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Unlocking funding success for generative AI startups: The crucial role of investor influence

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ABSTRACT

Generative AI (GAI) is transforming industries by enabling autonomous content creation. This study explores the impact of investor and technological influences on the funding of 556 GAI startups from 2010 to July 2024. Using principal component analysis, we find that investor influence significantly boosts funding across all levels, while technological influence is insignificant. The results highlight the crucial role of investor networks in securing financial resources for GAI startups. The study's implications suggest that entrepreneurs and policymakers should focus on building strong investor relationships to support the growth of GAI ventures.

1. Introduction

The rapid expansion of artificial intelligence (AI) has altered various businesses, ushering in a new era of technological innovation and economic growth (Besiroglu et al., 2024; Zhang, 2024). Among the many branches of AI, Generative AI (GAI) stands out not only for its transformative capabilities but also for its distinct characteristics in the AI landscape, having a profound impact on technology and business (Bilgram and Laarmann, 2023; Stahl and Eke, 2024). GAI refers to AI systems that can generate new content, such as text, images, music, and code, by learning from existing data (Bilgram and Laarmann, 2023; Chen et al., 2023). Technologies like GPT-3 and DALL-E exemplify the capabilities of GAI, pushing the boundaries of creativity and automation (Ardekani et al., 2024; Dowling and Lucey, 2023). Consequently, these advancements have catalyzed the emergence of numerous GAI startups, which leverage these technologies to create innovative products and services, driving new business models and economic opportunities. GAI startups are uniquely positioned in the current technological landscape due to their ability to generate novel content autonomously, distinguishing them from other AI subfields that focus more on data analysis, prediction, or optimization.

Moreover, AI technology-based startups are at the forefront of this transformation, using digital tools and big data systems to enhance their competitiveness and drive innovation (Lee et al., 2024). These startups are characterized by their agility, technological prowess, and ability to adapt to rapidly changing market conditions. In this dynamic landscape, securing adequate funding is crucial for the survival and growth of GAI startups. However, compared to other AI startups, GAI ventures face unique challenges in securing funding due to the novelty and uncertainty surrounding the long-term applications of content-generating technologies. Despite the growing significance of GAI, the determinants of funding success, particularly the roles of investor and technological influence, remain underexplored.

Recent studies highlight GAI's evolving impact on financial markets. Wang (2024) noted that herding in GenAI investments surged

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post-ChatGPT but declined over time. Almeida & Gonçalves (2024) observed increased market efficiency in AI-related crypto sectors after ChatGPT 3. Bonaparte (2024) cautioned about potential risks in an AI bubble. Chen et al. (2023) showed ChatGPT's ability to predict risk management and stock performance via sentiment analysis. Remolina & Gurrea-Martinez (2023) stressed the need for specific regulations due to ethical and legal risks in AI finance, collectively underscoring GAI's complex role in financial markets.

Studies also emphasize key factors in startup funding and valuation, urging strategic approaches. Trust in investor relationships is crucial (Kaiser and Berger, 2021). A U-shaped relationship between funding and market valuation suggests balanced capital raising (Nazir and Tbaishat, 2023). Active social media, especially LinkedIn, positively impacts funding (Singhal and Kapur, 2023). Investor influence, providing resources and credibility, is critical for success (Gill et al., 2024). VCs reduce uncertainty through syndication networks (Hyun and Kim, 2024), while crowd equity investors boost performance with market knowledge (Di Pietro et al., 2018). Technological integration attracts investment (Kim et al., 2023), with AI and machine learning predicting success (Setty et al., 2024). Furthermore, digital transformation enhances competitiveness through advanced technologies and data-driven decisions (Lee et al., 2024).

Despite the acknowledged importance of investor and technological influence, there is a paucity of research specifically examining their impact on the total funding amount received by GAI startups. Existing research tends to focus on general AI startups, yet GAI startups face distinct challenges, such as the ethical and intellectual property issues surrounding AI-generated content, which may deter certain investors. For instance, OpenAI raised over $11.3 billion largely due to strong investor networks, while smaller startups have struggled to secure significant funding without similar backing. These examples highlight how critical investor support is in ensuring the survival and success of GAI startups, particularly in a rapidly evolving and competitive landscape. Furthermore, while various factors influencing startup success have been identified, there is a lack of comprehensive frameworks that integrate both investor and technological influences using robust analytical methods. This gap is particularly evident in the context of GAI startups, where the rapid pace of technological innovation and evolving investor landscape necessitate a nuanced understanding of these influences.

This study aims to examine the impact of investor and technological influence on the total funding received by GAI startups. It also analyzes the trends and growth patterns of these startups from 2010 to July 2024. This study makes several significant contributions to the existing literature on GAI startups and venture capital. Firstly, it is one of the earliest studies to specifically examine the role of investor and technological influence on the total funding amount received by GAI startups. By constructing composite indices using principal component analysis (PCA) to measure investor and technological influence factors, this study provides a more nuanced and comprehensive understanding of these influences, which has been largely unexplored in previous research. Secondly, the study offers a detailed analysis of the status and trend of GAI startups, providing valuable insights into the growth patterns and funding dynamics of these startups from 2010 to July 2024. This longitudinal perspective is crucial for understanding the evolving landscape of GAI startups and identifying key factors that contribute to their funding success. Moreover, the study's findings have practical implications for entrepreneurs, investors, and policymakers. Entrepreneurs can use insights on key funding success factors to make strategic decisions and improve their chances of securing investment. Investors gain understanding of effective investment strategies and the role of technological integration in startup success. Policymakers can leverage these findings to create supportive measures that promote the growth of GAI startups, driving technological innovation and economic development.

2. Data and methods

2.1. Data and description

To examine the impact of investor and technological influence on funding received by GAI startups, we collected data from CrunchBase spanning the period from 2010 to July 2024. Crunchbase is a platform that provides detailed information about startups, including funding history, key personnel, and market trends (Lee and Geum, 2023; Żbikowski and Antosiuk, 2021). Initially, 720

Table 1
Variables and their descriptions.

Variable Type	Variable Name	Symbol	Description	Source
Explained Variable	Total Funding Amount	TFA	Total funding amount received by Generative AI startups (in million USD).	Crunchbase
Explanatory Variables	Investor Influence	INVESTOR	Composite index of the last funding type (e.g., seed, pre-seed, angel), number of funding rounds, number of investors, and number of lead investors.	Crunchbase & Author Calculation
	Technological Influence	TECH	Composite index of total IT spending (in USD), active available technology, and number of applications.	Crunchbase & Author Calculation
Control Variables	Startups Age	AGE	Age of the Generative AI startups.	Crunchbase
	Number of Employees	NOE	Range of employees in Generative AI startups (e.g., 1–10, 11–50, 50–100).	Crunchbase
	Number of Founders	NOF	Total number of founders of Generative AI startups.	Crunchbase
	Full Descriptions	FD	Comprehensive descriptions of Generative AI startups, including company and business details.	Crunchbase
	Organization Rank	RANK	Crunchbase rank of the company.	Crunchbase

companies were identified; however, those lacking headquarters, country of origin, or funding information were excluded, resulting in a final sample size of 556 startups. Consequently, Table 1 details the variables along with their descriptions and sources. The control variables—startup age, number of employees, founders, full descriptions, and organization rank—capture key aspects of firm maturity, size, and visibility that influence funding success, aligning with our study's focus on organizational traits.

As illustrated in Fig. 1, the year-wise distribution of GAI startups and their total funding amounts from 2010 to 2024 shows a notable increase in both the number of startups and their funding over the years. Significant peaks are observed in 2010, 2015, 2021, and 2023. Overall, 556 GAI startups received a cumulative funding of 49,602 million USD during this period.

Moreover, Fig. 2 summarizes GAI startups and their total funding in various countries. The United States leads with 305 GAI startups receiving 41,968 million USD in funding. The United Kingdom follows with 44 startups and 663 million USD, while India has 23 startups with 85 million USD. Furthermore, Germany and Canada each have 17 startups, with Germany receiving 1274 million USD and Canada 1070 million USD. Additionally, the "Others" category includes 150 startups from various countries, collectively receiving 4535 million USD.

Finally, Fig. 3 highlights the top GAI startups by funding, led by OpenAI with 11,300 million USD, followed by Anthropic at 8354 million USD, and xAI at 6385 million USD. Other notable startups include Magic Leap with 4069 million USD and Scale AI with 1603 million USD. Additionally, Inflection AI, Moonshot AI, and Mistral AI have received significant funding of 1525 million USD, 1274 million USD, and 1188 million USD, respectively. This data illustrates the growing trend and substantial investment in GAI startups over the years.

2.2. Principal component analysis

Principal Component Analysis (PCA) simplifies datasets by reducing dimensionality while retaining most variation (Abdi and Williams, 2010; Lončarski and Vidovič, 2019). In this study, factor analysis was performed to measure investor and technology influence through composite indices. The process involved standardizing variables, computing the covariance matrix, extracting eigenvalues to identify principal components, calculating factor loadings, and selecting components with the highest eigenvalues to create new indices (Abdi and Williams, 2010; Cerny and Kaiser, 1977; Kaiser, 1958, 1961). This approach clarified key factors influencing funding success by simplifying the dataset and emphasizing critical variables (Table 2).

The PCA outcomes indicate that for the INVESTOR component, the variables NOLI, NOI, and NFR have high factor loadings of 0.876, 0.860, and 0.837, respectively, with an eigenvalue of 2.481 and a KMO value of 0.763 (see Table 3). For the TECH component, ITspend and AAT have high factor loadings of 0.721 and 0.708, respectively, with an eigenvalue of 1.346 and a KMO value of 0.562. Bartlett's Test of Sphericity indicates that the components are significant with Chi-Square values of 782.657 and 49.493 and significance levels of 0.000 for both components. The extraction method used was PCA with Varimax rotation and Kaiser Normalization. A high KMO value (close to 1) indicates that the variables share a large proportion of common variance, making factor analysis

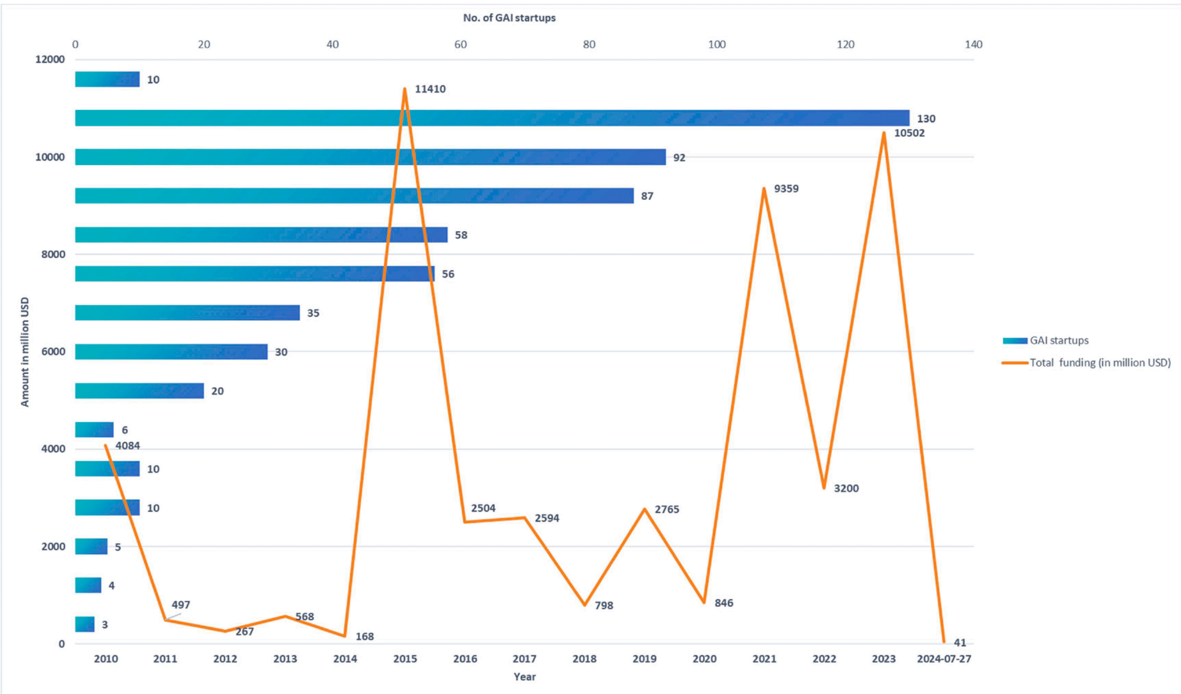

Fig. 1. Trend of Generative AI startups and total funding by year from 2010 to July 2024.

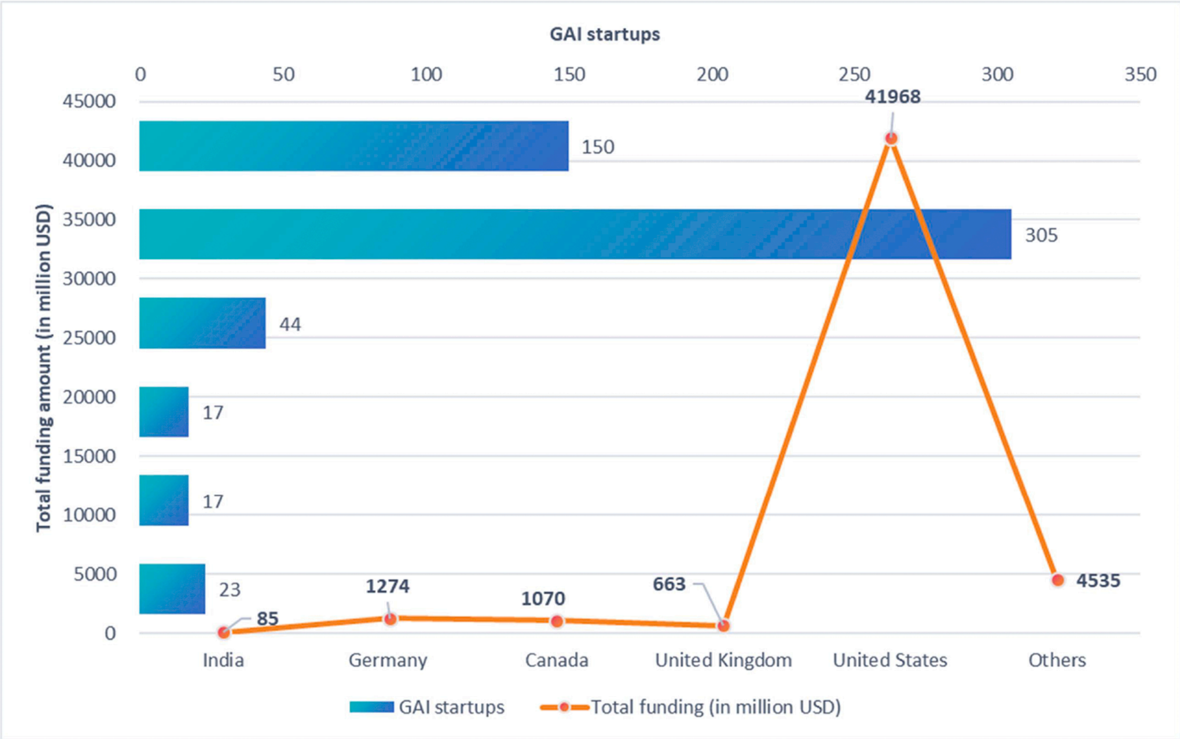

Fig. 2. Top five countries in Generative AI startups and funding.

appropriate (Cerny and Kaiser, 1977; Kaiser, 1958, 1961).

2.3. Econometric model

To examine the relationship between the total funding amount received by GAI startups and key influencing factors such as investor and technological influence, we employ a simple linear regression model. The model can be specified as follows:

$$TFA_i = \beta_0 + \beta_1 INVESTOR_i + \beta_2 AGE_i + \beta_3 NOE_i + \beta_4 NOF_i + \beta_5 FD_i + \beta_6 RANK_i + \epsilon_i \quad \text{(M1)}$$

$$TFA_i = \beta_0 + \beta_1 TECH_i + \beta_2 AGE_i + \beta_3 NOE_i + \beta_4 NOF_i + \beta_5 FD_i + \beta_6 RANK_i + \epsilon_i \quad \text{(M2)}$$

$$TFA_i = \beta_0 + \beta_1 INVESTOR_i + \beta_2 TECH_i + \beta_3 AGE_i + \beta_4 NOE_i + \beta_5 NOF_i + \beta_6 FD_i + \beta_7 RANK_i + \epsilon_i \quad \text{(M3)}$$

TFA_i is the total funding amount for startup $_i$, $INVESTOR_i$ represents the composite index for investor influence, and $TECH_i$ represents the composite index for technological influence. AGE_i, NOE_i, NOF_i, FD_i, and $RANK_i$ are the control variables representing the age, number of employees, number of founders, full description, and organizational rank of the startup, respectively, with β_0 as the intercept term, $\beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6$, and β_7 as the coefficients for the respective variables, and ϵ_i as the error term.

Furthermore, conventional regression models, like simple linear regression, assume a constant relationship between variables, limiting their ability to capture variations in explanatory influences across different levels of the dependent variable (Sawarni et al., 2023). To address this, we apply Methods of Moments Quantile Regression (MMQR), which examines heterogeneity across quantiles, offering a more detailed understanding of how investor and technological influences vary across funding levels (Machado and Santos Silva, 2019).

3. Results

3.1. Descriptive statistics

The descriptive statistics (Table 3) show that the TFA for startups has a mean of 6.392, a standard deviation of 1.065, and values ranging from 3.079 to 10.053. The TECH and INVESTOR indices are standardized with means close to zero and standard deviations of 1. Other variables such as AGE, NOE, NOF, FD, and RANK exhibit diverse means and ranges, reflecting varied startup characteristics. The pairwise correlations reveal significant relationships: TFA is positively correlated with TECH and INVESTOR, and strongly with NOE, but negatively with RANK. All correlations are significant at the $p < 0.01$ level, as shown in Table 4.

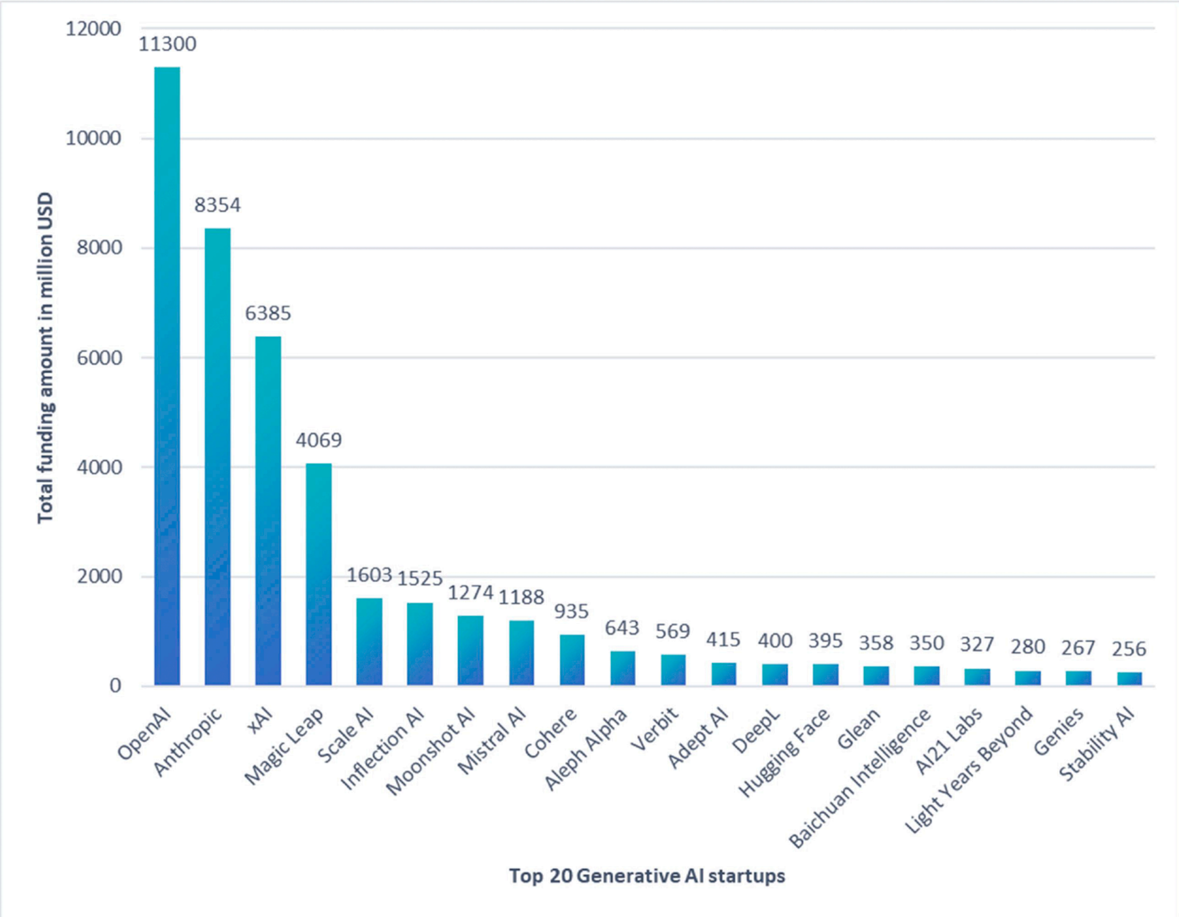

Fig. 3. Top 20 startups and their funding.

Table 2
Outcomes of PCA.

Variables	INVESTOR	TECH	
	Factor loading	Factor loading	Component Score
Last funding type (LFT)	0.523		0.211
Number of funding rounds (NFR)	0.837		0.337
Number of investors (NOI)	0.860		0.346
Number of lead investors (NOLI)	0.876		0.353
Total IT spending (ITspend)		0.721	0.536
Active available technology (AAT)		0.708	0.526
Number of applications (NAPPS)		0.570	0.424
Eigenvalues	2.481	1.346	–
KMO values	0.763	0.562	–
Bartlett's Test of Sphericity (Chi-Square)	782.657	49.493	–
Bartlett's Test of Sphericity (sig)	0.000	0.000	–

Notes: Extraction Method: Principal Component Analysis; Rotation Method: Varimax with Kaiser Normalization.

3.2. Benchmark regression

According to the empirical findings shown in Table 5, investor influence significantly impacts the total funding received by GAI startups across all models, indicating that investor networks likely facilitate access to resources, enhance credibility, and attract additional funding. They also provide mentorship and strategic guidance, helping startups scale effectively. This is evidenced by the highly significant positive coefficients for the INVESTOR variable in Models M2 and M3 ($p < 0.01$). Conversely, the non-significance of technological influence, represented by the TECH variable, may be due to market saturation or the perception that certain GAI technologies are not yet commercially viable. Additionally, the rapid pace of AI advancements could create uncertainty about long-

Table 3
Descriptive statistics.

Variable	Mean	Std. dev.	Min	Max
TFA	6.392	1.065	3.079	10.053
TECH	−2.46e-06	1.000	−1.060	4.268
INVESTOR	−3.57e-08	1.000	−1.435	6.501
AGE	3.488	2.847	0.000	14.000
NOE	1.917	1.122	1.000	8.000
NOF	1.904	1.345	0.000	11.000
FD	1.584	0.605	0.000	2.788
RANK	4.408	0.674	0.000	5.567

Table 4
Pairwise correlations.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) TFA	1							
(2) TECH	0.371***	1						
(3) INVESTOR	0.723***	0.423***	1					
(4) AGE	0.388***	0.553***	0.475***	1				
(5) NOE	0.593***	0.402***	0.600***	0.511***	1			
(6) NOF	0.303***	0.268***	0.328***	0.236***	0.243***	1		
(7) FD	0.168***	0.237***	0.199***	0.292***	0.283***	0.168***	1	
(8) RANK	−0.713***	−0.235***	−0.553***	−0.141**	−0.400***	−0.279***	−0.058	1

Note: Significant ** $p < 0.05$, *** $p < 0.01$.

Table 5
Benchmark regression.

	(M1)	(M2)	(M3)
	TFA (GAI)	TFA (GAI)	TFA (GAI)
INVESTOR		0.3446***	0.3415***
		(9.54)	(9.40)
TECH	0.0550		0.0260
	(1.67)		(0.84)
AGE	0.0549***	0.0336***	0.0298**
	(4.46)	(3.11)	(2.53)
NOE	0.2423***	0.1541***	0.1529***
	(7.95)	(5.17)	(5.12)
NOF	0.0370*	0.0167	0.0149
	(1.74)	(0.84)	(0.75)
FD	0.0145	0.0161	0.0138
	(0.31)	(0.37)	(0.32)
RANK	−0.8945***	−0.7121***	−0.7097***
	(−20.05)	(−15.56)	(−15.47)
Constant	9.5733***	9.0497***	9.0618***
	(41.26)	(40.81)	(40.77)
N	556	556	556
R^2	0.656	0.703	0.703
Adj. R^2	0.652	0.700	0.700

Notes*:* t statistics in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

term value, affecting funding decisions. Furthermore, the AGE and NOE variables consistently show positive and significant effects on total funding, while the RANK variable has a significant negative impact.

3.3. Heterogeneity analysis

In this section, we analyze the heterogeneity in the impact of investor and technological influence on funding received by GAI startups across different regions, as detailed in Table 6. The results show that investor influence remains consistently significant and positive across all models, including the top 5 countries, other countries, OECD and non-OECD countries, and regions such as Asia, Europe, and Latin & North America. This suggests that regions with stronger investor influence, like the United States and the United Kingdom, benefit from well-developed venture capital ecosystems and supportive regulatory frameworks, which encourage more investor engagement in high-tech sectors. Conversely, in regions such as Asia and Latin America, investor influence is still strong but may be shaped by emerging markets' growing focus on innovation and policies aimed at attracting foreign investment. In contrast,

Table 6
Heterogeneity analysis.

	(M1)	(M2)	(M3)	(M4)	(M5)	(M6)	(M7)
	Top 5 countries	Others	OECD	Non-OECD	Asia	Europe	Latin & north America
INVESTOR	0.3611***	0.2714***	0.3154***	0.3953**	0.5239***	0.2226***	0.3297***
	(9.02)	(3.32)	(8.67)	(2.56)	(4.00)	(2.92)	(7.68)
TECH	0.0144	0.0208	0.0104	−0.1083	−0.1570	−0.0189	0.0193
	(0.40)	(0.33)	(0.34)	(−0.74)	(−1.18)	(−0.35)	(0.50)
AGE	0.0289**	0.0367	0.0336***	0.0113	0.0208	0.0715***	0.0243*
	(2.16)	(1.52)	(2.89)	(0.23)	(0.47)	(3.37)	(1.67)
NOE	0.1092***	0.3611***	0.1560***	0.3098***	0.2119**	0.2514***	0.1328***
	(3.38)	(4.66)	(5.09)	(2.92)	(2.12)	(3.93)	(3.75)
NOF	0.0063	0.0303	0.0102	−0.0505	0.0533	−0.0310	0.0202
	(0.27)	(0.81)	(0.51)	(−0.66)	(0.63)	(−0.99)	(0.78)
FD	0.0529	−0.0551	0.0480	−0.0651	−0.2276	0.0293	0.0878
	(1.02)	(−0.69)	(1.07)	(−0.47)	(−1.58)	(0.40)	(1.57)
RANK	−0.7543***	−0.6007***	−0.7492***	−0.4785***	−0.4629***	−0.8187***	−0.7389***
	(−13.80)	(−7.08)	(−15.59)	(−3.56)	(−3.64)	(−8.65)	(−12.40)
Constant	9.3324***	8.1664***	9.2103***	7.6351***	7.9776***	9.2122***	9.1905***
	(35.11)	(19.56)	(39.72)	(10.99)	(12.64)	(20.33)	(31.38)
N	408	148	486	70	77	129	340
R^2	0.723	0.649	0.733	0.528	0.588	0.771	0.721
Adj. R^2	0.718	0.631	0.729	0.475	0.546	0.758	0.715

Notes*:* t statistics in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

technological influence is not significant in any region, which may reflect the global uniformity in access to technology, where differences in funding success are more likely attributed to variations in investor networks.

3.4. Robustness analysis

We enhance the robustness of our findings through MMQR, which reveals that investor influence consistently drives funding success across all quantiles (Q25, Q50, Q75, Q90), with significant coefficients ranging from 0.3083 to 0.4099. This indicates that investor support is crucial for securing funding at various stages, whether in early or later funding rounds. This insight suggests that investors should maintain strong engagement with startups throughout their growth trajectory, as their influence remains critical regardless of funding level. In contrast, technological influence (TECH) remains insignificant across quantiles, implying that technological advancements alone do not attract higher funding. These findings provide strategic implications for investors, who should prioritize building and leveraging networks to support GAI startups, particularly in competitive markets (Table. 7, Fig. 4).

4. Conclusion

We find that investor influence significantly affects the total funding received by GAI startups, while technological influence remains insignificant in the short term. This result, robust across models and quantiles, underscores the vital role of investor networks in driving funding success. For entrepreneurs, building strong investor relationships is crucial for scaling and sustainability. Policymakers

Table 7
Outcomes of MMQR regression.

Variables			Quantile (percentiles)			
	Location	Scale	Q25	Q50	Q75	Q90
INVESTOR	0.3415***	0.0442	0.3083***	0.3450***	0.3776***	0.4099***
	(8.20)	(1.61)	(6.17)	(8.35)	(8.72)	(7.67)
TECH	0.0260	−0.0191	0.0404	0.0245	0.0104	−0.0035
	(0.86)	(−0.95)	(1.11)	(0.81)	(0.33)	(−0.09)
AGE	0.0298**	−0.0024	0.0316**	0.0296**	0.0278**	0.0261*
	(2.54)	(−0.31)	(2.25)	(2.55)	(2.29)	(1.74)
NOE	0.1529***	0.0155	0.1413***	0.1541***	0.1656***	0.1769***
	(4.80)	(0.74)	(3.70)	(4.88)	(5.00)	(4.33)
NOF	0.0149	−0.0078	0.0208	0.0143	0.0086	0.0029
	(0.75)	(−0.59)	(0.87)	(0.73)	(0.42)	(0.11)
FD	0.0138	−0.0189	0.0280	0.0123	−0.0016	−0.0155
	(0.32)	(−0.66)	(0.54)	(0.29)	(−0.04)	(−0.28)
RANK	−0.7097***	−0.0072	−0.7043***	−0.7102***	−0.7155***	−0.7208***
	(−14.45)	(−0.22)	(−11.95)	(−14.59)	(−14.02)	(−11.45)
Constant	9.0618***	0.4893***	8.6938***	9.1005***	9.4615***	9.8196***
	(38.37)	(3.14)	(30.70)	(38.83)	(38.47)	(32.33)

Notes*:*t statistics in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

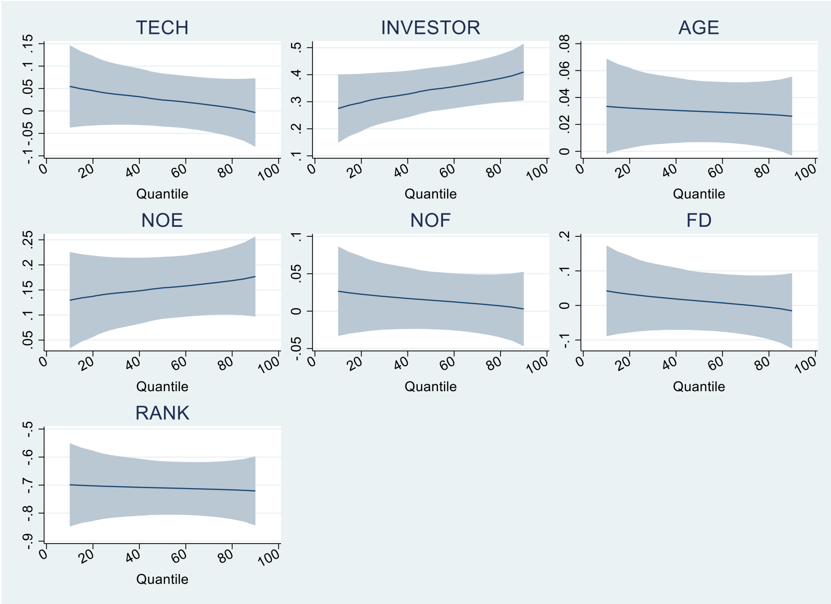

Fig. 4. Graphical outcomes of quantile regression.

should create supportive environments, such as innovation hubs, to strengthen investor-startup connections. Investors should focus on ethical considerations, ensuring their influence supports responsible AI development. Long-term, investor backing could enhance sustainability, while technological advancements may impact scalability as startups mature. Future research should explore the role of government funding and public-private partnerships, which could mitigate funding risks and address ethical concerns. Additionally, further studies are needed to examine how investor influence shapes ethical decision-making in GAI startups, offering a more holistic view of the industry. Moreover, we recommend exploring how different types of investors, such as venture capitalists, angel investors, and corporate investors, influence the funding outcomes and long-term success of GAI startups, providing a more nuanced understanding of investor dynamics.

CRediT authorship contribution statement

Abu Bakkar Siddik: Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Yong Li:** Software, Resources, Project administration, Methodology, Investigation, Conceptualization. **Anna Min Du:** Writing – review & editing, Visualization, Validation, Supervision, Resources, Project administration, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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