predict that structural embeddedness should positively influence innovation commercialization, a prediction this study tests in the Tanzanian university system.

## 2.2 Empirical Review

### 2.2.1 Structural Embeddedness and Innovation Commercialization

Structural embeddedness refers to the position an actor holds within the broader network, encompassing centrality, brokerage and the span of structural holes (Burt, 1992; Granovetter, 1992). Centrality captures how many direct connections and short paths to others an actor has; brokerage captures the extent to which an actor bridges otherwise disconnected parts of the network; and structural holes, Burt (1992) term for gaps between disconnected clusters, represent opportunities for brokers to arbitrage information between groups that lack direct ties. In academic settings, structural embeddedness manifests through research group membership, inter-university consortia, industry advisory boards, government taskforces, and cross-disciplinary co-authorship networks.

A substantial body of evidence links structural embeddedness to innovation outcomes. Ahuja (2000) found that structural centrality and bridging positions predicted patent output among chemicals-industry firms, attributing this to superior information access. Obstfeld (2005) showed that actors who bridge disconnected clusters, a tertius iungens orientation, are better positioned to combine disparate knowledge into novel ideas. In university technology transfer, the structural position of academic inventors within collaboration networks has been found to predict both patent filings and licensing revenue (Breschi & Catalini, 2010), and Owen-Smith and Powell (2004) documented that Boston-area universities embedded in dense local networks produced more commercially valuable research, partly because network density accelerated the diffusion of complementary knowledge needed for technology transfer.

The mechanism linking structural embeddedness to commercialization operates through at least three channels: structurally central actors receive information about commercial opportunities earlier, giving them a timing advantage (Phelps et al., 2012); actors who span structural holes gain access to non-redundant information that increases the odds of novel recombination (Burt, 1992); and structurally embedded actors accumulate reputational capital through network visibility, making them more attractive partners to industry collaborators and technology transfer intermediaries (Stuart et al., 1999).

In the African context, evidence is thinner but consistent in direction. Nsanzumuhire et al. (2023) found that university-industry interactions across sub-Saharan Africa remain largely unidirectional and short-term, suggesting that structurally diverse networks help sustain the engagement technology transfer requires. Kruss et al. (2015) documented how the structure of South African university-industry linkages shaped knowledge transfer, and Sassi and Mshenga (2025) similarly found collaboration outcomes across eight African universities to depend heavily on structural and institutional channels. Hayter et al. (2018) showed more broadly that network structure shapes commercialization pathways, and Perkmann et al. (2021) two-decade review found collaborative network characteristics to be among the most consistent predictors of commercial output, together supporting the expectation that structural embeddedness enhances innovation commercialization.

*$Ho_1$:* Structural embeddedness positively and significantly influences the commercialization of innovation among academic researchers in Tanzanian universities.

**2.2.2 The Moderating Role of Network Embeddedness**

The relationship between structural embeddedness and innovation commercialization is unlikely to be uniform across network environments. Although structural embeddedness provides researchers with advantageous positions for accessing knowledge, resources and collaboration opportunities, the extent to which these advantages translate into commercialization outcomes might depend on the broader network context. Network embeddedness is therefore conceptualised here as a contextual condition that shapes the strength of this relationship, and embeddedness theory suggests two competing mechanisms through which such moderation could occur.

The amplification hypothesis holds that network embeddedness strengthens the effect of structural embeddedness. In cohesive, resource-rich networks, central and well-connected actors gain access to more diverse knowledge and opportunities than similarly positioned actors in sparse networks, so favourable structural positions yield greater commercialization benefits (Phelps et al., 2012). Under this view, network embeddedness enhances the returns to structural embeddedness, producing a positive interaction effect.

The substitution hypothesis argues the opposite: that network embeddedness weakens the effect of structural embeddedness. In highly cohesive networks, information circulates widely enough that members benefit regardless of their structural position, so the additional advantage of occupying a central or brokerage position diminishes. Dense networks have been shown to generate redundant information flows that reduce the value of brokerage positions (Uzzi, 1996; Rowley et al., 2000; Zhou, 2022), and Hansen (1999) similarly found that strong ties can facilitate complex knowledge transfer in ways that reduce dependence on bridging ties. Under this view, network embeddedness substitutes for the advantages of structural embeddedness, producing a negative interaction effect.

Both mechanisms are theoretically plausible in Tanzanian public universities. Research is typically organised around individual principal investigators, with limited institutionalised research centres or sustained competitive funding (Maziku, 2021), and cross-university collaboration relies primarily on personal professional relationships rather than formal partnerships. Technology transfer capacity also remains underdeveloped across the sampled institutions, which generally manage commercialization activity through general research offices rather than dedicated technology transfer personnel (Mashoto, 2022), so university-industry engagement is correspondingly consultancy-based, with limited licensing or spin-off activity.

These conditions make informal professional networks the principal mechanism through which researchers access commercialization-related knowledge and contacts, helping to explain the strong association between network embeddedness and commercialization observed here ($r = 0.722$), while still leaving room for competing predictions about its moderating role. Resource constraints could raise the value of favourable structural positions within well-connected networks, consistent with amplification; equally, the close-knit nature of Tanzanian academic communities may facilitate broad diffusion of information, reducing the benefits of structural centrality and supporting substitution. Given these competing arguments, the direction of the moderating effect cannot be assumed in advance and is tested directly.

*$Ho_2$:* Network embeddedness significantly moderates the relationship between structural embeddedness and the commercialization of innovation.

**2.2.3 Network Embeddedness and Innovation Commercialization**

Where structural embeddedness concerns an actor's position within the network, network embeddedness concerns the character of the network itself: how integrated, resourced and information-rich it is as a whole (Rowley et al., 2000). This distinction matters because the same structural position can yield very different commercial outcomes depending on context. Two researchers who occupy identical brokerage positions may fare very differently if one is embedded in an active, resource-rich network and the other in a sparse, fragmented one.

Network embeddedness is not a matter of individual attitude or self-assessment; it is the actor's perception of objective network-level properties, the density, cohesion and collective resource availability of the surrounding innovation ecosystem (Rowley et al., 2000; Moran, 2005). Perceptual measurement is used here because complete sociometric mapping of all innovation-network ties is rarely obtainable in developing-country research settings (Nsanzumuhire et al., 2023), making perception-based measures the methodologically appropriate and theoretically grounded alternative (Inkpen & Tsang, 2005).

Empirical evidence indicates that overall network quality matters for innovation. Gilsing et al. (2008) showed that firms embedded in technologically dense alliance networks achieved higher rates of both exploration and exploitation. In university settings, the density and resource availability of collaborative networks has been linked to knowledge spillovers (Jaffe, 1989), faculty patenting rates (Zucker et al., 2002), and spin-off formation (Fini et al., 2011). More recent evidence reinforces this pattern: Odei and Novak (2023), analysing university knowledge-transfer activity in the United Kingdom, found that funding and patenting activity were significant determinants of spin-off creation, with patenting playing a mediating role between network resources and commercial outcomes. A systematic review by Romero-Sanchez, Perdomo-Charry and Burbano-Vallejo (2024) similarly found that public university spin-off creation depends heavily on the strength of university-industry collaboration mechanisms embedded within the network, not on any single actor's individual position. A well-connected, resource-rich network generates benefits for all embedded actors: information circulates faster, reciprocity norms encourage knowledge sharing, and shared infrastructure, laboratories, industry contact databases, technology transfer support, becomes available regardless of any one member's individual structural position.

In developing-country contexts, where institutional support for commercialization is weaker, network quality might matter even more: when technology transfer offices are understaffed and industry linkages remain sparse, the network becomes a substitute for formal institutional support (Kruss et al., 2015), with researchers drawing on personal connections to navigate regulatory gaps. Guerrero et al. (2020) found that the perceived richness of the institutional and network environment predicted both whether academics engaged in technology transfer and how much, across several developing-country university systems, and Cunningham et al. (2019) documented similar network-level effects among European researchers independent of individual characteristics. In such contexts, the network's collective resources may compensate for individual positional disadvantage.

*Ho₃*: Network embeddedness positively and significantly influences the commercialization of innovation among academic researchers in Tanzanian universities.

## III. METHODOLOGY

### 3.1 Research Philosophy and Design

A positivist research philosophy underpins this work, which holds that the phenomena under investigation, structural embeddedness, network embeddedness and innovation commercialization, exist as objective realities that can be measured independently of the observer through standardised instruments (Creswell & Creswell, 2018). This is appropriate given the study's aim of testing theory-derived hypotheses about relationships among observable constructs. Consistent with this stance, the study adopts a deductive approach: hypotheses derived from established network theory are subjected to empirical testing against data from a defined population of academic researchers.

The research design is cross-sectional and explanatory. A structured self-administered survey questionnaire collected quantitative data from academic researchers across five public universities in Tanzania at a single point in time. The explanatory design is appropriate because the study seeks to establish the existence, direction and strength of relationships among constructs, not merely describe their distribution. The cross-sectional design limits causal inference, patterns of association can be established but temporal ordering cannot be directly observed, a limitation returned to in Section 5.3.

### 3.2 Population and Sampling

A total of 384 questionnaires were distributed using proportionate stratified random sampling, with each participating university treated as a separate stratum. This approach ensured proportional representation of academic staff across the five universities and minimized potential institutional imbalance in the sample. Within each stratum, respondents were randomly selected from departmental staff lists obtained from the respective human resource offices.

Data were collected through in-person questionnaire administration. All distributed questionnaires were completed and returned during the data collection period, resulting in a 100% response rate. This was facilitated by trained research assistants who remained available during administration to clarify procedural questions and collect completed questionnaires immediately after completion.

Following the data screening procedures outlined in Section 3.5, responses that failed to meet predefined quality criteria, including substantial missing data, straight-lining patterns, multivariate outliers, and systematic response duplication, were excluded. As a result, 274 questionnaires were retained for analysis, representing a data retention rate of 71.4% (274/384). The distinction between response rate and retention rate is maintained throughout the manuscript: response rate indicates questionnaire completion, whereas retention rate reflects the proportion of responses that met the study's data quality requirements.

The final analytical sample of 274 respondents was considered adequate for Partial Least Squares Structural Equation Modelling (PLS-SEM). Based on the guideline proposed by Hair et al. (2022), the minimum sample size should be at least ten times the maximum number of structural paths directed toward an endogenous construct. In this study, the commercialization construct (CI) is predicted by structural embeddedness (SE), network embeddedness (NE), and their interaction term, resulting in a minimum requirement of 30 observations. The analytical sample substantially exceeds this threshold, providing sufficient observations for estimating the proposed structural relationships.

A post-hoc power analysis using G*Power 3.1 (Faul et al., 2009), based on the effect sizes actually observed (f-squared = 0.168 for structural embeddedness, 0.220 for network embeddedness, 0.033 for the interaction term), confirmed adequate power throughout: both direct effects achieved power exceeding 0.99, and the smaller interaction effect achieved power of 0.85 at alpha = .05 with N = 274, exceeding the recommended 0.80 threshold (Cohen, 1988).

Exclusions were not evenly distributed across institutions: rates ranged from 2.0% to 48.3%, with one institution accounting for 43 of the 110 excluded cases (39.1%), and a chi-square test confirmed this variation was significant (chi-squared(4) = 35.826, p < .001, Cramer's V = 0.305). The main exclusion criterion was systematic block duplication, detected through algorithmic screening for repeated Likert-scale response patterns with varying demographic characteristics. Because exclusions were not random, this institutional variation in data retention is acknowledged as a limitation; Table 1 provides the detailed exclusion and retention figures by university.

**Table 1**
*showing exclusion and retention figures by university*

| University | Initial sample | Removed (n) | Removal rate | Valid (n) | %valid sample |
|---|---|---|---|---|---|
| University 1 | 51 | 1 | 2.0% | 50 | 18.2% |
| University 2 | 129 | 38 | 29.5% | 91 | 33.2% |
| University 3 | 32 | 7 | 21.9% | 25 | 9.1% |
| University 4 | 83 | 21 | 25.3% | 62 | 22.6% |
| University 5 | 89 | 43 | 48.3% | 46 | 16.8% |
| University 6 | 51 | 1 | 2.0% | 50 | 18.2% |
| TOTAL | 384 | 110 | 28.6% | 274 | 100.0% |

*Note: All figures are from the actual cleaned dataset (N=274) and removal log (N=110).*

### 3.3 Measurement Instruments

All constructs were measured using reflective multi-item scales on a five-point Likert scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). A reflective measurement approach was appropriate because the indicators represent observable manifestations of underlying latent constructs (Hair et al., 2019). Measurement items were adapted from established literature and contextualized to the university innovation ecosystem in Tanzania.

#### 3.3.1 Structural Embeddedness (SE)

Structural embeddedness was measured using eight items adapted from Burt (1992) and Nahapiet and Ghoshal (1998). While Granovetter (1985) work provides the theoretical foundation for structural embeddedness, Burt (1992) and Nahapiet and Ghoshal (1998) were used as the primary sources for scale operationalization. The items were adapted from organizational network settings to capture researchers' structural positions within academic innovation networks, including network centrality, bridging roles, connectivity, and boundary-spanning activities across departments, universities, and industry partners. The construct demonstrated strong internal consistency (Cronbach's $\alpha = 0.907$).

#### 3.3.2 Network Embeddedness (NE)

Network embeddedness was initially measured using eight items capturing the broader innovation network's cohesion, density, resource accessibility and support for commercialization. During measurement assessment, three indicators (NE6-NE8) were excluded due to zero variance (identical responses across all observations), and NE4 was removed for cross-loading with the commercialization construct. The final NE construct comprised three indicators (NE1-NE3), meeting all reliability and validity thresholds; a sensitivity analysis using the recovered NE5 indicator confirmed this refinement did not alter substantive findings.

#### 3.3.3 Commercialization of innovation (CI)

Commercialization of innovation was measured using eight items adapted from the technology transfer literature, capturing patents, licensing, consultancy-based commercialization, spin-offs and other market applications. Following measurement assessment, CI3 was removed for cross-loading with network embeddedness, and CI8 was excluded because its outer loading (0.679) reduced construct AVE below threshold, leaving a final six-indicator construct (CI1, CI2, CI4, CI5, CI6, CI7). Indicator retention throughout followed established procedures for reflective measurement validation, guided by theoretical relevance and empirical assessment of reliability, convergent validity and discriminant validity.

### 3.4 Analytical Approach: PLS-SEM

Partial Least Squares Structural Equation Modelling (PLS-SEM) was employed to test the proposed research model. PLS-SEM was selected because it suits explanatory research involving complex models with latent constructs, direct relationships, and moderation effects (Hair et al., 2019), and because it relies on variance-based estimation and bootstrapping rather than maximum likelihood, making it less sensitive to violations of multivariate normality, relevant here given that retained indicators showed skewness values ranging from -0.86 to -0.13. PLS-SEM is also well suited to studies with moderate sample sizes and a predictive, theory-development orientation rather than strict confirmatory testing (Hair et al., 2022), and its evaluation procedures provide systematic criteria for assessing both measurement quality and structural relationships (Sarstedt et al., 2022).

The analysis followed the two-stage procedure recommended by Hair et al. (2019). First, the measurement model was assessed for reliability and validity: convergent validity through indicator loadings, average variance extracted (AVE) and composite reliability (CR), with loadings above 0.708 considered acceptable and items between 0.40 and 0.708 retained where overall construct reliability and AVE remained satisfactory; internal consistency through Cronbach's alpha and composite reliability above 0.70; and discriminant validity through the Fornell-Larcker criterion, heterotrait-monotrait ratio (HTMT), and cross-loadings. Second, the structural model was evaluated through path coefficients, bootstrapped t- and p-values, R-squared, effect sizes (f-squared), predictive relevance (Q-squared), and SRMR, with significance assessed via bootstrapping (5,000 subsamples, bias-corrected confidence intervals) using the standard path-weighting scheme with Mode A outer weights (Wold, 1982; Hair et al., 2019).

The moderating effect of network embeddedness (H2) was examined using the two-stage approach recommended by Chin et al. (2003) and Henseler and Chin (2010), selected over the product-indicator approach because the latter would generate 32 interaction indicators (8 SE indicators x 4 NE indicators), creating estimation and convergence challenges at this sample size (Henseler & Chin, 2010). The two-stage approach instead first estimates latent variable scores for SE, NE and CI from the main-effects model, then uses the standardised scores to create the interaction term (SE x NE), which is incorporated into the structural model alongside the direct effects, improving estimation stability at N = 274 (Chin et al., 2003; Hair et al., 2019). The significance of the moderation effect was assessed using bootstrapped confidence intervals, t-statistics and p-values based on 5,000 bootstrap subsamples.

### 3.5 Data Quality Screening

Data quality screening was conducted following Hair et al. (2019). From the initial dataset (N = 384), 110 cases were excluded due to anomalous response patterns, including systematic block duplication (n = 108) and invariant responding across questionnaire items (n = 2). Table 2 presents the detailed exclusion criteria and screening decisions. The resulting analytical sample of 274 valid responses exceeds the recommended sample requirements for PLS-SEM analysis (Hair et al., 2022).

**Table 2**
*Data Screening and Case Exclusion Summary*

| Exclusion criterion | Removed (n) | % of N=384 |
|---|---|---|
| Systematic block duplication of response patterns | 108 | 28.1% |
| Straight-line responding across all questionnaire items | 2 | 0.5% |
| Total excluded | 110 | 28.6% |
| Total retained | 274 | 71.4% |

A chi-square test was conducted to assess whether exclusions were evenly distributed across participating universities. The results indicated significant differences in exclusion rates across institutions ($\chi^2(4) = 35.826$, $p < .001$, Cramer's V = 0.305), with University 6 recording the highest exclusion rate (48.3%). This uneven distribution is acknowledged as a limitation, as the retained sample does not fully reflect the initial institutional composition. However, the available evidence does not confirm the underlying cause of this pattern; therefore, findings are interpreted with appropriate caution.

During measurement model preparation, the NE5 indicator was identified as missing from the cleaned dataset due to an export omission. The indicator was recovered from the original dataset through strict response-pattern matching using a 28-item response fingerprint, successfully recovering NE5 values for 205 respondents (74.8%) with no inconsistent matches. Because NE5 was unavailable for the complete sample, the primary analysis retained the original three-item NE model (NE1-NE3) on the full sample (N = 274); the recovered four-item NE model (N = 205, adding NE5) was used only for the sensitivity analysis reported in Section 4.6, which confirmed that substantive findings remained consistent across both specifications.

### 3.6 Ethical Considerations

Ethical approval was obtained from the Research Ethics Committee of the Nelson Mandela African Institution of Science and Technology (NM-AIST) prior to data collection, covering the full protocol, instruments and procedures across all five participating universities: the University of Dar es Salaam, Sokoine University of Agriculture, Dar es Salaam Institute of Technology, the University of Dodoma, and the Open University of Tanzania. All participants received written information about the study's purpose and procedures and gave informed consent before completing the questionnaire; participation was voluntary throughout, and respondents could decline any question or withdraw at any point without consequence to their employment or academic standing. No individually identifying information was collected; each respondent was assigned an anonymised numerical code, and all findings are reported in aggregate form only. Data were stored securely, in locked cabinets for paper questionnaires and on password-protected devices for electronic files, accessible only to the research team, and will be retained for five years post-publication before secure destruction in line with institutional data governance requirements.

## IV. FINDINGS & DISCUSSION

### 4.1 Respondent Demographics

The sample comprises 195 male respondents (71.2%) and 79 female respondents (28.8%), consistent with the documented gender imbalance in research-active positions at Tanzanian public universities (Tanzania Commission for Universities [TCU], 2021). This means findings may not generalise equally to female academics and the sample cannot determine whether gender moderates the embeddedness-commercialization relationship; future research using gender-stratified sampling could address this. The age distribution was concentrated in the 31-40 range (38.3%, n = 105, aged 31-35; 34.3%, n = 94, aged 36-40), reflecting a mid-career population with time to develop research networks, alongside a smaller early-career group (20.1%, n = 55, aged 26-30).

UDSM contributed the largest share of respondents (50.0%, n = 137), consistent with its status as the oldest and largest public university in Tanzania, followed by SUA (22.6%, n = 62), DIT (18.2%, n = 50) and UDOM (9.1%, n = 25); no respondents from OUT passed data quality screening. The sample included substantial proportions holding master's degrees (19.0%, n = 52) and doctoral-level qualifications (30.7%, n = 84, including PhD and professorial ranks), and most respondents had accumulated substantial institutional experience, with 34.7% (n = 95) reporting 7-10 years of service and 21.9% (n = 60) reporting more than 10 years. This profile suggests the sample captures researchers who have had the opportunity to develop the collaborative networks and structural positions the study's theoretical framework addresses. Table 3 presents the full demographic breakdown.

**Table 3**
*Demographic Characteristics of Respondents (N = 274)*

| Characteristic | Category | Frequency | Percentage |
|---|---|---|---|
| Gender | Male | 195 | 71.2 |
| | Female | 79 | 28.8 |
| Age | 20-25 | 1 | 0.4 |
| | 26-30 | 55 | 20.1 |
| | 31-35 | 105 | 38.3 |
| | 36-40 | 94 | 34.3 |
| | 41-50 | 19 | 6.9 |
| University | UDSM | 137 | 50.0 |
| | SUA | 62 | 22.6 |
| | DIT | 50 | 18.2 |
| | UDOM | 25 | 9.1 |
| Experience | <1 year | 18 | 6.6 |
| | 1-3 years | 61 | 22.3 |
| | 4-6 years | 40 | 14.6 |
| | 7-10 years | 95 | 34.7 |
| | >10 years | 60 | 21.9 |

*Note.* N = 274 after data quality screening. OUT respondents were not represented in the cleaned dataset.

### 4.2 Descriptive Statistics

Table 4 presents the means, standard deviations, skewness, and kurtosis for all 17 retained indicators across the three constructs. For structural embeddedness, mean values ranged from 3.40 (SE8: boundary-spanning activities) to 3.81 (SE5: participation in collaborative projects), indicating moderate-to-high agreement across all structural positioning items. The relatively high mean for SE5 suggests that collaborative project involvement is the most common form of structural engagement, while boundary-spanning, the least common, could reflect the institutional barriers to cross-university collaboration in the Tanzanian system.

Network embeddedness items showed means between 3.30 and 3.43, suggesting respondents perceived their networks as moderately cohesive, with slightly higher variability (SD 0.96-1.19) than structural embeddedness items, possibly reflecting genuine institutional differences in network quality. Commercialization items had means between 3.22 and 3.68, with the lowest mean corresponding to the most formal commercialization activity and the highest to more informal transfer mechanisms. All skewness values were mildly negative (-0.86 to -0.13) and kurtosis values close to zero (-0.64 to 0.21), confirming distributional properties suitable for PLS-SEM.

**Table 4**
*Descriptive Statistics for Retained Indicators*

| Indicator | Mean | SD | Skewness | Kurtosis | N |
|---|---|---|---|---|---|
| Structure1 | 3.57 | 1.08 | -0.86 | 0.21 | 274 |
| Structure2 | 3.57 | 1.05 | -0.62 | -0.10 | 274 |
| Structure3 | 3.56 | 1.04 | -0.73 | 0.14 | 274 |
| Structure4 | 3.50 | 1.11 | -0.71 | -0.10 | 274 |
| Structure5 | 3.81 | 1.11 | -0.67 | -0.42 | 274 |
| Structure6 | 3.56 | 1.09 | -0.80 | 0.08 | 274 |
| Structure7 | 3.51 | 1.00 | -0.55 | -0.15 | 274 |
| Structure8 | 3.40 | 1.15 | -0.53 | -0.47 | 274 |
| Network1 | 3.43 | 1.19 | -0.77 | -0.25 | 274 |
| Network2 | 3.37 | 0.96 | -0.13 | -0.57 | 274 |
| Network3 | 3.30 | 1.02 | -0.35 | -0.22 | 274 |
| Commercial1 | 3.58 | 1.12 | -0.73 | -0.07 | 274 |
| Commercial2 | 3.57 | 0.94 | -0.48 | -0.21 | 274 |
| Commercial4 | 3.29 | 1.09 | -0.14 | -0.64 | 274 |
| Commercial5 | 3.68 | 1.19 | -0.71 | -0.31 | 274 |
| Commercial6 | 3.54 | 1.05 | -0.54 | -0.28 | 274 |
| Commercial7 | 3.22 | 1.00 | -0.27 | -0.18 | 274 |

*Note.* All items measured on 5-point Likert scale (1 = strongly disagree, 5 = strongly agree). N = 274. Construct-level composite means (SD): SE = 3.56 (0.84), NE = 3.37 (0.86), CI = 3.48 (0.80).

### 4.3 Common Method Bias Assessment

Because all data were collected through a single self-report questionnaire at a single point in time, common method bias (CMB) was assessed via two diagnostics. Harman's single-factor test, entering all 17 retained indicators into an unrotated principal component analysis, showed the first component accounted for 43.30% of variance, below Podsakoff et al.'s (2003) 50% threshold. Kock (2015) full collinearity VIF approach showed all values below the 3.3 threshold (SE = 1.562, NE = 1.642, CI = 1.795). These results indicate common method bias is unlikely to distort the structural model estimates; Table 5 summarises the results.

**Table 5**
*Common Method Bias Assessment*

| Test | Result | Threshold |
|---|---|---|
| Harman's single factor | 43.30% | < 50% |
| Full collinearity VIF (SE) | 1.562 | < 3.3 |
| Full collinearity VIF (NE) | 1.642 | < 3.3 |
| Full collinearity VIF (CI) | 1.795 | < 3.3 |

*Note.* VIF = Variance Inflation Factor. Harman's test based on unrotated PCA with all 17 retained indicators. VIF threshold per Kock (2015).

### 4.4 Measurement Model Assessment

The measurement model was assessed in terms of indicator reliability (outer loadings), internal consistency reliability (Cronbach's alpha and composite reliability), convergent validity (average variance extracted), and discriminant validity (Fornell-Larcker criterion and HTMT ratio), following Hair et al. (2019). The results, presented in Tables 4 through 6, demonstrate that all criteria are satisfied.

#### 4.4.1 Convergent Validity and Internal Consistency

Table 6 presents the outer loadings and construct-level reliability statistics. All outer loadings exceed 0.708 or fall within the acceptable 0.40-0.708 range while maintaining adequate composite reliability and AVE. Structural embeddedness retained all eight original indicators (loadings 0.731-0.836, t-values 18.919-36.240, all $p < .001$). Network embeddedness retained three indicators (NE1-NE3) after removing NE4 for cross-loading on CI (loading differential of -0.011, below the 0.10 threshold), with retained loadings ranging from 0.776 to 0.836. Commercialization of innovation retained six of the original eight indicators (CI1, CI2, CI4-CI7), with loadings from 0.684 (CI2) to 0.803 (CI6).

Internal consistency reliability exceeds Hair et al.'s (2019) recommended thresholds across all constructs: Cronbach's alpha values are 0.907 (SE), 0.734 (NE) and 0.848 (CI), all above 0.70; composite reliability values are 0.925 (SE), 0.852 (NE) and 0.888 (CI), all above 0.70 and below the 0.95 ceiling that would indicate item redundancy; and average variance extracted values are 0.606 (SE), 0.657 (NE) and 0.571 (CI), all exceeding the 0.50 threshold for convergent validity. Two CI indicators (CI1 = 0.691, CI2 = 0.684) fall marginally below 0.708 but were retained: following Hair et al.'s (2019, p. 115) criterion, removal was tested and found to improve AVE only marginally (+0.009 to +0.011) while reducing composite reliability and Cronbach's alpha (-0.012 to -0.016); since the two criteria did not simultaneously improve and both items remain statistically significant at $p < .001$, they were retained.

**Table 6**

*Outer Loadings, Reliability, and Convergent Validity*

| Indicator | Loading | t-value | p-value | CA | CR | AVE |
|---|---|---|---|---|---|---|
| SE1 | 0.836 | 36.240 | <0.001 | 0.907 | 0.925 | 0.606 |
| SE2 | 0.810 | 34.383 | <0.001 | | | |
| SE3 | 0.784 | 22.578 | <0.001 | | | |
| SE4 | 0.803 | 31.970 | <0.001 | | | |
| SE5 | 0.757 | 24.459 | <0.001 | | | |
| SE6 | 0.769 | 20.153 | <0.001 | | | |
| SE7 | 0.733 | 19.126 | <0.001 | | | |
| SE8 | 0.731 | 18.919 | <0.001 | | | |
| NE1 | 0.836 | 26.303 | <0.001 | 0.734 | 0.852 | 0.657 |
| NE2 | 0.818 | 26.128 | <0.001 | | | |
| NE3 | 0.776 | 18.897 | <0.001 | | | |
| CI1 | 0.691 | 13.164 | <0.001 | 0.848 | 0.888 | 0.571 |
| CI2 | 0.684 | 14.340 | <0.001 | | | |
| CI4 | 0.776 | 27.627 | <0.001 | | | |
| CI5 | 0.769 | 24.193 | <0.001 | | | |
| CI6 | 0.803 | 36.344 | <0.001 | | | |
| CI7 | 0.802 | 28.415 | <0.001 | | | |

*Note.* CA = Cronbach's Alpha; CR = Composite Reliability; AVE = Average Variance Extracted. Bootstrap N = 5,000. Removed indicators: NE4 (cross-loading on CI, diff = -0.011), CI3 (cross-loading on NE), CI8 (loading = 0.680; removal improved CI AVE from 0.552 to 0.571). NE6-NE8 excluded prior to analysis (data compilation artefact).

### 4.4.2 Discriminant Validity

Discriminant validity, which assesses whether each construct is empirically distinct from the others, was evaluated using the Fornell-Larcker criterion and the heterotrait-monotrait (HTMT) ratio. Table 7 presents the Fornell-Larcker matrix: the square root of AVE for each construct (SE = 0.779, NE = 0.810, CI = 0.756) exceed its correlations with every other construct (SE-NE = 0.502, SE-CI = 0.562, NE-CI = 0.590), satisfying Fornell and Larcker (1981) criterion and confirming discriminant validity.

**Table 7**

*Fornell-Larcker Criterion for Discriminant Validity*

| | SE | NE | CI |
|---|---|---|---|
| SE | 0.779 | | |
| NE | 0.502 | 0.810 | |
| CI | 0.562 | 0.590 | 0.756 |

*Note.* Diagonal values (bold) represent the square root of AVE for each construct. Off-diagonal values are inter-construct correlations.

Table 8 presents the HTMT ratios. Henseler et al. (2015) recommend a threshold of 0.85 for conceptually distinct constructs and 0.90 for conceptually similar constructs. All HTMT values in this study fall below the conservative 0.85 threshold: SE-NE = 0.605, SE-CI = 0.626 and NE-CI = 0.729. The highest ratio (NE-CI = 0.729) is well below the threshold, indicating that even the most correlated pair of constructs is clearly distinguishable. These results, together with the Fornell-Larcker analysis, provide strong evidence that each construct captures a distinct theoretical domain.

**Table 8**
*Heterotrait-Monotrait (HTMT) Ratios*

| | SE | NE | CI |
|---|---|---|---|
| SE | -- | | |
| NE | 0.605 | -- | |
| CI | 0.626 | 0.729 | -- |

*Note.* All HTMT ratios are below the 0.85 conservative threshold (Henseler et al., 2015). HTMT = Heterotrait-Monotrait ratio of correlations.

### 4.5 Structural Model Assessment

Having established the psychometric adequacy of the measurement model, the analysis proceeds to the structural model. Before interpreting the path coefficients, collinearity among predictor constructs was assessed: the inner VIF value for both SE and NE as predictors of CI is 1.336, well below the threshold of 5.0 recommended by Hair et al. (2019) and the more conservative threshold of 3.3 recommended by Kock (2015), indicating no collinearity concern. The interaction term's contribution was evaluated in three ways. First, the effect size is small but non-trivial by Cohen's (1988) benchmarks (f-squared = 0.033). Second, the interaction coefficient is statistically significant (beta = -0.100, t = 2.496, p = .013, N = 274), with a bootstrapped 95% confidence interval of [-0.173, -0.015] that excludes zero. Third, Q-squared values from 10-fold cross-validation are 0.539 for the base model and 0.538 for the moderation model, showing comparable predictive accuracy across both specifications.

#### 4.5.1 Direct Effects

Table 9 presents the path coefficients, standard errors, t-statistics, p-values, 95% bias-corrected bootstrap confidence intervals, f-squared effect sizes, and hypothesis decisions. The base structural model (without the interaction term) explains 44.3% of variance in innovation commercialization (R-squared = 0.443). When the interaction term is included in the two-stage moderation model, R-squared increases to 0.461 (adjusted R-squared = 0.455). The path coefficients reported in Table 9 are from the full moderation model, which represents the final model specification. The cross-validated redundancy measure Q-squared = 0.410, which is substantially above the zero-threshold required for predictive relevance (Hair et al., 2019), indicates that the model predicts the endogenous construct well beyond chance. The standardized root means square residual (SRMR) = 0.072, which is below the 0.08 cut-off recommended by Henseler et al. (2016), confirms acceptable approximate model fit.

Structural embeddedness exerts a significant positive effect on innovation commercialization (beta = 0.314, t = 4.473, p < 0.001, 95% CI [0.195, 0.478]), with a confidence interval that excludes zero and an effect size (f-squared = 0.168) that qualifies as medium under Cohen's (1988) benchmarks (small = 0.02, medium = 0.15, large = 0.35). H1 is therefore supported: structural embeddedness positively influences innovation commercialization among academic researchers in Tanzanian universities.

H3 is likewise supported. Network embeddedness has its own significant positive effect on commercialization (beta = 0.362, t = 5.431, p < 0.001, 95% CI [0.231, 0.495]), and at f-squared = 0.220 the effect sits between Cohen's medium and large thresholds, marking it as a substantively important predictor. Notably, NE's direct effect (0.362) outweighs that of SE (0.314), which points to something worth dwelling on: the overall quality of a researcher's network environment appears to matter more for commercialization than where that researcher sits within the network.

**Table 9**
*Structural Model Results: Path Coefficients and Hypothesis Testing*

| Path | Beta | SE | t | p | 95% CI | f-sq | Decision |
|---|---|---|---|---|---|---|---|
| SE -> CI | 0.314 | 0.070 | 4.473 | <0.001 | [0.195, 0.478] | 0.168 | H1 Sup. |
| NE -> CI | 0.362 | 0.067 | 5.431 | <0.001 | [0.231, 0.495] | 0.220 | H3 Sup. |
| NE x SE -> CI | -0.100 | 0.040 | 2.496 | 0.013 | [-0.173, -0.015] | 0.033 | H2 Sup. |

*Note.* Bootstrap N = 5,000. R-sq = 0.461 (with interaction); Adj. R-sq = 0.455 (moderation model); Q-sq = 0.410; SRMR = 0.072. f-sq effect size benchmarks: 0.02 = small, 0.15 = medium, 0.35 = large (Cohen, 1988). Sup. = Supported.

#### 4.5.2 Moderation Analysis

The two-stage moderation analysis reveals a significant negative interaction between NE and SE on CI (beta = -0.100, t = 2.496, p = .013, 95% CI [-0.173, -0.015]), with the interval excluding zero. The effect size (f-squared = 0.033) is small by Cohen's (1988) general benchmarks, but as Hair et al. (2019) and Kenny (2018) note, interaction effects in field studies using survey data rarely exceed f-squared = 0.05 due to measurement error and range restriction;

the present effect falls within the range typically reported in comparable social science research and carries meaningful theoretical and practical implications.

Including the interaction term increased R-squared from 0.443 to 0.461 (Delta R-squared = 0.018), a modest but genuine gain beyond the direct effects alone. The negative interaction coefficient indicates a substitution effect: as network embeddedness increases, the positive effect of structural embeddedness on commercialization weakens. Simple slope analysis was conducted at three levels of NE, one standard deviation below the mean, at the mean, and one standard deviation above, with results presented in Table 10.

**Table 10**

*Simple Slope Analysis: Effect of SE on CI at Varying Levels of NE*

| NE Level | SE -> CI Slope | Interpretation |
|---|---|---|
| Low (-1 SD) | 0.414 | Strong positive effect |
| Mean | 0.314 | Moderate positive effect |
| High (+1 SD) | 0.215 | Attenuated positive effect |

*Note*. Simple slopes computed from moderation model: Slope = beta(SE) + beta(NExSE) x NE level, where NE is standardised (mean = 0, SD = 1).

The simple slope analysis shows a clear pattern: at low NE (-1 SD), structural embeddedness has a strong positive effect on commercialization (slope = 0.414); at mean NE, the effect is moderate (slope = 0.314); at high NE (+1 SD), it attenuates but remains positive (slope = 0.215). This is consistent with partial rather than complete substitution, structural embeddedness retains a positive influence at all observed levels of NE, but its marginal benefit diminishes as the surrounding network becomes denser and more resource-rich. Figure 1 depicts the structural model with path coefficients, and Figure 2 presents the simple slopes plot.

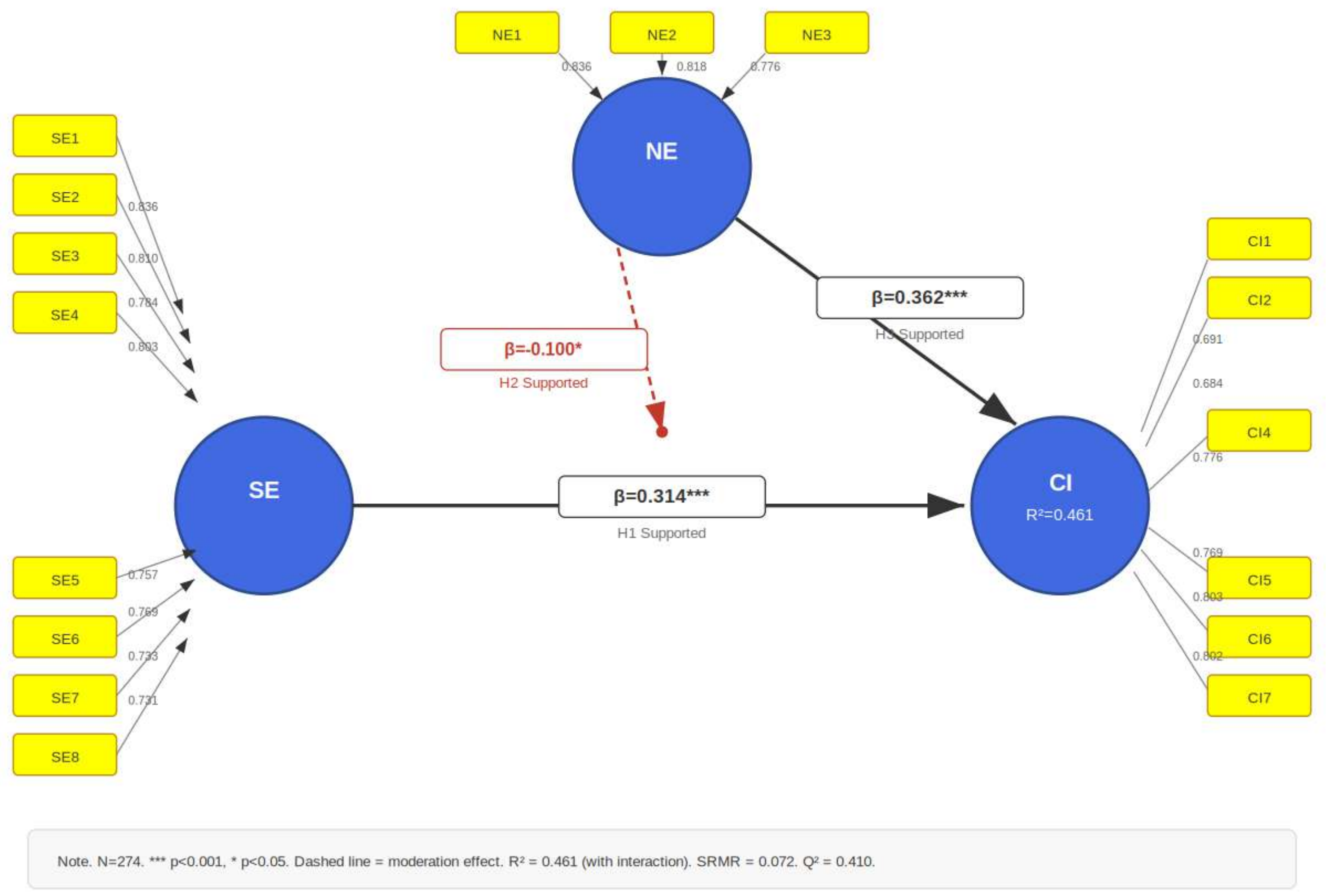


**Figure 1**

*Structural Model Results*

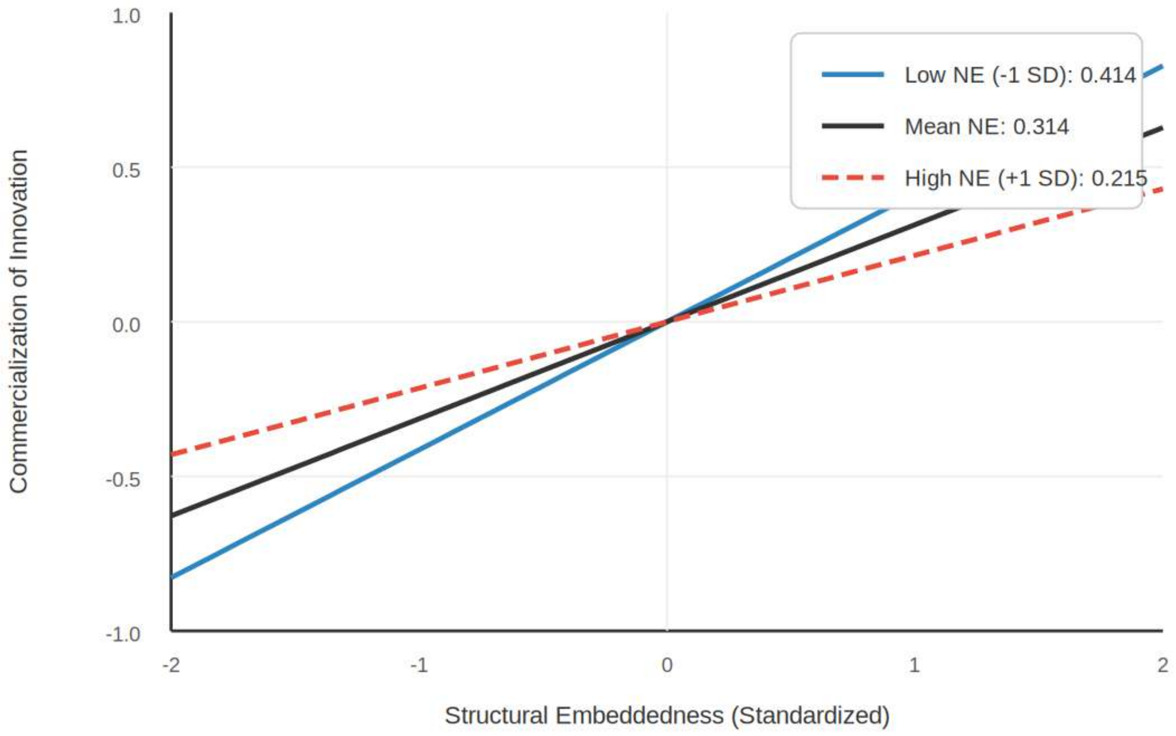


**Figure 2**

*Simple Slopes: Effect of Structural Embeddedness on Commercialization at Varying Levels of Network Embeddedness*

### 4.5.3 Model Quality Summary

Table 11 consolidates the key model quality indicators for the structural model. All criteria meet or exceed the recommended thresholds, providing confidence that the model is well-specified and the parameter estimates are trustworthy.

**Table 11**

*Summary of Model Quality Criteria*

| Criterion | Value | Threshold | Assessment |
|---|---|---|---|
| R-squared (moderation model) | 0.461 | > 0.25 substantial | Substantial |
| Adjusted R-squared | 0.455 | -- | -- |
| Q-squared (CI) | 0.410 | > 0 | Predictive relevance |
| SRMR | 0.072 | < 0.08 | Acceptable fit |
| f-sq (SE -> CI) | 0.168 | 0.15 = medium | Medium |
| f-sq (NE -> CI) | 0.220 | 0.15 = medium | Medium-large |
| f-sq (NExSE) | 0.033 | 0.02 = small | Small |

*Note.* R-sq thresholds per Hair et al. (2019). f-sq benchmarks per Cohen (1988). SRMR threshold per Henseler et al. (2016). Q-sq computed via cross-validated redundancy with omission distance d = 7.

### 4.6 Sensitivity Analysis: NE5 Specification

A sensitivity analysis assessed whether including a fourth Network Embeddedness indicator (NE5), available for a subsample of 205 cases, altered the study findings. The four-item NE specification showed satisfactory measurement properties (Cronbach's alpha = 0.799, CR = 0.868, AVE = 0.623). In this model, both SE (beta = 0.320, p < .001) and NE (beta = 0.562, p < .001) remained positive and significant predictors of CI, while the moderation effect was not significant (beta = -0.002, p = .930).

A post-hoc power analysis showed the N = 205 subsample had power of 0.73 to detect the observed interaction effect (f-squared = 0.019), below the 0.80 threshold, so this sensitivity analysis may have been underpowered to detect moderation; the primary model (N = 274, power = 0.85) forms the basis for the study's main conclusions. The three-item NE specification estimated on the same N = 205 subsample produced comparable direct effects (SE beta = 0.537, NE beta = 0.257, both $p < .01$), confirming that direction and significance held across specifications; the differences in coefficient magnitude reflect the broadened conceptual coverage from adding NE5 and a corresponding redistribution of variance between SE and NE, rather than model instability. The primary model, estimated on the full sample with complete data, is retained as the preferred specification. Overall, the sensitivity analysis confirms that the positive effects of structural and network embeddedness on commercialization are robust across alternative specifications.

### 4.7 Discussion

The starting question was how structural embeddedness influences the commercialization of innovation among academic researchers in Tanzanian universities, whether network embeddedness moderates this relationship, and whether network embeddedness independently predicts commercialization outcomes. The results, derived from PLS-SEM analysis of 274 respondents across five public universities with 5,000 bootstrap subsamples, provide support for all three hypotheses and yield theoretically and practically significant insights. This section discusses each finding in relation to prior empirical evidence, theoretical expectations, and contextual factors specific to the Tanzanian higher education system.

#### 4.7.1 Structural Embeddedness and Innovation Commercialization (H1)

The finding that structural embeddedness positively and significantly predicts innovation commercialization (beta = 0.314, $p < .001$, f-squared = 0.168) is consistent with network theory's core prediction that positional advantage translates into superior access to information, resources and opportunities (Granovetter, 1992). Researchers who occupy central positions in collaborative networks, bridge disconnected research groups, or span institutional boundaries are better positioned to identify commercial opportunities, attract industry partners, and navigate the path from laboratory discovery to market application.

This result is concordant with prior work in developed-country contexts: Ahuja (2000) showed that network centrality and bridging positions predicted patent output in the chemical industry, Breschi and Catalini (2010) found that academic inventors' structural position within co-authorship networks predicted licensing revenue, and Owen-Smith and Powell (2004) found that structurally embedded universities in the Boston biotechnology cluster generated more commercially valuable research. The present study extends this evidence to a developing-country university system where the mechanisms linking structural position to commercial outcomes likely operate somewhat differently, given weaker formal commercialization infrastructure.

The medium effect size (f-squared = 0.168) merits attention. Where university-industry linkages are sparse and formal technology transfer mechanisms remain underdeveloped, as in Tanzania, the returns to structural positioning might be amplified precisely because alternative pathways to commercialization, established technology transfer offices, patent attorneys, venture capital networks, are scarce. When the institutional infrastructure that typically supports commercialization elsewhere is weak or absent, the informal advantages conferred by structural position become more consequential, consistent with the resource-scarcity argument advanced by Kruss et al. (2015) in their analysis of South African university-industry interactions.

Practically, this finding suggests that strategies to improve academic researchers' structural positioning, encouraging inter-departmental committee participation, supporting cross-university co-authorship, creating opportunities to serve on industry advisory boards, can yield tangible commercialization benefits. Formal boundary-spanning roles, such as innovation liaison officers or departmental research coordinators tasked with maintaining cross-institutional networks, represent one mechanism through which structural embeddedness could be deliberately cultivated. This echoes Perkmann et al. (2021), who found that institutional mechanisms for connecting researchers to external partners consistently predicted engagement intensity across national contexts, and Hayter et al. (2018), who showed that deliberately, constructed bridging ties between academic inventors and industry contacts accelerated commercialization timelines.

#### 4.7.2 The Moderation Effect (H2): A Substitution Mechanism

The significant negative moderation (beta = -0.100, $p = 0.013$, f-squared = 0.033) is the most theoretically consequential finding of this study. The negative interaction indicates that as network embeddedness increases, the positive effect of structural embeddedness on commercialization weakens. The simple slope analysis quantifies this pattern: at low NE (-1 SD), the SE-CI slope is 0.414; at mean NE, it is 0.314; at high NE (+1 SD), it diminishes to 0.215. This pattern is consistent with the substitution hypothesis (Rowley et al., 2000; Uzzi, 1996) and contradicts the amplification hypothesis.

The substitution logic operates through a fairly intuitive mechanism. In sparse networks, information about commercial opportunities is concentrated among a few structurally well-positioned actors, so structural embeddedness carries a high premium. As the network becomes denser, information diffuses more broadly, and researchers who are not centrally positioned gain access to opportunities through the wider web of interconnections, reducing the positional advantage that structurally central actors would otherwise capture. This effect could be particularly salient in Tanzania given the limited development of formal commercialization infrastructure: where technology transfer offices and patent systems remain underdeveloped (Mashoto, 2022), commercialization depends more on informal channels, and dense networks provide broader collective access that reduces the marginal advantage of central structural position. This interpretation is consistent with Guerrero et al. (2020), who found that social capital plays a particularly important role in university-industry collaboration in emerging economies, and the stronger correlation between network embeddedness and commercialization ($r = 0.722$) relative to structural embeddedness ($r = 0.545$) in this study further supports it. Tanzania's collectivist cultural orientation (Hofstede, 1980) may also reinforce dense relational structures and resource-sharing norms that amplify these collective benefits, though comparative research across different institutional and cultural settings would be needed to establish how far this substitution effect generalises.

This dovetails with Uzzi (1996) observation that embeddedness carries both benefits and liabilities: dense networks provide trust and fine-grained information transfer, but can also create redundancy that shrinks the incremental value of any one researcher's bridging position. The small but significant interaction effect (f-squared = 0.033) is itself consistent with the wider methodological literature on moderation in field studies: Kenny (2018) notes that such effects rarely exceed f-squared = 0.05 once measurement error is accounted for, and Hair et al. (2019) recommend judging interaction effect sizes against the norms of the research domain rather than Cohen's (1988) general benchmarks. By that standard, where interactions between embeddedness dimensions have rarely been tested at all, the present finding offers meaningful evidence for the substitution mechanism.

### 4.7.3 Network Embeddedness and Innovation Commercialization (H3)

Network embeddedness exerts a stronger direct effect on commercialization (beta = 0.362, $p < .001$, f-squared = 0.220) than structural embeddedness, indicating that the overall quality, density and resource-richness of the surrounding network is an even more potent predictor than the individual researcher's structural position within it. This supports the theoretical argument that network-level properties generate positive externalities, accelerated information diffusion, shared commercialization infrastructure, normative support for commercial engagement, that benefit all embedded actors (Gilsing et al., 2008; Rowley et al., 2000).

This larger effect of NE relative to SE suggests that in the Tanzanian university context, collective network resources matter more than any individual researcher's positional advantage. This is plausible where successful commercialization depends on shared infrastructure, technology transfer offices, incubation facilities, intellectual property management systems, that no individual researcher can replicate alone: when such resources are present and functional, all researchers in the network benefit; when absent, even structurally well-positioned researchers struggle to convert discoveries into commercial value.

This carries a direct practical implication: university administrators and policymakers seeking to increase commercialization output should prioritise network-level interventions over individual-level ones. Investments in shared laboratories, joint industry engagement workshops, cross-departmental collaboration platforms and institutionally managed industry contact databases are likely to produce broader, more equitable commercialization gains than strategies that identify and support only a few structurally well-positioned researchers. This ecosystem-level perspective resonates with Guerrero et al. (2020) finding that overall entrepreneurial ecosystem quality, rather than individual academic entrepreneurs' characteristics, was the primary determinant of technology transfer output across their multi-country sample.

## V. CONCLUSION & RECOMMENDATIONS

### 5.1 Conclusion

This paper investigated the relationship between structural embeddedness and the commercialization of innovation among academic researchers at five Tanzanian public universities. Using PLS-SEM on data from 274 respondents with 5,000 bootstrap subsamples, the analysis tested three hypotheses derived from Granovetter's network theory. All three hypotheses received statistical support, with important differences in effect strength. The direct effects of structural embeddedness (beta = 0.314, $p < .001$, f-squared = 0.168) and network embeddedness (beta = 0.362, $p < .001$, f-squared = 0.220) on innovation commercialization were both significant with meaningful effect sizes. Network embeddedness showed a somewhat stronger effect than structural embeddedness, suggesting that the overall quality, accessibility and resource richness of the surrounding network environment may be at least as influential for commercialization outcomes as an individual researcher's own network position.

The moderation analysis supported the substitution mechanism (beta = -0.100, $p = .013$, f-squared = 0.033), with the bootstrapped 95% confidence interval (-0.173, -0.015) excluding zero. As network embeddedness increases, the marginal returns to structural embeddedness decline while remaining positive at the levels of network embeddedness observed in this sample. The effect size is small by conventional benchmarks, and future studies using larger samples, longitudinal designs, and objective commercialization indicators, patents, licences and spin-off formation, are needed to further validate the strength and generalisability of this moderation effect.

### 5.2 Recommendations

For university technology transfer offices and research administrators, the findings suggest that building the collective quality of the research network, through shared facilities, inter-departmental collaboration programmes, joint industry exposure events and multi-university research platforms, is likely to produce larger commercialization gains than interventions that focus narrowly on identifying and supporting a few structurally well-positioned researchers. As the network matures and becomes more resource-rich, the substitution effect implies that the need for strategic positioning by individual researchers diminishes, making commercialization benefits more broadly and equitably distributed across the academic community.

For national policymakers and funding agencies, the results support investing in university-industry partnership platforms, technology incubation hubs and inter-institutional research consortia that raise the overall embeddedness of the academic ecosystem, rather than channelling resources exclusively to individual flagship researchers or single elite institutions. COSTECH and TCU could usefully integrate network-building metrics into institutional performance frameworks, rewarding universities that demonstrate strong inter-institutional collaboration and industry engagement alongside conventional research output measures.

### 5.3 Limitations and Directions for Future Research

Several limitations qualify these findings. The cross-sectional design captures associations at a single point in time and cannot establish causal direction: it remains possible that researchers who have already commercialized innovations subsequently invest more in building their networks, rather than networks driving commercialization. Longitudinal designs would help disentangle this. All constructs were measured through self-report, which can invite social desirability bias, though the common method bias diagnostics in Section 4.3 suggest this is not a serious concern here. The sample, while adequately powered, was drawn from five universities using convenience access within each institution, and exclusion rates varied unevenly across them; results may not generalise beyond the sampled institutions without further testing. The moderation effect, while significant, is small in magnitude (f-squared = 0.033) and awaits replication in larger samples before its practical significance can be considered established. Finally, this study examined only two of the three dimensions of embeddedness identified in network theory; a companion study using the same sample (John et al., under review) examines relational embeddedness, and future work integrating all three within a single model would offer a fuller test of the theory. Despite these limitations, the consistency of the direct effects across specifications, and the theoretical coherence of the substitution mechanism identified here, suggest the core findings are unlikely to be artefacts of the specific sample or measurement choices made.

### Declaration of Interest

The authors declare that they do not have any known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

### Funding Declaration

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

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