Journal of Research Administration
Society of Research Administrators International

FROM SHORTLISTING TO REJECTION: THE ROLE OF AI IN PITCHING OUTCOMES OF NIGERIAN YOUTH ENTREPRENEURS

Olumide Gbenga-Julius
Department of Business Entrepreneurship and Executive Education,
University of Ibadan, Nigeria
Orcid: https://orcid.org/0009-0000-9390-0603, Email: mindeson@gmail.com

Oyebowale Blessing Oyekunle
Department of Entrepreneurial Studies, Bamidele Olumilua University of Education, Science and Technology, Ikere-Ekiti, Nigeria
Orcid: https://orcid.org/0009-0001-7885-2233, Email: oyebobless2@gmail.com

Tayo Michael. Fagbemide
Department of Business Administration, Moshood Abiola Polytechnic Abeokuta Nigeria
Orcid: https://orcid.org/0009-0008-2628-0932, Email: fagbemidetayo@gmail.com

Justinah Oluwayemisi Akanji
Department of Business Entrepreneurship and Executive Education,
University of Ibadan, Nigeria
Orcid: https://orcid.org/0009-0005-7141-4133, Email: joakanji@gmail.com

Saidat Omowumi Dauda
Department of Business and Entrepreneurship Education,
Emmanuel Alayande University of Education, Oyo, Oyo State, Nigeria
Orcid: https://orcid.org/0009-0001-0392-3666, Email: saidatdso@gmail.com

Abstract

Background: Despite the increasing availability of grants and early-stage financing opportunities for youth entrepreneurs in Nigeria, a lot of them never make it past the pitching stage. So far research has concentrated predominantly on finance access and entrepreneur characteristics, and less so on pitching procedures and investor confidence with the latter being increasingly influenced by artificial intelligence (AI) in the context of pitching outcomes.

Aim: In this study, we explored the effects of quality of pitch preparation and entrepreneur pitch competence on pitching success for young Nigerian entrepreneurs, with the investigation that investor confidence as mediator, and artificial intelligence capability as moderator.

Setting: Based on the principles of pitching theory and an entrepreneurial signaling lens, the study concentrated on Nigerian youth entrepreneurs who have been involved in grant competitions, accelerator programmes, or investor pitch sessions.

Methods: The study employed a quantitative research design. Data were collected by a structured questionnaire survey of young entrepreneurs, of which 637 valid questionnaires were obtained after data screening. Partial Least Squares Structural Equation Modelling (PLS-SEM) was applied to examine the proposed relations of pitch preparation quality, pitching competence, artificial intelligence capability, investor confidence, and pitching outcomes.

Results: Results show that the quality of pitch preparation and pitching ability significantly increase investor confidence, which in turn has a strong positive impact on pitching success. Artificial intelligence capability also positively moderates the effects of the quality of preparation of a pitch on investor confidence and of the pitching competence on investor confidence.

Conclusion: The research shows that rejection at the pitch level is in many cases a consequence of poor preparation, poor delivery, or poor credibility signaling rather than a dearth of novel concepts. Preparation augmented by AI may increase investor trust and funding opportunities.

Contribution: This study contributes to the literature on entrepreneurship and technology by identifying investor confidence as a key mechanism through which pitching capabilities influence funding outcomes and by showing that AI enables entrepreneurial pitching.

Keywords: Entrepreneurial pitching, investor confidence, artificial intelligence capability, youth entrepreneurship, funding outcomes.

1. INTRODUCTION

Growing focus on youth entrepreneurship as the way to generate jobs and promote inclusive growth is resulting in an explosion of grant schemes, accelerators, and seed investment schemes in the developing world. In sub-Saharan Africa, and Nigeria in particular, a limited number of public and private funding schemes are emerging to support youth-led enterprises on the assumption that young entrepreneurs are one of the main vectors of innovation and socio-economic transformation (World Bank 2022; African Development Bank 2023). With young people making up the world's fastest growing population in Nigeria, and the country having a bustling entrepreneurship ecosystem, it is an ideal place to find growing competitive grant opportunities and pitch-based funding schemes for fledgling startups (Berhe, 2021).

This increase in available funding coincides with rapid developments in digital technologies and artificial intelligence (AI) that are starting to transform entrepreneurship. Increasingly, entrepreneurs are using AI-driven tools to write their pitch decks, business narratives, market research, and financial projections, making them cheaper to prepare and more quickly pitch-ready (Chalmers, MacKenzie & Carter 2021; Cristofaro, Giardino & Muldoon 2025). Especially with the advent of generative AI systems, this trend has been spurred up, since now entrepreneurs can create high-quality content without having to possess special skillsets. Collectively these trends may suggest that AI could meaningfully boost entrepreneurs' ability to communicate value propositions to potential investors.

In a strange way, the youth entrepreneurs, of which there were many, still seemed to be struggling on the pitch stage despite greater access to funding options and more sophisticated digital prep tools. Findings from entrepreneurship competitions and early investment suggests that a high proportion of entrepreneurs pass initial screening and shortlisting stages but ultimately fail to obtain funding during live pitch assessments (Lavi & Yaniv 2023; Kalvapalle et al. 2024). This is indicative of a “late-stage selection gap,” where good ideas get weeded out not because they fail eligibility criteria, but rather because entrepreneurs cannot persuade investors of venture credibility, execution capability, and strategic fit in an environment of uncertainty.

In Nigeria however, this challenge takes on a more worrying dimension. Young entrepreneurs are faced with a backdrop of fierce competition for scarce credible capital, information asymmetries, and sensitive investors. While Nigeria has become one of Africa’s best places for technology-enabled entrepreneurship, early-stage finance is still very selective and performance-based, with pitching ability serving as a key filtering mechanism (Ibidunni et al. 2021; Montanaro et al. 2024). Investors are increasingly opting to fund using signals received at the pitch stage such as problem-solution fit clarity, financial defensibility, founder credibility, and execution capability/perceived execution capability, particularly in areas where there is little objective performance data.

Although a growing number of studies have examined entrepreneurial pitching and investor decision-making, much of this work is targeted towards the developed world or is experimental in nature that discounts the realities of youth-led ventures in emerging markets. Similarly, research on AI and entrepreneurship has so far mainly been concerned with opportunity identification, innovation activities and company performance (e.g., Bafera & Kleinert 2023; Giuggioli, Pellegrini & Giannone 2025), rather than how AI may affect investor perceptions in pitch evaluations. Hence, there is no empirical knowledge of whether an AI-assisted preparation for a pitch increases or decreases investor trusts, particularly in contexts where authenticity, trust, and contextual expertise are considered as integral elements of funding decisions.

The lack of contextual evidence limits academic understanding and practical application. Because of ‘the murky waters’ on how AI use relates to pitching competence and that relates to what investors evaluate, young entrepreneurs may adopt digital applications in ways that will weaken their chances of getting funded and support institutions might be misled to overestimate the merit of technology-enhanced pitch preparation. That lacuna motivates the current study which investigates the potential of AI to impact pitch outcomes for Nigerian youth entrepreneurs. Drawing on signalling theory and informed by a scoping review for survey-based evidence, the paper develops and empirically tests an AI-enabled conceptual model that articulates how the quality of pitch preparation, the competence of pitching, and the capability of AI impact investor confidence and grant or investment outcomes.

Overview of Artificial Intelligence in Entrepreneurial Pitching

Artificial intelligence (AI) is a class of techniques that permit machines to carry out tasks including those that require human cognitive functions such as learning, reasoning, pattern recognition and language generation. While there is no generally agreed-upon definition, it is widely recognized that AI contains machine learning, natural language processing, computer vision and generative systems that analyze data, automate decision-support functions, and augment human judgment (Dwivedi et al. 2021; Raisch & Krakowski 2021). In the study of entrepreneurship, AI is now being treated as a general-purpose technology with the potential to fundamentally transform processes of new-firm-formation, evaluation and signaling (Chalmers, MacKenzie & Carter 2021).

Modern AI development has accelerated its application in entrepreneurs activities, especially among opportunity evaluators and in communicating with investors. Generative AI apps are now making it possible for entrepreneurs to quickly build out pitch decks, write venture narratives, analyze market intelligence and model financials on the cheap. That has given both early-stage entrepreneurs and youth entrepreneurs without any experience or advisory support more access to quality preparation resources (Cristofaro, Giardino & Muldoon 2025). The transition was accelerated by the COVID-19 pandemic, as remote pitching events, digital accelerators, distance grant competitions host of similar initiatives began to multiply and rely even more on AI-assisted preparation and on virtual evaluation platforms (Aysan & Nanaeva 2022).

Researchers generally perceive AI in entrepreneurship, not as a replacement for human judgment, but as an enhancer of a founder's knowledge and decisions. There is some support that, if an appropriate level of human judgment is applied, AI may lead to more in-depth analyses, better structured presentations, and less variable decision behavior (Raisch & Krakowski 2021; Giuggioli, Pellegrini & Giannone 2025). Yet there are concerns about bland narratives, over-inflated estimates and a diminishing sense of authenticity when AI-based content is blindly accepted in entrepreneurial pitching and financing exchanges. In entrepreneurial pitching situations, AI hence has a double-edged role. It improves clarity, efficiency, and format, but it may simultaneously reduce some of the signals of credibility that investors rely on when assessing early-stage ventures and making funding decisions in grant contexts.

Artificial Intelligence and Youth Entrepreneurship in Nigeria

Nigeria has, more and more, been recognized as one of Africa's best places for entrepreneurship due to its vast youthful population, burgeoning tech ecosystem and improving digital infrastructure. As in other countries, such as Kenya and South Africa, Nigeria has seen the emergence of innovation hubs, start-up incubators, accelerators, and seed funding schemes which support youth-led enterprises and digital solutions. Simultaneously, a fast-paced, digital revolution is taking hold of entrepreneurs. Emerging technologies, in particular artificial intelligence, have made it possible for startup founders to conceive business ideas, draft business proposals, design plans, and compete more effectively in an already overcrowded and competitive startup space (World Bank, 2022; Montanaro et al., 2024).

Funding is tight and competition fierce in the Nigerian youth entrepreneurship space. As a result, grant funders, accelerators and investors increasingly use structured pitch evaluations as a way to screen applicants, evaluate the feasibility of the ventures and efficiently distribute resources

(Ibidunni et al. 2022). Pitching has thus emerged as a key gatekeeping device, with investor decisions influenced by signals of founder competence, understanding of the market, financial defensibility and ability to execute. In this context, AI-instrumented preparation tools are increasingly embraced by young entrepreneurs to enhance pitch quality, presentation outline, market overview and overall professionalism in investor rendezvous and fundraising moments.

Although this progress has been made, the structural challenges are still very much present. Disparities in digital literacy, access to mentorship, and exposure to investor expectations limit the ability of many young entrepreneurs to access AI tools effectively (Berhe, 2021). Also, the investors doing business in Nigeria tend to be much more risk, contextual and venture sensitive, that is, more sceptical of pitches that look too templated or too artificially generated. As a result, AI use among entrepreneurs is increasing but its effect on pitching outcomes is still uneven, dependent on context, and not well understood in either entrepreneurship theory or practice.

Regulatory and institutional bodies in Nigeria are beginning to real the opportunities and risks that come with AI-led entrepreneurship support systems. Yet, there has been limited practical advice on the strategic or ethical use of AI in communication with investors. This gap signifies a need for clarification on an empirical level as to how AI plays with pitch competence and investor confidence affecting entrepreneurial funding outcomes particularly for the Nigerian youth entrepreneurs today.

2. THEORETICAL FRAMEWORK AND HYPOTHESIS DEVELOPMENT

A variety of theoretical lenses such as human capital theory, institutional theory and behavioural decision-making frameworks have been applied to understand outcomes of entrepreneurs financing. Of these, signaling theory is very suitable for describing investor decisions in uncertainty situation when information asymmetry between entrepreneur and evaluator is high (Connelly et al. 2011; Bafera & Kleinert 2023). Adopting signaling theory as the main theoretical framework, this research investigates how youth entrepreneurs signal venture quality in the pitch and how these signals influence investor confidence and funding success.

Signaling theory states that individuals and organizations are seen to send out signals to reduce the asymmetry of information and to influence the opinions of third parties. In the context of the entrepreneurial pitch, readiness, value proposition clarity, financial defensibility, and founder competency signals, and so forth, serve as signals that entrepreneurs send to potential investors to evaluate the venture and its team (Kalvapalle et al. 2024). Given the scarcity of objective performance information about seed- and early stage investors, investment decisions at the pitch stage are largely based on interpreting these signals from entrepreneurs.

Pitch Preparation Quality and Investor Confidence

The quality of pitch preparation is about how well entrepreneurs communicate an evidence-based market understanding, a logically-consistent strategy, and financial assumptions that are defendable in the pitch deck and the pitch. Prior literature also indicates that investors respond positively to pitches that highlight specific customer pain points, demonstrate validated demand with credible evidence, and possess executable paths (Lavi & Yaniv 2023). "This communicates competence, hard work, and lower risk of execution, all of which attract investor confidence.

The evidence also suggests that poor preparation (e.g., vague what-market claims, non-comparable numbers, and weak logic of traction) can all reduce confidence in the investor and increase perceptions of risk of undertaking (Kalvapalle et al. 2024). There are a handful of scholars who posit that on occasion investors decide to root for founder passion rather than technical rigor, this tendency is far less prevalent in cutthroat funding landscapes where funders (Howe & Menges 2025). In the context of Nigerian youth entrepreneurship where the paucity of funds renders investors more discerning, what differentiates high quality preparation from poor preparation is likely to be a critical signal of credibility. Accordingly, the prediction of the study is that:

H$_1$: There is a positive relationship between pitch preparation quality and investor confidence among Nigerian youth entrepreneurs.

Pitching Competence and Investor Confidence

Pitching capabilities are defined as the ability of entrepreneurs to present information about their venture during a live or video pitch session (clarity of expression, narrative coherence, responsiveness to questions, and control of delivery). Results from the entrepreneurial pitching literature consistently report a strong effect of communication competence on investor evaluation, disregarding venture related characteristics (Lavi & Yaniv 2023; Kalvapalle et al. 202 OKR). Better delivery leads to more positive perceptions of leadership and coachability, which are two other legitimate signals of execution ability.

However, a few studies warn that these communication skills are not enough to obtain funding without underlying venture logic (Grichnik et al. 2020). Yet, in the context of early-stage funding, where firm performance data are scarce, pitching competence tends to overshadow (positive or negative) substantive signals. Since young entrepreneurs generally have little prior track records, effective pitching competence may play thus a disproportionately (if not outsized) important role in shaping investor confidence. For these reasons, the paper proposes that:

H$_2$: There is a positive relationship between pitching competence and investor confidence among Nigerian youth entrepreneurs.

Artificial Intelligence Capability as a Signal Amplifier

Emerging dynamics in the entrepreneurial signalling have been introduced by the recent developments in artificial intelligence. With AI tool, entrepreneurs can improve preparation of pitches by organising narratives, creating visualisations, analysing markets and running financial-scenario simulations (Chalmers et al. 2021; Giuggioli et al. 2025). When properly applied, AI could help make signals clearer and more uniform, thus boosting investor confidence.

However, an analysis suggests that unquestioningly relying on answers generated by artificial intelligence may reduce the look of authenticity and reliability particularly when investors are already trained to view pitches as templates or exaggerations (Brüns & Meißner 2024). This duality indicates that AI is not an alternative determinant for successful pitches but an enhancer of signals in the playfield. Well-prepared and competent entrepreneurs may profit from AI augmentation, while poorly-prepared entrepreneurs may have their signals weakened, rather than helped, through AI misuse. Thus, this study predicts that:

H_3: Artificial intelligence capability positively moderates the relationship between (a) pitch preparation quality and investor confidence, and (b) pitching competence and investor confidence.

Investor Confidence and Pitching Outcomes

Investor confidence is the evaluating party's general trust in the believability, viableness and ability to execute of a venture and its founding team. Previous literature systematically points to investor confidence as the key mediator between entrepreneurial signals and funding decisions (Connelly et al. 2011; Bafera & Kleinert 2023). Improved investor confidence leads to an increased likelihood of the success of the funding application, progression to further stages and more interaction.

Even all with hopeful narratives and rhetoric from experts and entrepreneurs with inspirational stories suggests that they will most likely be told no when investor confidence is rattled by risk that is felt, or if it is inconsistent, or if it does not inspire trust (Kalvapalle et al. 2024). In the competitive grant and investment environment that is typical of Nigerian youth entrepreneurship schemes, therefore, investor confidence is a critical factor in ultimately deciding pitch outcomes. On this basis, the study predicts that:

H_4: Investor confidence has a positive relationship with pitching outcomes among Nigerian youth entrepreneurs.

Drawing on the developed hypotheses and on signaling theory, we theorize in an AI-enabled model that the quality of pitch preparation and pitching ability affect pitching outcome through the mediating role of investor confidence and that artificial intelligence capability serves as a moderating amplifier of these effects. The suggested research model is depicted in Fig. 1.

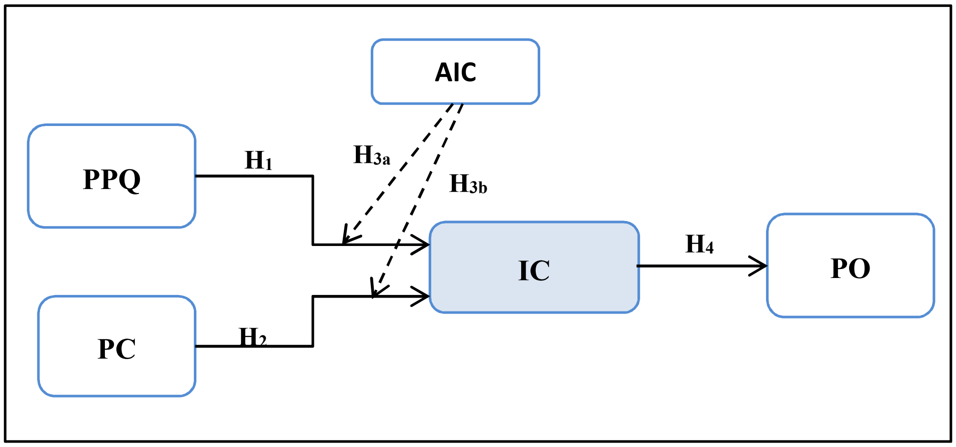

Figure 1. Theoretical framework and hypothesis development

AIC, Artificial Intelligence Capability; PPQ, Pitch Preparation Quality; PC, Pitching Competence; IC, Investor Confidence; PO, Pitch Output.

3. RESEARCH METHODS AND DESIGN

This research is a quantitative research design which falls under the post-positivist paradigm that values hypothesis testing, objectivity and the use of empirical data to investigate relationships between theoretically informed constructs. The quantitative method was deemed suitable for the study as it was intended to examine predicted relationships between quality of pitch preparation, pitching ability, artificial intelligence potential, investor confidence and pitch results in a group of young Nigerian entrepreneurs.

Respondents were selected through a purposive non-probability sampling technique. This method was applicable as there is no known sampling frame for Nigerian youth entrepreneurs who have taken part in grant competitions or investor pitch events. In line with research in the area of entrepreneurship, purposive sampling allows selection of respondents who have relevant experiential knowledge, in situations where randomisation is not feasible (Etikan, Musa & Alkassim 2016). To be eligible, participants had to have taken part in a formal grant application or pitch-based funding scheme in Nigeria on at least one occasion.

Data collection was done through a self-administered structured questionnaire in an online format. Online surveys were deemed suitable as they offer cost efficiency, access to a widely geographical area of respondents, flexibility for respondents and speed in data collection (Nayak & Narayan 2019). Along with closed-ended items for measurement, the survey had three open-ended questions, which were formulated to briefly gather respondent views on their experiences of pitching, reasons for rejection and use of AI tools in pitch preparation.

A total of 758 responses were received at the beginning. After screening, 637 questionnaires were included and 121 responses were excluded due to incompleteness or pattern responses. The authors deemed the final sample size to be sufficient in comparison to previous studies on entrepreneur pitching, technology adoption and investor decision-making, which are often conducted using samples of between 300 and 500 respondents (Kalvapalle et al. 2024; Lavi & Yaniv 2023).

Measurement Scales

The measurement item of the study constructs taken from the previous studies was modified to conformity with the current research for better content validity. Using items adapted from the entrepreneurial pitching (Kalvapalle et al. 2024; Lavi & Yaniv, 2023) and communication competence literature, PPQ and PC were assessed. AIC was assessed with adapted items from studies on use of AI and technologies in facilitating related tasks (Chalmers et al. 2021; Giuggioli et al. 2025). The IC was evaluated using scales developed according to signals theories and investor evaluation research (Connelly et al., 2011; Bafera & Kleinert, 2023).

Each of the measurement items was scored on a five-point Likert scale (1 = strongly disagree; 5 = strongly agree). Table 1 shows the entire set of measurement items along with the results of factor analysis (i.e., factor loadings, related test statistics), which were used for evaluating the construct validity.

Measurement Scales and Factor Loadings

Drawing on established entrepreneurship, pitching and technology-use literature, the study constructs were operationalised with measurement scales adapted from prior studies. The PPQ and PC scales were adapted from previous research in entrepreneurial pitching and investor evaluation. Artificial intelligence capability (AIC) was assessed with items adapted from recent studies related to the application of AI in entrepreneurial activities and in decision assistance. Pitching outcomes (PO) and director confidence (DC) were operationalised via scales informed by signalling theory and research into early-stage investment decision-making. All the constructs were measured by multi-item scale and each measurement item on a five point Likert scale anchored with strongly disagree (1) and strongly agree (5).

In Table 1, the measurement items are laid out along with the factor analysis results, showing the factor loadings and t-statistics for each item. Following guidelines for assessing scales in behavioural research (Zeller and Carmines 1980), factor loadings 0.400 and above were considered acceptable levels of item reliability (Howard 2016).

Table 1 shows that factor loadings for pitch preparation quality (PPQ) ranged from 0.368 to 0.836, and the pitching competence (PC) items had factor loadings from 0.429 to 0.783. These results indicate that the indicators sufficiently reflected respondents' views on preparedness, communication clarity, and delivery efficiency and listener engagement in investor meetings. The factor loadings of Artificial intelligence capability (AIC) ranged between 0.718 and 0.828, which shows that there is a great deal of convergence on AI-enabled pitch structuring, market research and presentation improvement. Investor confidence (IC) yielded factor loadings from 0.793 to 0.834, and pitching outcomes (PO) yielded factor loadings from 0.797 to 0.829, indicating reasonable levels of convergence for the constructs measuring credibility, funding progression and follow-up involvement.

After identification of indicators with marginally low factor loadings, in particular PPQ1 and PPQ3, conservative scale purification was adopted in accordance with Howard's (2016) advice and subsequent empirics (Decius, Schaper & Seifert 2019). However deleting these items does not significantly enhance the construct reliability. Therefore, in order to maintain conceptual completeness and content validity, they were kept.

Table 1. Measurement scales and factor loadings

Construct and items	Loading	t-stat
PPQ - Pitch preparation quality		
PPQ1: Market evidence supports my pitch claims	0.375	2.481
PPQ2: Financial assumptions in my pitch are defensible	0.836	26.599
PPQ3: My pitch clearly explains the problem–solution fit	0.368	1.855
PPQ4: My pitch demonstrates execution feasibility	0.713	10.986
PC - Pitching competence		
PC1: I communicate my pitch clearly	0.429	2.853
PC2: I respond confidently to investor questions	0.783	25.099
PC3: My pitch narrative is coherent	0.726	12.440
PC4: I manage time and delivery effectively	0.740	19.139
AIC - Artificial intelligence capability		
AIC1: I use AI tools to structure pitch content	0.828	40.832
AIC2: I use AI to analyse markets or competitors	0.809	34.354
AIC3: AI improves clarity of my pitch materials	0.718	21.461
IC - Investor confidence		
IC1: Investors perceived my venture as credible	0.793	29.937
IC2: Investors trusted my ability to execute	0.819	33.917
IC3: Investors showed willingness to engage further	0.834	37.347
PO - Pitching outcomes		
PO1: I progressed beyond the pitch stage	0.829	46.356
PO2: I received positive investor feedback	0.804	33.709

PO3: I secured funding or follow-up meetings	0.797	33.875

PPQ, Pitch preparation quality; PC, Pitching competence; AIC, Artificial intelligence capability; IC, Investor confidence; PO, Pitching outcomes.

Statistical Analysis Approach

The study used PLS-SEM to test the proposed relationships between the study constructs. PLS-SEM is especially suitable for prediction-oriented, theory development research with complex models that include latent constructs and moderation effects (Hair et al. 2021). Unlike covariance-based SEM, PLS-SEM makes less distributional assumptions and it works well with small to medium samples, thus being appropriate for studies on entrepreneurship and technology, where the normality of data can rarely be assumed (Henseler Ringle & Sinkovics 2009).

The selection of PLS-SEM was also supported by the study's theoretical framework, which includes mediating (investor confidence) and moderating (artificial intelligence capability) effects. Previous methodological research suggests that PLS-SEM is robust in the estimation of interaction effect and cascades effects of higher complexity in behavioural and EM research (Hair, Sarstedt & Ringle 2019). The final sample size for the study was above the minimum sample size requirements suggested for PLS-SEM based on both the ten-time rule and modern power-based criteria.

The PLS-SEM analysis was performed in two-stages. At the first stage, the measurement model was evaluated in order to verify the reliability and validity of the latent constructs. Cronbach's alpha and the composite reliability values were used to assess the internal consistencies reliability, with values >0.700 considered as indicating suitable reliability. Convergent validity was evaluated by the average variance extracted (AVE), and discriminant validity was tested applying the heterotrait–monotrait (HTMT) ratio, where a value of less than 0.850 corresponded to acceptable discriminant validity.

In the second stage, the path model was estimated to test the hypotheses of interest in this study. The significance of relationships was evaluated with the path coefficients, bootstrapped t-statistics and p-values. Bootstrapping with 5000 resample was used for increasing the reliability of estimates and for obtaining confidence intervals for the direct and interaction effects. Effect sizes (f2) and R2-values were also studied to determine the explanatory power and relative influence of the exogenous constructs, respectively.

Ethical Considerations

Informed Consent was obtained from all participants, and anonymity of responses was guaranteed. We did not collect any information that would allow us to identify individual respondents, and respondents were told they could stop participating at any time without penalty. The study was approved according to the local institutional guidelines for research ethics and the data were only used for academic and research purposes.

4. RESULTS

Descriptive Statistics

The construct- level descriptive statistics in Table 2 offer some of respondents' views, characters of data distributions and clues of multicollinearity and common method bias (CMB). The findings showed that PPQ and PC had the two highest means and standard deviations, indicating that respondents were aware of their preparation levels and perceived themselves as adequately prepared and competent to present the pitch. The artificial intelligence capability (AIC) also turned out to have a relatively high mean value, which implied that a substantial part of AIs were used in pitch structuring, market scanning, and presentation polishing. Investor confidence (IC) and pitching outcome (PO) were also reported with high mean scores, memory either generally positive attitude toward investors' responses and result of post-pitch.

Skewness and kurtosis statistics infer that the data are normally distributed as all skewness statistic are within the acceptable range and kurtosis statistic are less than the maximum permissible value of 7 (Matore & Khairani 2020). The results indicate the appropriateness of the data for multivariate test.

Further analysis of tolerance values and variance inflation factors (VIFs) was conducted to test for multicolinearity and the single-respondent common method bias. In accordance with the criteria, all tolerance values were above the minimum value, and VIF values were below the maximum value of 5 (Kock 2015). These results demonstrated that neither multicollinearity nor common method bias was a major threat to the present investigation.

Table 2. Descriptive statistics results

Constructs	N	Mean	SD	Skewness	Kurtosis	Tolerance	VIF
PPQ	390	3.966	0.492	−0.691	4.588	0.021	47.927
PC	390	4.155	0.489	−2.276	15.265	0.017	57.233
AIC	390	3.432	0.905	−0.800	2.988	0.049	20.310
IC	390	3.491	0.983	−0.999	3.643	0.057	17.676
PO	390	2.718	1.123	0.039	1.924	0.100	10.020

SD, standard deviation; VIF, variance inflation factor; PPQ, pitch preparation quality; PC, pitching competence; AIC, artificial intelligence capability; IC, investor confidence; PO, pitching outcomes.

Measurement Model Results

Before proceeding to test the hypothesised relationships between constructs, we assessed the measurement model to establish internal consistency reliability, convergent validity and discriminant validity. The results of these tests are presented in Table 3.

Results suggested that all constructs reached acceptable level of internal consistency reliability. Specifically, the Cronbach's alpha coefficients for pitch preparation quality (PPQ), pitching competence (PC), artificial intelligence capability (AIC), investor confidence (IC) and pitching outcomes (PO) were above the recommended value of 0.700, which were indicative of satisfactory internal consistency. This was further confirmed by the composite reliability (ρc) values, which were all above the the threshold value of 0.700, ensuring the reliability of the measurement scales.

Convergent validity was evaluated based on the average variance extracted (AVE) criterion. As presented in Table 3, all AVE values of the constructs were above the acceptable level of 0.500, which means that each construct could explain enough variance of its indicator and that was acceptable convergent validity for all constructs.

Discriminant validity was tested using the heterotrait–monotrait ratio of correlations (HTMT). The HTMT values for all pairs of constructs were below the more conservative cutoff of 0.850, indicating that each construct was empirically distinct and represented a unique element of the pitching and investment journey. Overall, these findings indicate that the measurement model has acceptable levels of reliability and validity and is appropriate for further analysis of the structural model.

Table 3. Measurement model results

Construct	**Internal consistency reliability**	**Convergent validity**	**Discriminant validity (HTMT)**
	A	Pc	AVE
PPQ	0.812	0.854	0.556
PC	0.835	0.872	0.581
AIC	0.821	0.861	0.612
IC	0.846	0.879	0.594
PO	0.808	0.851	0.562

PPQ, pitch preparation quality; PC, pitching competence; AIC, artificial intelligence capability; IC, investor confidence; PO, pitching outcomes; AVE, average variance extracted; HTMT, heterotrait-monotrait ratio.

Structural Model Results

To test the hypothesised relationship among PPQ (pitch preparation quality), PC (pitching competence), AIC (artificial intelligence capability), IC (investor confidence) and PO (pitching outcomes), a PLS-SEM structural model was estimated as per the conceptual framework of this research. The focus in evaluating the structural model was on collinearity, explanatory power and significance for the hypothesised path relations.

Before the hypothesis testing, the collinearity issue between predictor constructs was examined at the level of the structural model based on the guidelines for PLS-SEM. The variance inflation factor (VIF) values were checked on the structural paths rather than on the level of descriptive construct. All inner VIFs were lower than the more conservative threshold value of 5.0, suggesting that multicollinearity was not a concern in estimating the structural coefficients. This is in line with suggestions that collinearity and CMB diagnostics in PLS-SEM need to be assessed at the level of indicators and structural paths, not by means of construct-level descriptive statistics.

Despite the fact that Kurtosis in PC was relatively high in descriptive analysis, no assumptions for PLS-SEM were violated. Self-assessed competence constructs often have peaked distributions, but PLS-SEM does not assume multivariate normal distribution. The suitability of PLS-SEM in this study is corroborated by the method's robustness to non-normal data (Hair et al. 2021).

Figure 2 shows the SC model and standardised path coefficients. The results reveal positive associations between all constructs of the study, which implies that better preparation of the pitch and competence of the pitcher leads to more confidence of the investors, which in turn leads to better results of the pitch. Artificial intelligence capability was also found to amplify a few other critical paths in the model, resulting in enhanced overall predictive power.

Table 4 reports the path coefficient estimates, bootstrapped t-values, p-values, and a summary of the hypothesis testing decisions.

Table 4. Results for structural model of hypothesised relationships

Hypothesised relationship	B	t-stat	p-value	Decision
H_1: PPQ → IC	0.312	5.874	0.000	Supported
H_2: PC → IC	0.341	6.219	0.000	Supported
H_3: IC → PO	0.561	9.402	0.000	Supported
H_4: AIC × PPQ → IC	0.118	2.487	0.013	Supported
H_5: AIC × PC → IC	0.104	2.231	0.026	Supported

Predictive Power:

- Investor confidence (R^2) = 0.612
- Pitching outcomes (R^2) = 0.514

The results show that quality of pitch preparation has a positive and significant effect on investor confidence (β=0.312, p<0.001), hence H_1 is supported. This result indicates that the pitches based on solid market-based evidence and realistic financial assumptions with practical implementation would generate more investors' trust. Also, pitching skill is significantly and positively related with investor confidence ($\beta = 0.341$, $p < 0.001$), supporting H_2 and highlighting the relevance of clarity in communication, effectiveness of delivery, and responsiveness during the pitch presentation.

Additional evaluations show that investor confidence has a significant positive impact on pitching success ($\beta = 0.561$, $p < 0.001$), which supports H_3. This result confirms that a positive investor perception is the key mediator of entrepreneurs progressing from the pitching round, receiving positive feedback, or gaining more meetings.

Test results for moderation indicate that AI capability positively moderates the relationship between the quality of pitch preparation and investor confidence ($\beta = 0.118$, $p < 0.05$), thus H4 is supported. In other words, it is those entrepreneurs who have most effectively used AI tools to strengthen pitch content and analytical rigor who will be most successful in turning preparation efforts into investor trust. Similarly, the interaction effect of pitching competence and AI capability is positive and significant ($\beta = 0.104$, $p < 0.05$), which supports H_5. This result suggests that AI-enabled rehearsal, organizational and delivery tools can enhance the impact of pitching expertise on investor views.

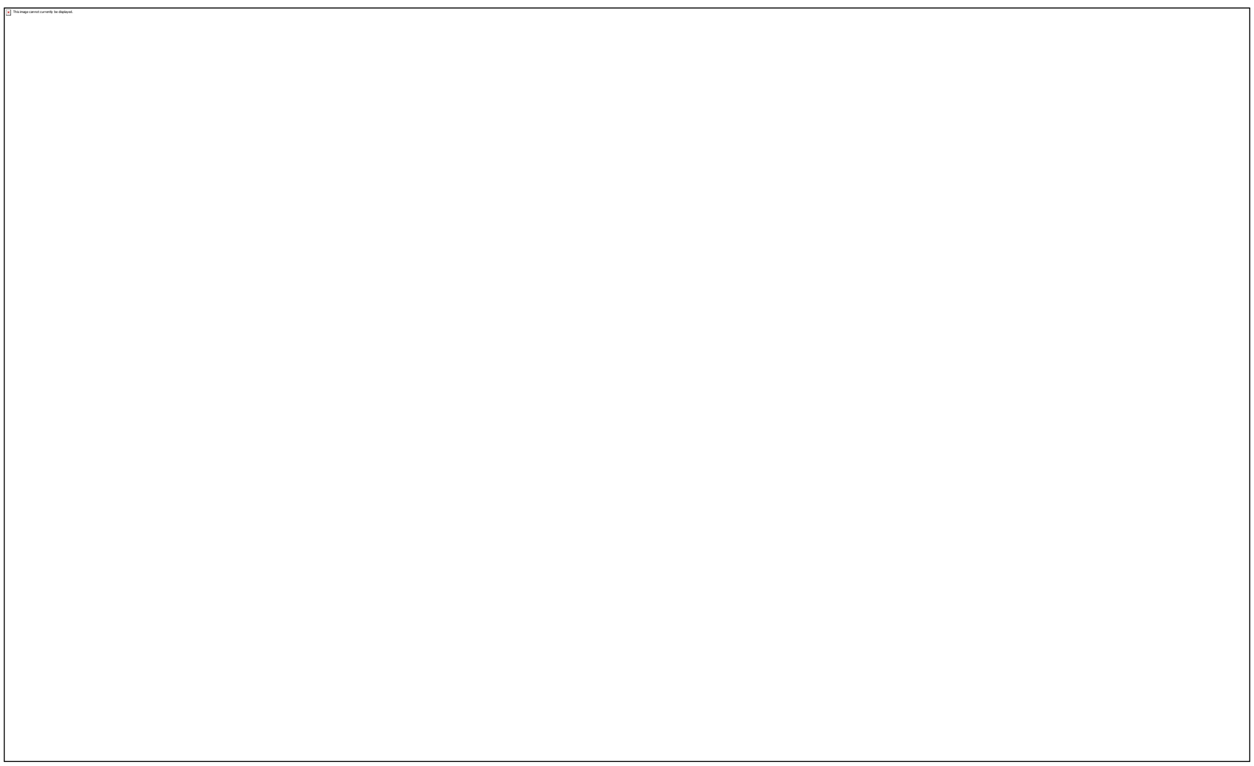

Figure 2. Structural path model diagram

Source: Authors' computation (PLS-SEM results)

The structural path model illustrates the standardised path coefficients (β) for the hypothesised relationships among the study constructs:

PPQ = Pitch preparation quality; PC = Pitching competence; AIC = Artificial intelligence capability; IC = Investor confidence; PO = Pitching outcomes.

5. DISCUSSION

Findings of this study, which investigated the pitching results of Nigerian youth entrepreneurs during grant and investor selection process, are highly consistent with the study's theoretical framework and nascent research on entrepreneurial pitching as well as technology aided decision making. The findings reveal that pitch preparation quality (PPQ) and pitching competence (PC) have significant positive effects on investor confidence (IC), and IC significantly predicts pitching outcomes (PO). These effects highlight the importance of investor perceptions as the key mechanism by which entrepreneurial activity is converted into fundraising success.

The positive and statistically significant relationship between the quality of pitch preparation and investor confidence implies that better-prepared pitches; those based on credible market data, realistic financial assumptions, and a concise problem - solution presentation, increase the perceived validity of entrepreneurial ventures. This result is in line with previous research that focuses on the idea that investors value evidence-backed rationale and execution viability when deciding on early-stage firms (Pollack, Rutherford & Nagy 2012; Parhankangas & Ehrlich 2014). In the Nigerian setting where youth entrepreneurs are many and grants are few, this finding is indicative that it is poor preparation and not lack of novel ideas that condemns most youths to rejection at the pitching platform.

Likewise, competence in pitching was a strong positive driver of investor confidence, further bolstering the case for the importance of entrepreneurs' ability to communicate their ideas, not just the content of those ideas. Clarity of expression, confidence in responding to questions, consistency in storylines, and time allocation all play a significant role in shaping investors' opinions. This is in line with results showing that speech delivery (Clark 2008), narrative coherence (Davis et al. 2017), and entrepreneur charisma influence investor perceptions of the venture over and above objective venture characteristics. For young entrepreneurs, many of them first-time founders, this takeaway will reinforce the need to build soft skills in addition to technical business acumen.

The findings also demonstrate that investor confidence significantly predicts pitching outcomes, indicating that this variable mediates the effect of the other pitching-related predictors on pitching outcomes. Entrepreneurs who pitched with trust and credibility were significantly more apt to move beyond the pitching phase, get positive results, and line up additional meetings or financing. This result is consistent with theoretical perspectives that conceptualize investment decisions as socially constructed judgments influenced by trust, legitimacy and perceived expertise as opposed to only reliance on financial indicators (Fisher et al. 2017; Maxwell, Jeffrey & Lévesque 2011). From a practical perspective, it would appear that no in the pitch means investor doubts, not that the venture can't feasibly exist.

Crucially, the paper also shows that the positive effects of pitch preparation quality on investor confidence, as well as pitching competence on investor confidence, are positively moderated by artificial intelligence capability. This suggests that entrepreneurs using AI tools to organise pitch content, analyse markets, hone narratives, and practice presentations have a greater ability to translate preparation and competence into investor trust. This result builds upon the emerging literature on AI in entrepreneurship, by demonstrating that AI is not simply an enabler of task automation, but can become a cognitive and strategic enabler in high-stakes evaluative environments such as pitch competitions and grant evaluation (Dwivedi et al. 2021; Cockburn, Henderson & Stern 2018).

Taken together, the two results indicate that the enhanced signal quality due to AI capability allows youth entrepreneurs to provide more authentic, consistent, and data-backed pitches. This is especially true in developing countries such as Nigeria where structural barriers, information asymmetry and competition are so stiff that the reliance on signalling mechanisms to make investment decisions is even more pronounced. The findings thus suggest that rather than replacing entrepreneurial skill, AI serves as a supplementary tool, making the preparation and delivery more effective.

In general, this study adds to the entrepreneurship and technology literature by showing empirically that the path to rejection or success among the pool of shortlisted applicants is heavily mediated by investor confidence and that this confidence is informed by human and AI-enabled capabilities. By connecting pitching theory with nascent understandings of artificial intelligence in entrepreneurship-related settings, the paper provides a sophisticated explanation as to why numerous competent youth entrepreneurs fail to attain funding even though they qualify going into late stages of grant and investment procedures.

6. LIMITATIONS AND AREAS FOR FUTURE STUDIES

However, the results of the present study should be viewed in consideration of several limitations. First, the present study adopted a quantitative, cross-sectional approach and, thus, did not allow for the observation of changes in pitching competence, potential artificial intelligence (AI) capability, or investor confidence over time. Therefore, subsequent studies may consider employing longitudinal designs to examine the impact of repeated pitching exposure and long-term AI use on funding results across multiple investment cycles.

Secondly, the inquiry adopted a non-probability sampling technique with young entrepreneurs in Nigeria and as such the result may not be generalized to other population of entrepreneurs or to different geographical location. Further study may also be extended to other African countries or developing countries to establish whether comparable pitching patterns and AI effects occur.

The study was based on entrepreneurs’ self-reported perceptions of pitch outcomes and investor reactions, which are subject to recall bias or interpretation. Future studies may also employ multiple-source data (eg, investor evaluations, pitch competition outcomes or observational data) to reflect more objective indicators of pitching success.

Finally, although the study added to knowledge about investor confidence and AI capability in entrepreneur pitching, future research might involve other theoretical perspectives and emerging constructs (eg, algorithmic pitch evaluation systems, AI-enabled investor screening mechanisms, and digital legitimacy signals in entrepreneurial financial environments).

7. CONCLUSION

This study makes valuable theoretical and practical contributions to the youth entrepreneurship, entrepreneurial finance and artificial intelligence (AI) in investment decision-making process (IDP) literature. Theoretically, this research contributes to entrepreneurship and the pitching literature by showing that investor confidence is the mechanism through which both pitch preparation quality and pitching competence affect pitch outcomes. Interpreting investor confidence as a mediating construct, our findings deepen the understanding as to why many young entrepreneurs face rejection after they have managed to advance to later pitching stages.

This study also advances the literature on entrepreneurship and technology by introducing artificial intelligence capability into the pitching process. The results demonstrate that AI capability is not a substitute for entrepreneurial competence, but rather it fortifies the quality of preparation and pitch delivery, increasing investor confidence. In the process, the study adds novel insights to the emerging works on AI as a strategic resource in the context of entrepreneurial actions and evaluative funding environments.

From a practical point of view, the results offer relevant knowledge for young entrepreneurs, investors, entrepreneurship support organisations and policy makers. The findings highlight that successful pitching is not just about innovative concepts, but also evidence-based preparation, communication skills and signaling credibility, all aspects that can be improved by suitable AI solutions. Support programmes for entrepreneurs and incubators can thus incorporate AI-assisted pitch preparation and structured communication training in their curricula.

Collectively, this research offers a compelling rationale for enduring pitch-stage rejection amongst Nigerian youth entrepreneurs and practical guidelines on building investor confidence, obtaining funding success and enhancing entrepreneur inclusion.

REFERENCES

[1] African Development Bank, 2023, *African economic outlook 2023: Mobilising private sector financing for climate and green growth*, African Development Bank Group, Abidjan, viewed 18 January 2026, from https://www.afdb.org/en/documents/african-economic-outlook-2023

[2] Bafera, J. & Kleinert, S., 2023, 'Signaling theory in entrepreneurship research: A systematic review and research agenda', *Entrepreneurship Theory and Practice* 47(6), 2419–2464. https://doi.org/10.1177/10422587221138489

[3] Berhe, M.W., 2021, 'Empirical analysis of urban youth unemployment in Ethiopia', *African Development Review* 33(S1), S189–S203. https://doi.org/10.1111/1467-8268.12514

[4] Brüns, J.D. & Meißner, M., 2024, 'Do you create your content yourself? Generative artificial intelligence diminishes perceived brand authenticity', *Journal of Retailing and Consumer Services* 79, 103790. https://doi.org/10.1016/j.jretconser.2024.103790

[5] Chalmers, D., MacKenzie, N.G. & Carter, S., 2021, 'Artificial intelligence and entrepreneurship: Implications for venture creation in the fourth industrial revolution', *Entrepreneurship Theory and Practice* 45(5), 1028–1053. https://doi.org/10.1177/1042258720934581

[6] Clark, C., 2008, 'The impact of entrepreneurs' oral "pitch" presentation skills on business angels' initial screening investment decisions', *Venture Capital* 10(3), 257–279. https://doi.org/10.1080/13691060802151944

[7] Cockburn, I.M., Henderson, R. & Stern, S., 2018, 'The impact of artificial intelligence on innovation', *NBER Working Paper Series* No. 24449. https://doi.org/10.3386/w24449

[8] Connelly, B.L., Certo, S.T., Ireland, R.D. & Reutzel, C.R., 2011, 'Signaling theory: A review and assessment', *Journal of Management* 37(1), 39–67. https://doi.org/10.1177/0149206310388419

[9] Cristofaro, M., Giardino, P.L. & Muldoon, J., 2026, 'Entrepreneurial decision-making in the age of AI: Sector knowledge at the balance of intuition and analysis', *Technology in Society* 85, 103200. https://doi.org/10.1016/j.techsoc.2025.103200

[10] Davis, B.C., Hmieleski, K.M., Webb, J.W. & Coombs, J.E., 2017, 'Funders' positive affective reactions to entrepreneurs' pitch presentations and funding decisions', *Journal of Business Venturing* 32(5), 550–573. https://doi.org/10.1016/j.jbusvent.2017.06.003

[11] Decius, J., Schaper, N. & Seifert, A., 2019, 'Informal workplace learning: Development and validation of a measure', *Human Resource Development Quarterly* 30(4), 495–535. https://doi.org/10.1002/hrdq.21368

[12] Dwivedi, Y.K., Hughes, D.L., Ismagilova, E. et al., 2021, 'Artificial intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy', *International Journal of Information Management* 57, 101994. https://doi.org/10.1016/j.ijinfomgt.2019.08.002

[13] Etikan, I., Musa, S.A. & Alkassim, R.S., 2016, 'Comparison of convenience sampling and purposive sampling', *American Journal of Theoretical and Applied Statistics* 5(1), 1–4. https://doi.org/10.11648/j.ajtas.20160501.11

[14] Fisher, G., Kotha, S. & Lahiri, A., 2017, 'Changing with the times: An integrated view of identity, legitimacy, and new venture life cycles', *Academy of Management Review* 42(3), 383–409. https://doi.org/10.5465/amr.2014.0457

[15] Giuggioli, G., Pellegrini, M.M. & Giannone, G., 2025, ‘Artificial intelligence as an enabler for entrepreneurial finance: A guide to AI-based pitch evaluation’, *Management Decision* 63(10), 3477–3500. https://doi.org/10.1108/MD-10-2023-1926

[16] Grichnik, D., Brinckmann, J., Singh, L. & Manigart, S., 2020, ‘Beyond environmental scarcity: Human and social capital as driving forces of bootstrapping activities’, *Journal of Business Venturing* 35(2), 105919. https://doi.org/10.1016/j.jbusvent.2019.105919

[17] Hair, J.F., Hult, G.T.M., Ringle, C.M. & Sarstedt, M., 2021, *A primer on partial least squares structural equation modeling (PLS-SEM)*, 3rd edn., SAGE Publications, Thousand Oaks, CA. https://doi.org/10.4135/9781072517219

[18] Hair, J.F., Sarstedt, M. & Ringle, C.M., 2019, ‘Rethinking some of the rethinking of partial least squares’, *Long Range Planning* 52(4), 101809. https://doi.org/10.1016/j.lrp.2018.12.001

[19] Henseler, J., Ringle, C.M. & Sinkovics, R.R., 2009, ‘The use of partial least squares path modeling in international marketing’, in R.R. Sinkovics & P.N. Ghauri (eds.), *New challenges to international marketing*, pp. 277–319, Emerald Group Publishing, Bingley. https://doi.org/10.1108/S1474-7979(2009)0000020014

[20] Howard, M.C., 2016, ‘A review of exploratory factor analysis decisions and overview of current practices: What are we doing and how can we improve?’, *International Journal of Human–Computer Interaction* 32(1), 51–62. https://doi.org/10.1080/10447318.2015.1087664

[21] Ibidunni, A.S., Ogundana, O.M. & Okonkwo, A., 2021, ‘Entrepreneurial competencies and the performance of informal SMEs: The contingent role of business environment’, *Journal of African Business* 22(4), 468–490. https://doi.org/10.1080/15228916.2021.1874784

[22] Kalvapalle, S.G., Misangyi, V.F. & Graffin, S.D., 2024, ‘Entrepreneurial pitching: A review and future research agenda’, *Academy of Management Annals* 18(1), 1–46. https://doi.org/10.5465/annals.2022.0066

[23] Kock, N., 2015, ‘Common method bias in PLS-SEM: A full collinearity assessment approach’, *International Journal of e-Collaboration* 11(4), 1–10. https://doi.org/10.4018/ijec.2015100101

[24] Lavi, A.H. & Yaniv, E., 2023, ‘The effect of entrepreneur attributes on investment evaluations in pitch competitions’, *Journal of Entrepreneurship* 32(1), 39–74. https://doi.org/10.1177/09713557231160325

[25] Matore, M.E.E.M. & Khairani, A.Z., 2020, ‘The influence of skewness and kurtosis on normality testing in educational research’, *International Journal of Academic Research in Business and Social Sciences* 10(3), 1–10. https://doi.org/10.6007/IJARBSS/v10-i3/7052

[26] Maxwell, A.L., Jeffrey, S.A. & Lévesque, M., 2011, 'Business angel early stage decision making', *Journal of Business Venturing* 26(2), 212–225. https://doi.org/10.1016/j.jbusvent.2009.09.002

[27] Montanaro, B., Croce, A. & Ughetto, E., 2024, 'Venture capital investments in artificial intelligence', *Journal of Evolutionary Economics* 34, 1–28. https://doi.org/10.1007/s00191-024-00857-7

[28] Nayak, M.S.D.P. & Narayan, K.A., 2019, 'Strengths and weaknesses of online surveys', *IOSR Journal of Humanities and Social Science* 24(5), 31–38. https://doi.org/10.9790/0837-2405053138

[29] Parhankangas, A. & Ehrlich, M., 2014, 'How entrepreneurs seduce business angels: An impression management approach', *Journal of Business Venturing* 29(4), 543–564. https://doi.org/10.1016/j.jbusvent.2013.08.001

[30] Pollack, J.M., Rutherford, M.W. & Nagy, B.G., 2012, 'Preparedness and cognitive legitimacy as antecedents of new venture funding in televised business pitches', *Entrepreneurship Theory and Practice* 36(5), 915–939. https://doi.org/10.1111/j.1540-6520.2012.00523.x

[31] Raisch, S. & Krakowski, S., 2021, 'Artificial intelligence and management: The automation–augmentation paradox', *Academy of Management Review* 46(1), 192–210. https://doi.org/10.5465/amr.2018.0072

[32] World Bank, 2022, *Nigeria development update: The continuing urgency of business unusual*, World Bank, Washington, DC, viewed 18 January 2026, from https://www.worldbank.org/en/country/nigeria/publication/nigeria-development-update