Effects of Academic Mobility on Researcher's Productivity: The Case of African Scholars in Chinese Universities

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Abstract

We hypothesize that academic mobility enhances scientists' human and social capital, positively influencing academic performance through metrics, publications, research projects, and co-authorship. Using partial least squares structural modeling on a sample of 204 African academics in Chinese institutions, we find that mobility components, particularly the length of stay in China and moving between host institutions, significantly impact cognitive and tacit knowledge. For mobility to boost productivity (publications, projects, and metrics), academics must develop networks with editors, reviewers, and key authors while extending their human capital. Thus, social and human capital are crucial intervening variables in demonstrating academic mobility's role in enhancing early academics' productivity.

***Keywords*:** academic mobility, researcher, productivity, human capital, social capital

Introduction

Proficient scientists enhance their skills through mobility and active engagement (Y. Chen et al., 2023; Habicht et al., 2021). Career trends and research output are key in academic mobility. In recent decades, China has attracted international academics, notably through the Thousand Talents Plan, initiated in the late 2000s to boost its universities' global rankings (B. Wang & Chen, 2021). Measures were introduced to simplify visas for foreign researchers (T. Kim, 2017; Li et al., 2018). Despite extensive research, the impact of mobility remains underexplored, with notable exceptions like Jonkers & Tijssen (2008), Liu et al. (2021), and Zhao et al. (2020). In Asia, postdoctoral experience significantly influences research performance (Horta, 2009; Jung, 2020). Halevi et al. (2016) examined mobility across disciplines, stressing the need for accurate evaluation of international mobility (Netz et al., 2020).. Further

studies should differentiate between types of mobility and their impact (Horta et al., 2018; Siemers, 2016). While most research uses bibliometric data to study mobility's effect on productivity, few have examined the mediating role of human and social capital using self-assessment methods in specific contexts. These studies often focus on country-level assessments using CVs or bibliometric analyses (Abramo et al., 2022; Halevi et al., 2016; Liu et al., 2021; Momeni et al., 2022). This study applies Bozeman's model to explore how ST human and social capital mediate the relationship between mobility and productivity, addressing the following research questions:

- RQ1. How does accumulating scientific and technical human capital (STHC) gained from mobility affect researcher productivity?

a. publications in peer-reviewed journals?
b. citations and h-index?
c. co-authorship and research project?

- RQ2. How does accumulating social capital (SC) affect researchers' productivity during their stay abroad?

By addressing the research questions, we contribute to the ongoing discussion on the complex relationship between academic mobility and its impact on research output among African scientists in Chinese universities.

Theoretical Foundations and Hypothesis Development

Mobility and Researcher's Productivity

Our theoretical framework is based on the Scientific and Technical Human Capital (STHC) approach and Social Capital Theory (SCT), which aim to model the mediating roles of human, technical, and social capital in connecting academic mobility with research productivity.

Studies on the impact of mobility in various settings have produced inconsistent findings. Cross-border mobility facilitates international knowledge-sharing (Shen et al., 2022), and bibliometric indicators can trace text origins. However, empirical data on mobility duration's impact remain inconclusive. A direct relationship exists between foreign experience and collaborative paper production (Jonkers & Tijssen, 2008; Momeni et al., 2022). Mobility enhances scientific and technical human capital by fostering collaborations, correlating with frequently cited papers (Yamashita & Yoshinaga, 2014). Long-term early-career overseas experiences have a significant impact on research output (Gao & Liu, 2021). Geographic mobility varies among disciplines, with assistant professors showing the highest mobility (He et al., 2019).

Some analyses, like Fernández-Zubieta et al. (2016), show a generally favorable impact on mobility but also note temporary adverse effects after job transitions.

H1: Subsequent components of mobility increase academic research productivity.

H1.a. Mobility duration positively affects research productivity.

Staying at Different Host Institutions

Host universities provide opportunities for mobile researchers to develop unique forms of human capital. The accumulation of tacit knowledge and skills is directly proportional to the number of diverse host institutions (Catalini, 2018; Lane et al., 2019). Scholars must transition between affiliations to acquire more expertise and broaden their professional connections. A researcher's number of connections, whether two or three, may have a substantial impact (Halevi et al., 2016).

The number of connections that may be obtained and the extent of the network expand in proportion to the number of host institutions (Bäker et al., 2021). Nevertheless, by accumulating social capital through overseas stays, researchers may enhance their likelihood of acquiring further expertise in diverse working settings and scientific methodologies (Bauder et al., 2017).

H1.b. Staying in different host institutions positively affects research productivity.

Highly Ranked Institutions

Fernández-Zubieta et al. (2016) found that inter-organizational movement positively impacts academic performance only when moving to "superior" departments, while downward mobility harms research efficiency. Tartari et al. (2020) confirmed that mobility benefits performance primarily within well-resourced institutions. Bäker et al. (2021) showed a positive relationship between research output and affiliation changes, though Bolli and Schläpfer (2015) disputed this in a single field study. The role of top institutions in research productivity has led scholars to examine how department size influences mobile academics. Research has extensively explored the link between department size and research performance (Abramo et al., 2022; Aksnes et al., 2013; Bauer et al., 2013).

H1.c. Staying at highly-ranked institutions positively affects research productivity.

Sized Departments Affect Researchers' Productivity

A large-scale study of Chinese doctoral students abroad found that larger research

institutions were particularly productive (Shen et al., 2017). However, studies show mixed effects of department size on research productivity; for example, research in German-speaking countries revealed that larger departments can negatively impact performance (Bäker, 2015). Size measures social capital, reflecting contact with researchers in relevant areas. Deville et al. (2015) found that institutional size has little effect on publication intensity but is positively linked to publication impact. Larger departments tend to recruit more skilled researchers, which may enhance internal collaboration and publication impact, even when accounting for author-specific factors (Dubois et al., 2014).

H1.d. Sized department positively affects research productivity.

Social Capital and Research Productivity

Social capital theory is widely applied to academic research performance (Nahapiet & Ghoshal, 1998) and intellectual capital (Zhang & Wang, 2017). Faculty use social capital to enhance research capacity, productivity, and adaptability. Empirical data shows that postdoctoral training boosts publication impact (Lawson et al., 2015; McAlpine, 2018), and researchers relocating to China often see increased productivity and prominence. However, the superior performance of local Chinese researchers raises questions about China's recruitment strategy. Social capital within institutions benefits early-career researchers by providing access to knowledge, resources, and career sponsorship (Catalano et al., 2021). International mobility enhances social capital, improving research performance (Ryazanova & McNamara, 2019) by expanding networks and sharing research. Establishing international connections enhances resource availability for knowledge generation and innovation (Patrício et al., 2018). and boosts research efficiency, leading to influential publications with global collaborators (Jonkers & Cruz-Castro, 2013a). Co-authorship, a key measure of research collaboration, is linked to an increase in highly cited multi-author articles. Expanding social capital through new networks and ties, including connections with journal editors or reviewers, significantly benefits publications and citations (Ackers, 2008; Groves et al., 2018).

H2. The accumulation of social capital positively impacts researcher productivity.

- H2a. Accumulation of social capital mediates the relationship between mobility and research publications.

- H2b. Accumulation of social capital mediates the relationship between mobility and a researcher's co-authorship.

- H2c. Accumulation of social capital mediates the relationship between mobility and publication metrics.

- H2d. Accumulation of social capital mediates the relationship between mobility and research projects.

Scientific and Technical Human Capital Mediates the Relationship Between Mobility and Researchers' Productivity

Human capital encompasses an individual's intellectual capacity, knowledge, expertise, and physical well-being (Becker, 1962), with talent and specialized skills being crucial (Coff, 2002). Bozeman et al. (2001a) define "scientific and technical human capital (STHC)" as researchers' collective abilities, technical expertise, connections, and resources, including tacit knowledge, craft knowledge, and know-how. These attributes enhance scientific output, such as grant writing, financial management, recruiting collaborators, and engaging in professional discussions. However, recent debates highlight the need for discipline-specific frameworks in academic mobility research(Xu et al., 2022, p. 422). The STHC model has been widely applied in various studies (Bozeman & Corley, 2004; Turpin et al., 2010; J. Wang et al., 2017).

Lee and Bozeman (2005) and Bozeman and Corley (2004) used STHC to study scientific collaboration through CVs and surveys, showing that academics gain valuable tacit knowledge abroad, including research methods, theories, and literature. (Bozeman et al., 2001b; Horta, 2013; Jonkers & Cruz-Castro, 2013b; Laudel & Bielick, 2019).

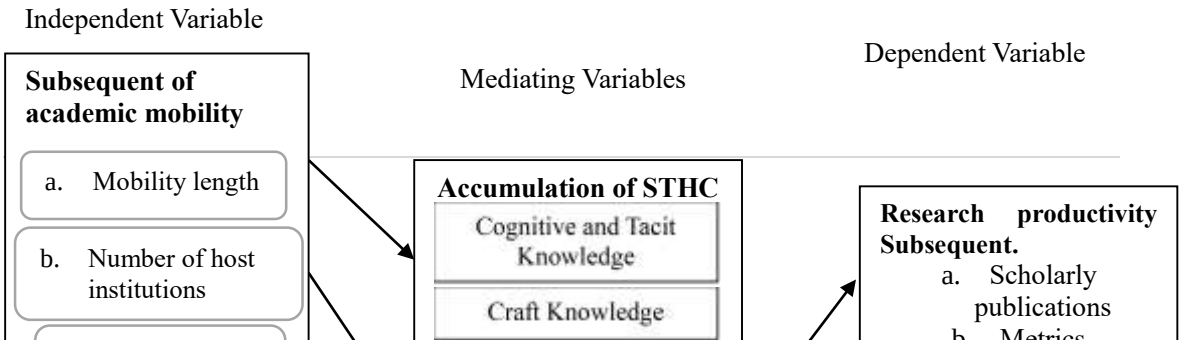
H3: Scientific and technical human capital (STHC) mediates mobility and subsequent research productivity.

- H3a: STHC mediates the relationship between mobility and research publications.

- H3b: STHC mediates the relationship between mobility and the researcher's co-authorship.

- H3c: STHC mediates the relationship between mobility and productivity metrics.

- H3d: STHC mediates the relationship between mobility and research projects.



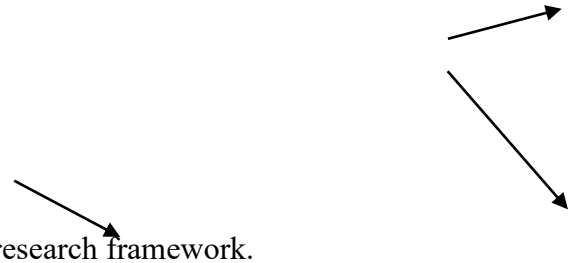


Figure 1. Conceptual research framework.

Methodology

Design

The research used a quantitative survey method. An English questionnaire, based on prior studies, was distributed via www.wenjuan.com. QR codes were sent through WeChat and QQ groups to 500 foreign researchers affiliated with 211 and 985 university projects aimed at boosting Chinese institutions' global rankings (Lin & Wang, 2021). With a 48% response rate, 204 completed surveys were suitable for analysis, excluding 110 irrelevant responses. The questionnaire had three sections: demographics and mobility background, S&T human capital (Bozeman & Corley, 2004) and social capital constructs, and research productivity, all measured on a five-point Likert scale.

Data Collection and Measurement of Variables

Participants' anonymity and confidentiality were ensured during the two-month data collection from 1 February to 28 April 2023. The research model included seven latent variables with items adapted from existing literature. Mobility (independent variable) was measured by the length of stay in China, number of host institutions, presence at top institutions, and department size as presented in the conceptual framework (figure 1), using methods from Ejermo et al. (2019), Abramo et al (2022), and Kato & Ando (2013). Research productivity (dependent variable) was assessed with a 27-item scale, covering publications, co-authorship, research metrics, and projects, based on Halevi (2016), Franzoni (2015), Chen et al. (2023), Gureyev et al. (2020), Horta et al. (2020), and Liu et al. (2021). S&T human capital (mediating variable) included 14 items on craft, cognitive, and tacit knowledge, using a 5-point Likert scale grounded in Bozeman's approach (2001a; Bozeman & Corley, 2004) and Nahapiet and Ghoshal (1998), with components from Schläpfer (2015), Jonkers and Tijssen (2008), and Gureyev et al. (2020). Three experts validated the questionnaire, and a pilot study with 30 respondents tested the model. After omitting six items, 21 items remained,

confirming validity and reliability.

Data Analysis Method

Partial least squares structural modeling (PLS-SEM) was used to evaluate the theoretical framework, assessing relationships between dependent and independent variables while ensuring the reliability and validity of latent variables (J. Hair et al., 2021; J. F. Hair et al., 2019, 2020). We utilized Smart PLS (v4) and SPSS (v24) for descriptive statistics and factor analyses. The PLS-SEM process involves two steps: first, validating the reliability and accuracy of components and manifest variables, including the heterotrait-monotrait ratio (HTMT), average variance extracted (AVE), composite reliability (CR), outer loadings, and Cronbach's alpha (α) (Hair et al., 2019). Reflective models use outer loadings to examine construct-indicator connections, with internal consistency evaluated using CA and CR metrics. AVE measures convergent validity (Fornell & Larcker, 1981), while HTMT assesses discriminant validity (Dijkstra & Henseler, 2015).

Findings

Demographic Information of Respondents

Notably, among participants, 56.37% were male, and 43.62% were female. Respondents aged 31-35 made up 47%. Postdoctoral research fellows comprised 48%, associate professors 32%, faculty members 15%, and lecturers 3.43%. Most participants (52%) were from social sciences and humanities, with 32.84% in natural sciences and technology, and 15.68% in medical and agricultural sciences.

Descriptive Statistics

Table 1. *Descriptive Statistics of the Respondents*

	M*	SD*	Sk*		K*	
			Stat*	SE*	Stat*	SE*
Age	3.3781	.89630	.382	.172	-1.548	.341
Gender	1.542	.36207	1.929	.172	2.739	.341
Discipline	2.4080	.61866	1.251	.172	.481	.341
Position	3.6915	1.51472	.265	.172	-1.288	.341
Research Experience	2.4129	.96106	.080	.172	-.938	.341
Mobility length	3.7711	.63825	.240	.172	-.650	.341
Different host institutions	2.0299	1.14416	.609	.172	-1.136	.341
Staying at top institutions	2.5174	.55762	.455	.172	-.841	.341
Department Size	3.5423	.67041	.850	.172	-.418	.341

**Notes: Mean, Sk=skewness, K=kurtosis, SD=standard deviation, SE=standard*

Error, Stat=Statistics.

Skewness ranged from 0.080 to 1.929, and kurtosis from 0.091 to 2.739, meeting SEM's normal distribution requirements (Hair et al., 2010). As shown in table 1, age and position had the highest demographic values (M=3.3781, SD=0.89630/M=3.6915, SD=1.51472), while department size and mobility length led in mobility components, outperforming stays at different host and top institutions (M=3.7711, SD=0.63825/M=3.5423, SD=0.67041).

Table 2. *Kaiser-Meyer-Olkin Test S&T Human and Social Capital*

Subscale	KMO test	Bartlett's Test of Sphericity	Approx. Chi-Square df Sig.
Cognitive & Tacit Knowledge (CTK)	.739		146.152 15 **.000***
Craft Knowledge (CK)	.649		218.983 10 **.000***
Social Capital (SC)	.852		107.019 21 **.000***

Note. KMO: Kaiser-Meyer-Olkin Measure of Sampling Adequacy

Table 2 presents the KMO test scores for all S&T human and social capital subscale items, which varied from 0.649 to 0.852, above the threshold of 0.6. These findings indicate that factor analysis is appropriate for this matrix (Tabachnick & Fidell, 2007).

Evaluation of the Measurement Model

We assessed the measurement model using internal consistency, convergent validity, and discriminant validity. Convergent validity required loadings of at least 0.60, composite reliability (CR) above 0.70, and average variance extracted (AVE) over 0.50 (Dijkstra & Henseler, 2015; Hair et al., 2021). Items with loadings below 0.708 were excluded, removing twelve items (CTK1, CTK2, CTK6, CK1, CK2, SC1, SC2, SC3, SPub4, Co-AU2, RP1, RP2, M4), leaving 21 items. Tables 3 and 4 present the final data for loading, CR, AVE, variance inflation factors (VIF), and HTMT. All VIF values were below 3.3, indicating no common method bias. Discriminant validity was confirmed with HTMT values ranging from 0.101 to 0.861, within the strict criterion of below 0.85 (Henseler et al., 2015).

Table 3. *Measurement Model Tests Results*

Latent Variable	Indicator	Convergent Validity		Composite Reliability		
		Loading>0.70	AVE>0.50	(rho_a) 0.60-0.90	CR>0.7	VIF Inner
Cognitive & Tacit Knowledge (CTK)	CTK3	0.699	0.533	0.766		1.477
	CTK4	0.845				
	CTK5	0.804				
Craft Knowledge (CK)	CK3	0.865	0.668	0.857		1.770
	CK4	0.749				
	CK5	0.834				
Social Capital (SC)	SC4	0.663	0.517	0.758		1.246
	SC5	0.870				
	SC6	0.697				
Scholarly Publications (SPub)	SPub1	0.935	0.624	0.825		1.074
	SPub2	0.855				
	SPub3	0.708				
Co-authorship (Co-Au)	Co-Au1	0.754	0.749	0.899		1.627
	Co-Au3	0.896				
	Co-Au4	0.936				
Metrics (M)	M1	0.759	0.552	0.688		1.021
	M2	0.946				
	M3	0.709				
Research Project (RP)	RP3	0.894	0.719	0.836		1.248
	RP4	0.799				

Note. Authors' calculation based on SMART Pls 4.

Table 4. *Discriminant Validity: Heterotrait-monotrait (HTMT) Criterion*

	Co-Au	CTK	CK	DepS	M	MobL	HUniv	RP	SPub	SC	TUniv
Co-Au											
CTK	0.267										
CK	0.174	0.861									
DepS	0.028	0.071	0.099								
M	0.386	0.437	0.191	0.286							
MobL	0.109	0.048	0.199	0.069	0.095						
HUniv	0.289	0.383	0.212	0.08	0.034	0.071					
RP	0.178	0.251	0.314	0.054	0.366	0.154	0.171				
SPub	0.633	0.284	0.288	0.078	0.299	0.147	0.249	0.161			
SC	0.138	0.44	0.804	0.076	0.536	0.143	0.183	0.154	0.168		
T Univ	0.229	0.457	0.277	0.152	0.236	0.214	0.377	0.188	0.101	0.296	

Note. Co-Au; co-authorship; CTK: cognitive and tacit knowledge; CK: craft knowledge; M: productivity metrics; MobL: mobility lenght; HUniv: number of host universities; RP: research projects; SPub: scholarly publications; SC: social capital. TUniv: Staying

at Top Chinese universities.

Some authors suggest a threshold of 0.85 (Kline & St, 2022) while Gold et al. (2001) argue for a value of 0.90. We used p-values, t-values, and bootstrapping with 5000 sub-samples (Nitzl et al., 2016; Rasoolimanesh et al., 2021; X. Zhao et al., 2010) to test the hypotheses and the mediating effects of social, scientific, and technical human capital between researchers' productivity and mobility.

The path coefficient (-1 to +1) predicts relationships between variables in the structural model (J. F. Hair et al., 2019). Results in table 5 and figure 2 showed cognitive/tacit knowledge positively affected co-authorship (β=0.085, *t-value*=2.108, *p*=0.018**), but not metrics, projects, or publications. Craft knowledge significantly impacted metrics (β=0.096, *t-value*=1.676, p=0.047), projects (β=0.131, *t-value*=2.251, p=0.012), and publications (β=0.101, *t-value*=2.559, *p*=0.005), with no effect on co-authorship. Social capital only positively affected metrics (β=0.106, *t-value*=2.357, *p*=0.009***). Mobility length significantly impacted cognitive (β=0.074, *t-value*=1.658, *p*=0.049*) and craft knowledge (β=0.076, *t-value*=3.086, *p*=0.001***), while different host institutions influenced social capital (β=0.085, *t-value*=3.728, *p*=0.000***). Department size positively affected craft knowledge (β=0.073, *t-value*=1.903, *p*=0.029**) but not cognitive knowledge or social capital. Top universities positively impacted cognitive/tacit knowledge (β=0.08, *t-value*=4.797, *p*=0.000***), craft knowledge (β=0.092, *t-value*=4.112, *p*=0.000***), and social capital (β=0.068, t=5.301, *p*=0.000***).

Table 5. *Path Coefficient and Hypothesis Testing*

Path Coefficient	Std β	t-value	*p*-value	95% CI	Supported?
Cognitive and Tacit Knowledge -> Co-authorship	0.084	2.125	**0.017****	0.315	Yes
Cognitive and Tacit Knowledge -> Metrics	0.105	1.419	0.078	0.045	No
Cognitive and Tacit Knowledge -> Research Project	0.14	0.664	0.253	0.344	No
Cognitive and Tacit Knowledge -> Publications	0.083	0.819	0.206	0.222	No
Craft Knowledge -> Co-authorship	0.12	0.371	0.355	0.237	No
Craft Knowledge -> Metrics	0.097	1.658	**0.049****	0.314	Yes
Craft Knowledge -> Research Project	0.129	2.293	**0.011****	-0.081	Yes
Craft Knowledge -> Research Publications	0.101	2.548	**0.005*****	0.413	Yes
Depart Size -> Cognitive and Tacit Knowledge	0.073	1.093	0.137	0.201	No
Depart Size -> Craft Knowledge	0.073	1.903	**0.029****	0.265	Yes

Depart Size -> Social capital	0.081	1.118	0.132	0.231	No
Mob length -> Cognitive and Tacit Knowledge	0.074	1.658	**0.049****	0.252	Yes
Mob length -> Craft Knowledge	0.076	3.086	**0.001*****	0.364	No
Mob length -> Social capital	0.076	0.866	0.193	0.065	Yes
Number of Host Univ -> Cognitive and Tacit Knowledge	0.077	2.083	**0.019****	-0.025	Yes
Number of Host Univ -> Craft Knowledge	0.118	1.34	0.09	0.343	No
Number of Host Univ -> Social capital	0.085	3.728	**0.000*****	0.444	Yes
Social capital -> Co-authorship	0.107	0.121	0.452	0.168	No
Social capital -> Metrics	0.106	2.357	**0.009*****	-0.093	Yes
Social capital -> Research Project	0.119	0.624	0.266	0.272	No
Social capital -> Research Publications	0.1	1.541	0.062	0.042	No
Top Univ -> Cognitive and Tacit Knowledge	0.08	4.797	**0.000*****	0.528	Yes
Top Univ -> Craft Knowledge	0.092	4.112	0.000***	0.543	Yes
Top Univ -> Social capital	0.068	5.301	0.000***	0.469	Yes

Note. *** $p < 0.005$, ** $p < 0.05$, β (beta coefficients), *** represents the significance level. p values and t-values were calculated using the consistent PLS-SEM (PLS-SEM) algorithm by Smart-PLS (V4) with standard settings and the bootstrap resampling of 5,000.

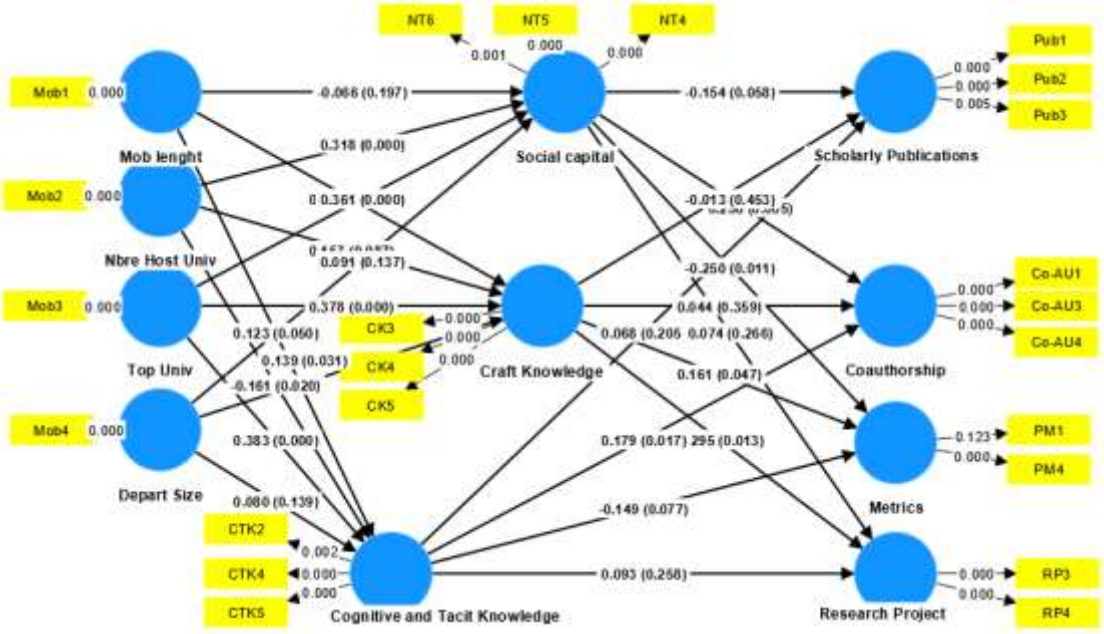


Figure 2. Bootstrap image for path analysis and p-value performed by the authors.

Model fit summary.

The model's fit was assessed using SRMR, NFI, and chi-square (X2). As shown on table 6, the Goodness-of-Fit (GOF) index evaluated the model's adequacy (Henseler et al., 2012; Tenenhaus et al., 2004). Our model yielded an SRMR of 0.014, NFI of 0.944, and X2 of 1142.362, indicating a satisfactory fit and effective explanation of

factors influencing research output.

Table 6. *Goodness-of-fit of the model*

	Estimated model
SRMR	0.014
d_ULS	5.592
d_G	0.797
Chi-square	1142.362
NFI	0.944

Note: SRMR, standardized-root-mean-square-residual; d_ULS, unweighted least squares discrepancy, d_G, geodesic discrepancy; NFI, normed fit index.

Discussion and Implications

Some hypotheses were partially, others fully supported. The PLS-SEM analysis showed that mobility, especially the length of stay in China and movement between host institutions, significantly influences cognitive and tacit knowledge. Longer stays and mobility within Chinese universities enhance these knowledge areas. These findings align with Gureyev (2020), who noted that researcher mobility boosts knowledge creation, accumulation, and transfer. International mobility also positively impacts research productivity (Ryazanova & McNamara, 2019). Additionally, being an early academic at top Chinese universities enhances cognitive, tacit, and craft knowledge, as well as social capital. Prestigious universities like Beijing Normal University and Shanghai Jiaotong University offer access to research resources and expand academic networks, connecting researchers with key experts such as reviewers, editors, and association members.

Academics benefit from staying at various host institutions, especially prestigious ones, to enhance research performance and accumulate social capital. Tartari et al. (2020) confirmed that mobility boosts performance, particularly when relocating to highly regarded universities. A recent study highlighted that social capital aids in forming international knowledge networks (Shen et al., 2022). However, social capital did not significantly impact publications or co-authorship, contrary to Momeni et al. (2022), who linked co-authorship networks with diversified social capital. Our results suggest that social capital in China is complex and variable. Chen et al. (2023) found that academic mobility increases social capital, evidenced by citations and h-index. Jonkers

and Tijssen (2008) also argued that overseas experience enhances scientific and social capital. We found that staying at top universities significantly impacts cognitive, tacit, and craft knowledge, as well as social capital. Our findings highlight key factors Chinese institutions should prioritize to enhance research productivity and retain foreign researchers, including policies on publications, graduate programs, staff evaluations, international collaboration, and expanding research centers.

Limitations and Research Directions

The combined theories in our study, relating to scientific and technical human capital, social capital, mobility have been developed and validated within the case of foreign academics in Chinese universities. This is suggestive that these theories are likely to be transferable to other contexts. However, the study has some limitations. The first limitation concerns the generalization of the findings. The study was focused on researchers from African countries, which is a small part of the total number of highly skilled foreigners in different Chinese universities. The findings may not apply to other groups of academics. The second limitation is that we restricted our theoretical foundations only to S&T human capital theory and social capital theory, while for further research we might add cultural capital and Bourdieu's notion of capital. Besides that, it is difficult to address the academic mobility phenomenon since it is rooted in several fields and does not adhere to a coherent theoretical framework. The overall phenomenon of researcher mobility is becoming the focus of studies from different disciplines that range from research policy (Freeman & Hirsch, 2008; Lundvall et al., 2002) to knowledge transfer to productivity (Figueiredo et al., 2017; Gao & Liu, 2021b; Halevi et al., 2016). Nevertheless, some theoretical or analytical tools, including forms of capital in line with Bourdieu's theoretical framework (Xu et al., 2022), symbolic capital (Kim, 2015), ethnic capital (Farrer, 2014), analysis of social ties (Rezaei & Mouritzen, 2021), and cross-cultural adaptation models (Chen & Zhu, 2022), have been used more frequently than others. Some research (Huang et al., 2022) did not use such theoretical frameworks, owing to their inductive and exploratory methodological approaches. However, future research might find other pertinent determinants that may help increase the explanation of the developed research model.

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