Digital Immigrant Nomads and Artificial Intelligence: Opportunities and Challenges for Palestinian Academics – Structural Challenges as an Intermediary Factor

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Abstract: - The present study explores how the uptake of artificial intelligence (AI) tools relates to participation in digital freelance work among Palestinian academics who operate as digital nomads. Attention is directed to the ways these academics deploy AI applications across cross-border professional domains—research, teaching, and consulting among them—while confronting critical technical, financial, and political hurdles produced by geopolitical fragmentation. An explanatory sequential mixed-methods design guided the investigation. Quantitative data came from an electronic survey completed by 150 academics affiliated with universities in the West Bank and Gaza Strip (N=150, a figure established through G*Power statistical analysis) and were processed with Partial Least Squares Structural Equation Modeling (PLS-SEM) in Smart PLS 4, applying a bias-corrected bootstrapping procedure built on 5,000 resamples. To complete the empirical model, semi-structured interviews were held with 15 Palestinian academics, and the material was examined through thematic analysis until theoretical saturation had been reached. The results confirm that AI adoption produces a significant direct enhancement of digital academic work (β=0.420, 95% CI [0.312, 0.521], $p<0.001$), whereas severe structural barriers exert a strong direct negative impact (β=-0.360, 95% CI [-0.471, -0.242], $p<0.001$). The indirect path linking structural barriers to digital work through AI adoption proved statistically non-significant (β=-0.046, 95% CI [-0.122, 0.021], p=0.280), a finding that demonstrates AI tools cannot buffer or bypass structural and financial blockades. Taken together, the predictors explain 28% of the variance in digital work (R^2=0.280, adjusted R^2=0.270). Urgent work on institutional policies, cross-border payment gateways, and national university frameworks is required if Palestinian academics are to take a fuller part in the global knowledge economy.

Key-Words: - Artificial Intelligence (AI), Digital Nomadism, Academic Freelancing, Knowledge Economy, Structural Impediments, PLS-SEM, Bootstrapping, Palestine.

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1 Introduction

Work has undergone sweeping change over the past two decades, a transformation propelled by the digital revolution and the widening reach of high-speed internet. Among the most visible expressions of this shift stands the rise of the digital nomad lifestyle alongside remote freelance labor. Artificial intelligence (AI) has since become a central engine of productivity for this working model, applied intensively in data analysis, task automation, content generation, and decision-making (Brynjolfsson & McAfee, 2023). Current estimates hold that upwards of 60% of digital nomads depend on AI-powered tools on a daily basis to get their work done (Reichenberger, 2023).

Academics in Palestine—and early-career scholars above all—contend with punishing structural conditions. Movement between the West Bank, the Gaza Strip, and destinations abroad remains restricted by geopolitical constraints and institutional blockades; research funding opportunities have thinned out; and the local academic job market leaves very little room for newcomers (Khalidi, 2021). Many respond to these pressures by pursuing digital avenues that allow them to apply their academic knowledge beyond conventional physical borders, thereby operating as digital nomads.

1.1 Research Question and Objectives

At the heart of the study lies one core question: can artificial intelligence open the door of the digital nomad model to Palestinian academics and enable them to turn their expertise into a sustainable, independent income stream in spite of structural constraints?

The research pursues the following specific objectives:

To gauge how widely digital freelance work has spread among Palestinian academics.

To establish the degree to which AI tools feature in their professional activities, whether in research, teaching, or consulting.

To assess the bearing of structural obstacles—technical, financial, and political—on digital academic work.

To test, by means of structural equation modeling, whether AI adoption mediates or softens the damaging influence of structural barriers.

2 Theoretical Framework and Literature Review

2.1 The Digital Nomad Phenomenon and Remote Work

A digital nomad is, at bottom, a knowledge worker whose digital tools and internet connection free their work from any fixed location, so that professional output continues at a steady pace while they live—whether for a while or for good—away from the workplace they would traditionally occupy [17], [19]. What separates digital nomads from traditional expatriates or tourists is their capacity to keep income-generating activity running continuously without a physical office of any kind [21]. Viewed through a managerial lens, such workers strain conventional human resource practices in areas ranging from taxation and regulatory compliance to cross-border social security and employees' sense of organizational belonging ([5].

Hybrid and digitally mediated work practices gathered pace across the globe in the wake of the COVID-19 pandemic [12]. Inside Palestine, academics have taken to global gig platforms—Upwork and Fiverr among them—as a way of working around the saturated academic labor market and the restrictions of the local economy [15].

2.2 Theoretical Foundations

Three theoretical lenses are woven together in this study:

Knowledge-Based Economy Theory, which concentrates on turning knowledge and intellectual capital into services that can be traded across global markets [7]

The AI-Augmented Work Framework, which maintains that AI adds to human labor rather than displacing it, recasting professionals as augmented producers of knowledge [2]

Digital Exclusion and Infrastructure under Occupation, which clarifies how geopolitical control and structural blockage can constrain technological infrastructure and access to digital resources [15]

2.3 AI as an Enabling and Threatening Factor for Digital Nomads

Digital workers draw real strength from AI applications: routine tasks get automated, multilingual translation becomes easier (DeepL is a case in point), data analytics grow sharper, and research efficiency climbs [6], [22]. Access to cloud-based AI tools, the evidence suggests, ranks among the foremost drivers of remote worker efficiency [18]. Yet the same rapid strides in natural language processing place lower-tier freelance tasks at risk, obliging workers to keep refreshing their skills [8], [3]

2.4 Structural Challenges in the Palestinian Context

Palestinian digital workers carry the weight of severe structural constraints: power outages strike frequently, advanced network infrastructure sits out of reach, data costs run high, and average internet speeds trail well behind global standards [23]. On top of these come financial blockades—opening international payment accounts (PayPal or Wise, for instance) faces restriction—and travel limitations, both of which sharply curtail any full participation in the global nomad economy [14], [15].

3 Methodology and Statistical Analysis

This study adopts an explanatory sequential mixed-methods design. Its quantitative strand subjects the structural hypotheses to testing through PLS-SEM, while its qualitative strand probes the operational subtleties and contextual mechanisms that underlie the statistical picture.

3.1 Sample Justification and Quantitative Data Collection

Sample size determination: A power analysis was run in G*Power 3.1 ahead of data collection. For a structural model carrying two principal predictors, with an effect size of $f^2=0.15$, $\alpha=0.05$, and statistical power $(1-\beta) =0.95$, the minimum required sample came out at N=107. The valid sample ultimately secured—150 Palestinian academics—clears this floor comfortably and therefore supplies statistical power adequate for PLS-SEM estimation [10]

Data collection: Between March and October 2025, a structured online survey circulated among universities in the West Bank and the Gaza Strip. In total, 150 completed responses passed validation, none of which showed the hallmarks of speeding or careless answering. The demographic makeup of respondents appears in Table 1 (Appendix).

Explanation of Table 1: Table 1 (Appendix). lays out the demographic distribution of the quantitative sample (N=150). The sample strikes a representative balance by gender (58.0% male, 42.0% female) and by region (65.3% West Bank, 34.7% Gaza Strip). Beyond that, more than 80% of participants report active involvement in digital freelancing, and 47.3% carry one to three years of remote work experience.

3.2 Measurement Model Assessment (Outer Model)

The measurement model was appraised, in line with [10], for indicator reliability, internal consistency, convergent validity, and discriminant validity.

Indicator reliability and internal consistency: All retained items posted standardized outer loadings above the 0.70 benchmark (within a range of 0.812 to 0.892), a sign of high indicator reliability. Cronbach's Alpha (α) and Composite Reliability (ρc) values likewise all topped 0.80, which secures robust internal consistency (Table 2 (Appendix)).

Convergent validity: The Average Variance Extracted (AVE) served as the gauge for convergent validity. Every latent construct returned an AVE figure above 0.50 (Digital Work = 0.682, AI Use = 0.731, Structural Barriers = 0.764), confirming that each construct captures more than half of the variance in its own indicators [9].

Explanation of Table 2: Table 2 (Appendix) condenses the evaluation of the outer measurement model. All standardized indicator loadings (λ) clear the 0.70 cutoff, so indicator reliability stands confirmed. Internal consistency holds given that Cronbach's Alpha ($\alpha>0.80$) and Composite Reliability ($\rho c>0.80$) satisfy accepted criteria, while AVE figures above 0.50 for every construct verify convergent validity. Indicator Variance Inflation Factors (VIF) stay below 3.3 throughout, ruling out any multicollinearity concern.

Discriminant validity assessment: Establishing discriminant validity means demonstrating that a construct stands empirically apart from every other construct in the structural model. Two tests were applied. Under the Fornell–Larcker criterion, the square root of each construct's AVE (√AVE) must exceed its highest correlation with any other latent variable (Table 3A (Appendix)). Under the Heterotrait-Monotrait Ratio of Correlations (HTMT), all values came in beneath the strict 0.85 threshold (Table 3B).

Explanation of Tables 3A and 3B: Table 3A (Appendix) and Table 3B (Appendix) together validate discriminant validity. In Table 3A (Appendix), the bold diagonal entries (√AVE) outrank every off-diagonal correlation. In Table 3B (Appendix), every HTMT value sits below 0.85, and none of the 95% confidence intervals encloses 1.0—compelling evidence that the three constructs are empirically distinct from one another.

3.3 Structural Model Assessment (Inner Model)

Structural relationships and hypotheses were put to the test through a nonparametric bootstrapping routine—5,000 resamples, bias-corrected and accelerated (BCa)—executed in SmartPLS 4.

Explanatory power (R^2 justification): For Digital Work, the structural model posts an R^2 of 0.280 (adjusted R^2=0.270). Physical sciences habitually record higher R^2 values, but behavioral and socio-political research—in which human agency operates under extreme environmental constraints—regards R^2 figures between 0.20 and 0.35 as an acceptable and meaningful amount of explained variance [10], [4]. What this means concretely is that 28% of the variation in academic digital freelancing flows directly from the combined force of AI adoption and structural barriers.

Explanation of Table 4: Table 4 (Appendix) assembles the direct path coefficients estimated via PLS-SEM bootstrapping. AI Use exerts a statistically significant positive direct effect on Digital Work ($\beta=+0.420$, $p<0.001$), and H1 is thereby upheld. Structural Barriers, in contrast, register a statistically significant negative direct effect on Digital Work ($\beta=-0.360$, $p<0.001$), which supports H2. The path from Structural Barriers to AI Use falls short of significance ($\beta=-0.110$, $p=0.215$), indicating that structural barriers do not, in any direct way, stop an individual academic from deciding to work with AI software.

3.4 Mediation Model Specification and Analysis

Whether AI adoption mediates the relationship between structural barriers and digital academic work was evaluated by estimating direct and indirect effects in line with [24].

Explanation of Table 5: Table 5 (Appendix) lays out the decomposition of the mediation model. The indirect path ($\beta=-0.046$, $p=0.280$) has zero inside its

95% confidence interval [-0.122, 0.021], which settles the matter: AI adoption does not mediate the relationship between structural barriers and digital academic work. The total effect (β=-0.406) equals the direct effect (β=-0.360) plus the non-significant indirect effect (β=-0.046).



Fig. 1: Fully Validated PLS-SEM Structural Model Path Diagram

Source: created by the authors.

Detailed explanation of Figure 1: Figure 1 presents the structural equation model complete with empirical path coefficients (β), p-values, and R^2 values. Each rectangle stands for a principal latent construct, and arrows mark the hypothesized causal directions. Structural Barriers press down directly and negatively on Digital Work (β=-0.360, p<0.001), while AI Use lifts it directly (β=+0.420, p<0.001). The indirect mediation route (β=-0.046, p=0.280) carries no statistical weight, which demonstrates that individual AI proficiency cannot offset macro-level structural obstacles.



Fig. 2: Micro-Level Capability vs. Macro-Level Structural Impact Diagram

Source: created by the authors.

Detailed explanation of Figure 2: Figure 2 captures the tension between technological empowerment at the micro level and structural constraint at the macro level. The vertical axis measures effect magnitude on academic digital freelancing. Micro-level uptake of AI tools sharpens individual task efficiency (β=+0.420), yet macro-level structural barriers—financial blockades and electricity outages among them—impose a severe direct constraint (β=-0.360) that technical tools alone are powerless to remove.

Detailed explanation of Figure 3: Figure 3 charts the methodological integration. Phase 1 saw quantitative PLS-SEM testing establish the statistical path coefficients. In Phase 2, qualitative interviews (N=15) supplied the contextual explanation for the quantitative results—above all by clarifying why AI adoption fails to mediate structural obstacles (AI can resolve neither international payment restrictions nor power grid failures).

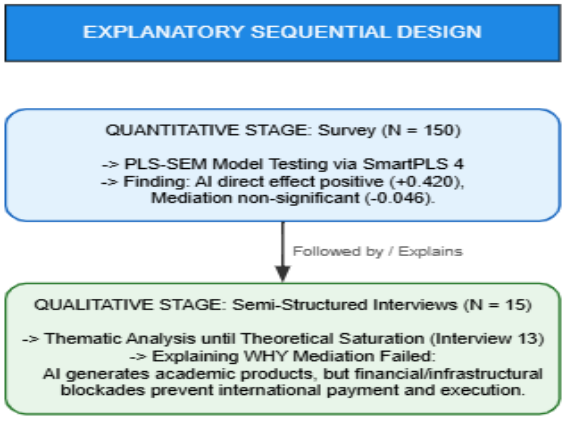


Fig. 3: Explanatory Sequential Mixed-Methods Design Integration Flowchart

Source: created by the authors.

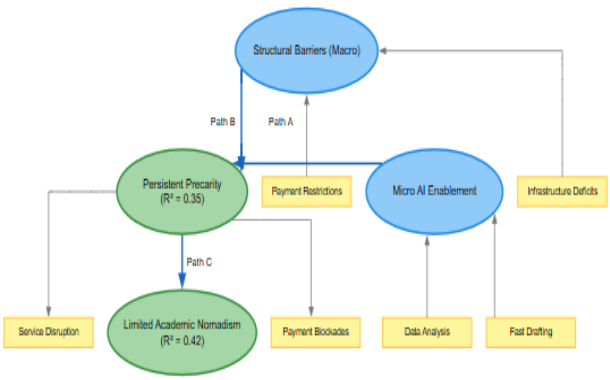


Fig. 4: Contextual Mechanism of Palestinian Academic Digital Nomadism

Source: created by the authors.

Detailed explanation of Figure 4: Figure 4 sketches the operating reality of Palestinian academic digital nomads. At the micro level, AI applications do permit rapid content generation and research assistance; at the macro level, structural barriers breed persistent precarity. Academic digital nomadism therefore stays hemmed in unless institutional and financial frameworks are put in place.

4 Qualitative Results and Triangulation

Semi-structured interviews with 15 Palestinian academics were carried out to round out the quantitative findings.

4.1 Qualitative Sampling and Saturation Rigor

Participants were recruited through purposive sampling that cut across institutional affiliations, academic ranks, and geographic locations (the West Bank versus the Gaza Strip). Data collection pressed on until theoretical saturation arrived at the thirteenth interview, the point at which no new thematic codes surfaced; two further interviews were then held to confirm that the codes had indeed saturated. The transcripts underwent inductive coding following [1] six-phase thematic analysis framework.

Explanation of Table 6: Table 6 (Appendix) profiles the qualitative sample (N=15). Participants come from a spread of disciplines, regions, and ranks, furnishing balanced qualitative insight into the points where structural barriers and AI tools meet across different settings.

4.2 Qualitative Findings and Triangulation

The qualitative analysis brought to light key themes that speak directly to the empirical structural equation model:

AI as an individual capability amplifier (accounting for path β=+0.420): Generative AI, participants reported, slashes the production time needed for technical writing, coding, and literature synthesis. P01 remarked: "Copilot and ChatGPT handle up to 40% of routine coding and drafting, allowing me to secure higher-value contracts on global freelancing platforms."

The inviolability of structural financial blockades (accounting for the non-significant mediation, β=-0.046): The interview evidence makes plain why AI cannot mediate structural obstacles. AI may raise output quality, yet it has no way around financial exclusion. P04 stated: "I can produce world-class academic writing using AI tools, but when a client attempts to wire funds, PayPal does not operate in Palestine, and local bank transfers incur crippling fees or rejection. AI improves my work, but it cannot fix the financial border."

Infrastructural instability and precarity (accounting for the direct path, β=-0.360): Real-time digital academic consulting runs headlong into electricity blackouts and unstable network connections. P09 observed: "During virtual teaching sessions with overseas clients, power drops force disconnects. AI tools cannot run without stable internet and power."

Explanation of Table 7: Table 7 (Appendix) maps the qualitative findings onto the quantitative PLS-SEM model, securing methodological triangulation across the study's two phases.

Explanation of Table 8: Table 8 (Appendix) sets out the final triangulation matrix, which braids together the quantitative statistical paths, the qualitative themes, and the illustrative participant quotations in confirmation of their convergence.

5 Conclusion and Policy Recommendations

5.1 Main Conclusions

This study has assembled empirical and qualitative evidence on the dynamics that bind AI adoption, structural obstacles, and digital nomadism among Palestinian academics. The quantitative PLS-SEM model demonstrates that AI tools significantly strengthen individual digital freelancing capacity ($\beta=+0.420$, $p<0.001$) even as structural impediments extract a heavy direct penalty ($\beta=-0.360$, $p<0.001$). The mediation analysis delivers the crucial finding: AI adoption neither mediates nor cushions the force of structural barriers ($\beta=-0.046$, $p=0.280$). Technological tools can enlarge what individuals accomplish at the micro level, but they stand helpless before macro-level financial and geopolitical exclusion.

Managerial and Policy Implications

Financial infrastructure solutions: Palestinian monetary authorities, acting together with universities, should join forces with international fintech providers to build secure cross-border payment mechanisms that carry only modest fees.

Institutional university support: Higher education institutions need to draft formal policies

that give hybrid academic freelancing a legitimate place, and to establish incubator hubs fitted out with stable solar power and high-speed satellite internet.

Targeted AI upskilling and gender support: Programs should concentrate on advanced AI integration and prompt engineering, with grants aimed specifically at female academics so as to counterbalance the precarity that remote work can bring.

Recommendations for Future Research

The study points to the value of further qualitative research into training mechanisms for employees who fall into the "digital immigrants" category, to be backed by specialized training packages.

Declaration of Generative AI and AI-assisted Technologies in the Writing Process

During the preparation of this work, the author(s) utilized artificial intelligence (AI) technologies solely for the purpose of linguistic refinement and grammatical correction. Following the application of these tools, the author(s) comprehensively reviewed, verified, and edited the resulting text. The author(s) maintain full accountability and responsibility for the accuracy, integrity, and final content of the publication.

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Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

The authors contributed in the present research, at all stages from the formulation of the problem to the final findings and solution.

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Conflict of Interest

The authors have no conflicts of interest to declare that are relevant to the content of this article.

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APPENDIX

All statistical tables supporting the analyses reported above are appended at the end of the article.

Table 1. Demographic Profile of Quantitative Survey Respondents (N=150)

Demographic Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	87	58.0%
	Female	63	42.0%
Geographic Location	West Bank	98	65.3%
	Gaza Strip	52	34.7%
Academic Rank	Lecturer / Teaching Assistant	48	32.0%
	Assistant Professor	62	41.3%
	Associate Professor / Full Professor	40	26.7%
Digital Freelancing Experience	Less than 1 year	29	19.3%
	1 – 3 years	71	47.3%
	More than 3 years	50	33.4%

Source: created by the authors.

Table 2. Construct Reliability, Convergent Validity, and Indicator VIF Metrics

Latent Construct	Indicator Code	Outer Loading (λ)	Indicator VIF	Cronbach's Alpha (α)	Composite Reliability (ρc)	Average Variance Extracted (AVE)
Digital Work	DW1	0.812	1.84	0.842	0.895	0.682
	DW2	0.845	2.12			
	DW3	0.830	1.95			
	DW4	0.815	1.88			
AI Use	AI1	0.862	2.31	0.865	0.916	0.731
	AI2	0.871	2.45			
	AI3	0.840	2.08			
	AI4	0.847	2.18			
Structural Barriers	SB1	0.885	2.65	0.881	0.928	0.764
	SB2	0.892	2.82			
	SB3	0.860	2.24			
	SB4	0.858	2.21			

Table 3. A: Discriminant Validity – Fornell–Larcker Criterion

Latent Construct	Digital Work	AI Use	Structural Barriers
Digital Work	**0.826**		
AI Use	0.461	**0.855**	
Structural Barriers	-0.412	-0.110	**0.874**

Source: created by the authors.

Note: Bold diagonal entries give the square root of AVE (√AVE); off-diagonal entries give inter-construct Pearson correlations.

Table 3. B: Discriminant Validity – Complete HTMT Matrix

Pairwise Construct Comparison	HTMT Ratio	95% Bootstrapped CI	Threshold Criterion
AI Use ↔ Digital Work	0.542	[0.380, 0.685]	< 0.85
Structural Barriers ↔ Digital Work	0.485	[0.312, 0.628]	< 0.85
Structural Barriers ↔ AI Use	0.128	[0.045, 0.241]	< 0.85

Source: created by the authors.

Table 4. Structural Path Coefficients and Hypothesis Testing

Hypothesis & Structural Path	Original Sample (β)	Sample Mean (M)	Std. Dev. (STDEV)	T-Statistic	P-Value	95% Confidence Interval	Conclusion
H1: AI Use → Digital Work	+0.420	0.422	0.054	7.778	< 0.001	[0.312, 0.521]	Supported (***)
H2: Structural Barriers → Digital Work	-0.360	-0.363	0.058	6.207	< 0.001	[-0.471, -0.242]	Supported (***)
H3: Structural Barriers → AI Use	-0.110	-0.115	0.089	1.236	0.215	[-0.285, 0.062]	Not Supported (ns)

Source: created by the authors.

Table 5. Mediation Analysis (Direct, Indirect, and Total Effects)

Effect Path	Effect Type	Coefficient (β)	Std. Error	T-Statistic	P-Value	95% Bootstrapped CI	Conclusion
SB → DW (Total Effect)	Total	-0.406	0.061	6.655	< 0.001	[-0.521, -0.282]	Significant (***)
SB → AI → DW	Indirect	-0.046	0.038	1.211	0.280	[-0.122, 0.021]	No Mediation (ns)
SB → DW (Direct Effect)	Direct	-0.360	0.058	6.207	< 0.001	[-0.471, -0.242]	Significant (***)

Source: created by the authors.

Table 6. Demographic Profile of Qualitative Interview Participants (N=15)

Participant Code	Gender	Academic Rank	Discipline	Region	Primary AI Tools Used
P01	Female	Assistant Prof.	Computer Science	Gaza Strip	ChatGPT, GitHub Copilot
P02	Male	Associate Prof.	Engineering	West Bank	Midjourney, Elicit
P03	Female	Lecturer	English Literature	West Bank	DeepL, Grammarly
P04	Male	Assistant Prof.	Social Sciences	Gaza Strip	Claude, Consensus
P05	Female	Assistant Prof.	Information Technology	West Bank	ChatGPT, Copilot
P06	Male	Lecturer	Business Administration	West Bank	ChatGPT, Canva AI
P07	Female	Assistant Prof.	Linguistics	Gaza Strip	DeepL, QuillBot
P08	Male	Assistant Prof.	Data Analytics	West Bank	ChatGPT, Python AI
P09	Female	Lecturer	Media & Communication	Gaza Strip	Runway, ChatGPT
P10	Male	Associate Prof.	Civil Engineering	West Bank	MATLAB AI, Elicit
P11	Female	Assistant Prof.	Education	West Bank	ChatGPT, Grammarly
P12	Female	Lecturer	Computer Science	Gaza Strip	GitHub Copilot, ChatGPT
P13	Male	Assistant Prof.	Economics	West Bank	Stata AI, ChatGPT
P14	Female	Assistant Prof.	Translation Studies	Gaza Strip	DeepL, Trados AI
P15	Male	Lecturer	Environmental Science	West Bank	GIS AI, Claude

Source: created by the authors.

Table 7. Summary of Qualitative Themes and Empirical Explanatory Value

Qualitative Theme	Core Operational Narrative	Alignment with Quantitative Path
1. Individual Productivity Multiplication	AI applications cut the time spent drafting research and make freelance services more competitive.	Explains the positive direct path AI → DW (β=+0.420).
2. Financial & Infrastructural Impasse	Global payment platforms (PayPal) are absent and electricity supply is unstable, which restricts delivery.	Explains the negative direct path SB → DW (β=-0.360).
3. Non-Mediation Realities	Even advanced AI software cannot process international banking transactions or supply electricity.	Explains the non-significant mediation SB → AI → DW (β=-0.046).

Source: created by the authors.

Table 8. Methodological Triangulation Matrix

Quantitative Finding (PLS-SEM)	Qualitative Theme	Illustrative Participant Quote	Triangulation Synthesis
AI → DW (β=+0.420, p<0.001)	Task Automation & Speed	"AI allows me to compete globally by cutting writing time in half." (P03)	Convergence: AI operates as a technical multiplier at the micro level.
SB → DW (β=-0.360, p<0.001)	Financial & Infrastructure Block	"Power outages and lack of PayPal prevent scaling my business." (P07)	Convergence: Macro-structural obstacles impose direct negative control.
SB → AI → DW (β=-0.046, p=0.280)	Structural Immunity to AI	"AI creates the service, but cannot collect the money." (P04)	Convergence: Accounts for the statistical non-significance of the mediation.

Source: created by the authors.