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Fueling financial development: The crucial role of generative AI financing across nations

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A B S T R A C T

This study examines the impact of Generative AI (GAI) financing on financial development (FD) across 21 countries using cross-sectional data from 2020 to 2022. Employing both simple linear regression and two-stage least squares (2SLS) to address endogeneity, we find that GAI financing significantly contributes to financial development, with stronger effects observed in Asian and non-European regions. Regional heterogeneity is evident, highlighting varying impacts across different subcontinents. Policy implications suggest promoting GAI ecosystems, attracting foreign investment, and enhancing publicity for GAI startups. The study highlights the need for future research on the ethical implications and dynamic effects of GAI financing.

1. Introduction

The rise of Generative Artificial Intelligence (GAI) has revolutionized various industries (Dowling and Lucey, 2023; Dwivedi et al., 2023; Siddik et al., 2024), transforming the way businesses operate and impacting broader economic systems. As a subset of AI, GAI uses machine learning models to generate content, including text, images, and videos, mimicking human creativity and intelligence (Chakraborty et al., 2024; Dwivedi et al., 2023; Hermann and Puntoni, 2024). In recent years, GAI financing, the funding allocated to GAI startups and projects, has rapidly expanded as investors recognize the disruptive potential of these technologies. During a rapid emergence, GAI startups have attracted huge funding from investors, with over $25B in funding[1] in 2023 alone. However, the link between GAI financing and financial development (FD), particularly at a macroeconomic level, remains underexplored. This study seeks to bridge this gap by analyzing how GAI financing influences financial development across different countries and regions.

Financial development refers to the growth and maturity of financial institutions and markets, characterized by improved access, efficiency, and depth (Asteriou and Spanos, 2019; Meniago and Asongu, 2018; Nasreen et al., 2020). The literature on financial development typically focuses on traditional sectors, including banking, microfinance, and equity markets (Ashraf, 2018; Banna et al., 2022; Mhadhbi et al., 2021; Wu and Bowe, 2010). However, the advent of disruptive technologies like GAI is reshaping the financial landscape (Ardekani et al., 2024; Dowling and Lucey, 2023; Dwivedi et al., 2023), necessitating a closer examination of how such

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[1] Retrieved from https://dealroom.co/guides/generative-ai

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innovations drive financial growth. GAI has the potential to revolutionize financial services, improve decision-making processes, and enhance market efficiency. Yet, despite its growing prominence, research on the relationship between GAI financing and financial development remains limited.

In the rapidly evolving finance sector, digital technologies are reshaping traditional models and driving impactful innovation. From mobile banking and digital wallets to fintech and robo-advisors, digital finance has transformed consumer behavior and redefined financial systems globally (Cong et al., 2024). A growing body of research emphasizes AI's transformative potential: Ardekani et al. (2024) introduced FinSentGPT, a sentiment analysis model surpassing traditional methods, while Pan et al. (2024) demonstrated AI's role in strengthening regulatory oversight. Daníelsson et al. (2022) also highlight AI's potential risks, such as amplifying systemic vulnerabilities despite its efficiencies. (Siddik et al., 2024) found that investor influence significantly enhances funding for GAI startups, while technological influence is limited, underscoring the importance of investor networks in supporting GAI expansion. Although these studies illustrate AI's broad impact, they do not specifically address GAI financing's role in advancing financial development.

Despite extensive research on AI's impact on financial systems (Ardekani et al., 2024; Pan et al., 2024; Sachan et al., 2024), a gap remains in understanding how GAI financing contributes to macro-level financial development. Most studies focus on AI's technical applications, but few examine how the funding of GAI startups affects broader financial growth, particularly in developing regions. As GAI technologies become increasingly integrated into financial services (Almeida and Gonçalves, 2024; Dowling and Lucey, 2023; Dwivedi et al., 2023), it is essential to assess their economic impact, especially regarding financial system growth and maturity. To address this gap, our study investigates the impact of GAI financing on financial development using cross-sectional data from 2020 to 2022. It explores three key questions: (1) How does GAI financing influence financial development across countries? (2) What role does publicity exposure play in securing GAI financing? (3) Are there significant regional differences in GAI financing's impact on financial development? This study aims to provide a comprehensive understanding of GAI financing's effects on financial development at both country and regional levels.

The novelty of this study lies in its focus on GAI financing as a driver of financial development, a relationship largely overlooked in the literature. While previous studies have examined AI's role in financial systems, they have not addressed GAI financing's macro-economic implications. By analyzing cross-sectional data across multiple countries, this study offers a unique view on how GAI startups contribute to financial development. Additionally, introducing publicity exposure as an instrumental variable provides insights into how media visibility affects investor confidence and funding. The study also explores regional heterogeneity, offering valuable insights for policymakers to promote financial growth across different subcontinents.

2. Materials and methods

2.1. Data and variables

We examine the impact of GAI financing on the financial development of 21 selected countries using a cross-sectional dataset. Our measure of GAI financing is based on the total funding (in USD million) received by GAI startups established between 2010 and 2022, with data sourced from Crunchbase, a comprehensive platform providing information on startups, investments, and funding activities (Lee and Geum, 2023; Uddin et al., 2024; Żbikowski and Antosiuk, 2021). We selected countries that had at least two GAI startups with recorded funding, resulting in a final sample of 384 startups across 21 countries.

To assess GAI financing's influence on financial development, we collected financial development index data from the International Monetary Fund (IMF) for the years 2020, 2021, and 2022. Although our analysis focuses on these three years, reflecting the most recent and reliable data available, we acknowledge that this limited time frame may restrict insights into longer-term dynamic effects. However, our choice of a cross-sectional approach, with data from 2020 to 2022, allows for a focused analysis of short-term impacts in a rapidly evolving technological context. Additionally, we incorporated control variables at both company and country levels, detailed in Table 1, to ensure the robustness of our findings. To further address potential endogeneity concerns, we employed Publicity

Table 1
Variable descriptions.

Variable Type	Variable Name	Symbol	Description	Source
Dependent Variable	Financial Development	FD	A composite index measuring the development of financial institutions and markets, based on depth, access, and efficiency, for the years 2020, 2021, and 2022.	IMF
Independent Variable	Generative AI Financing	GAIF	The natural logarithm of total funding (in million USD) received by individual Generative AI startups.	Crunchbase
Control Variables	Number of Employees	NOE	A categorical variable representing the range of employees in GAI startups (e.g., 1–10, 11–50, 51–100).	Crunchbase
	Startup Age	AGE	The number of years since the GAI startup was founded.	Crunchbase
	Startup IT Spending	ITspend	The natural logarithm of total annual IT spending by the startup (in USD).	Crunchbase
	Foreign Direct Investment	FDI	Net inflows of foreign direct investment as a percentage of GDP for the years 2020, 2021, and 2022.	WDI
	National Income	NI	The natural logarithm of adjusted net national income (current USD) for the years 2020, 2021, and 2022.	WDI
Instrumental variable	Publicity Exposure	PE	The natural logarithm of total media coverage, including press mentions, articles, and news features.	Crunchbase

Exposure as an instrumental variable.

The status and trends of GAI startups across 21 countries reveal significant variation in both the number of startups and the funding they have received, as shown in Fig. 1. The United States dominates the landscape, with 229 startups securing over $34.9 billion in funding, far surpassing any other country. The United Kingdom follows, with 31 startups receiving $642.75 million. Other countries such as Germany and Canada also stand out, with 17 and 16 startups receiving $1.27 billion and $1.07 billion, respectively. In contrast, smaller markets like Argentina, Estonia, and South Korea have fewer startups, typically receiving less than $10 million in funding. Countries like Australia, Brazil, Israel, and France have moderate numbers of startups, each securing between $67 million and $487 million. The data indicates that while the U.S. is the clear leader, European and Asian countries are also seeing meaningful developments in GAI funding, albeit on a smaller scale. This diverse distribution highlights the growing global interest in GAI, though investment is highly concentrated in a few key markets.

2.2. Econometric models

To examine the impacts of GAI financing on financial development, we utilize simple linear regression models for the years 2020, 2021, and 2022. The models for each year are specified separately, as shown in the following equations:

For the year 2020:

$$FD_c=\beta_0+\beta_1 GAIF_c+\beta_2 NOE_c+\beta_3 Age_c+\beta_4 ITspend_c+\beta_5 FDI_c+\beta_6 NI_c+\epsilon_c \quad \text{(M1)}$$

For the year 2021:

$$FD_c=\beta_0+\beta_1 GAIF_c+\beta_2 NOE_c+\beta_3 Age_c+\beta_4 ITspend_c+\beta_5 FDI_c+\beta_6 NI_c+\epsilon_c \quad \text{(M2)}$$

For the year 2022:

$$FD_c=\beta_0+\beta_1 GAIF_c+\beta_2 NOE_c+\beta_3 Age_c+\beta_4 ITspend_c+\beta_5 FDI_c+\beta_6 NI_c+\epsilon_c \quad \text{(M3)}$$

Where:

FD_c represents financial development for country $_c$ for the years (2020, 2021, and 2022). $GAIF_c$ is the total funding received by GAI

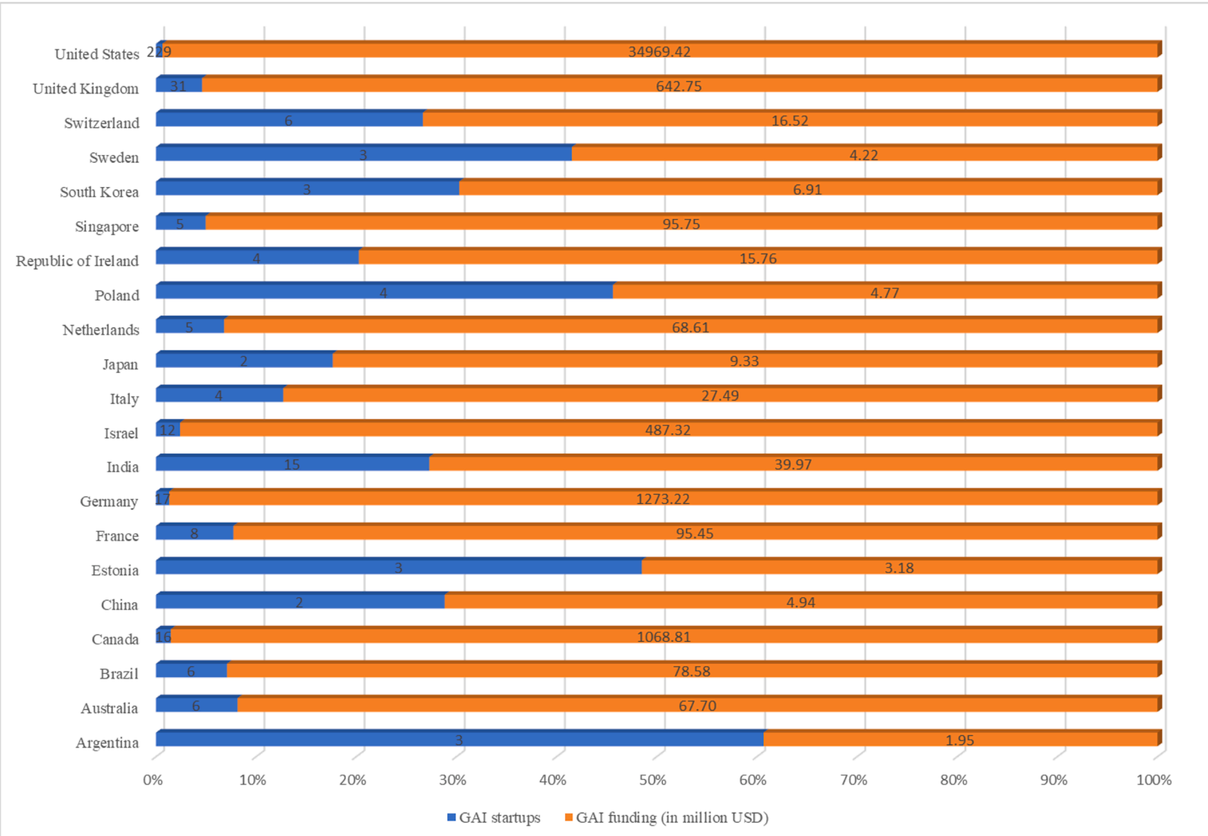

Fig. 1. The status of GAI startups with their respective funding in the sample countries.

startups in country $_c$. β_2 to β_6 are control variables for country $_c$. ϵ_c is the error term for country $_c$ for the years (2020, 2021, and 2022).

To overcome potential endogeneity issues and enhance the robustness of our base model, we introduce the two-stage least squares (2SLS) method. This approach helps mitigate any bias that may arise from endogeneity in the relationship between GAI financing and financial development. By using 2SLS, we address potential reverse causality or omitted variable bias that could affect the accuracy of the estimated coefficients. Moreover, we conduct a heterogeneity analysis based on subcontinent-wise divisions. This allows us to examine whether the impacts of GAI financing on financial development vary across different regions. The subcontinent-wise analysis helps identify whether regional factors, such as economic conditions or institutional differences, lead to variations in the effects of GAI financing on financial development. This analysis is crucial to understanding the broader applicability of our findings across diverse geographic contexts.

3. Results and discussion

3.1. Descriptive statistics

The descriptive statistics provide insights into the variables used in the analysis across the years 2020, 2021, and 2022, as shown in Table 2. Financial development shows relatively stable means across the three years, with slight variation in standard deviation. GAIF has a mean of 6.59 (logarithmic form), with a considerable range from 3.65 to 10.05. Control variables such as NOE, startup age, and IT spending show moderate variation across observations.

The correlation matrices indicate the relationships between the variables, as shown in Table A1(a-c in Appendix). For all years, GAIF has a positive and significant correlation with FD (around 0.22), suggesting a moderate association. IT spending also shows a positive correlation with FD, while FDI exhibits a strong negative relationship with FD, particularly in 2020 and 2022. NI consistently shows a strong positive correlation with FD, reinforcing its importance as a control variable. Additionally, the correlation between GAIF and NOE (0.639), indicating that as the financing increases, the number of employees tends to increase as well. Similarly, GAIF and IT spending are positively correlated (around 0.202), meaning that startups with higher financing also tend to spend more on IT infrastructure.

3.2. Benchmark regression

The benchmark regression results (Table 3) show that GAIF consistently has a positive and significant impact on FD across all three years (2020, 2021, and 2022). The coefficients for GAIF range between 0.018 and 0.031, indicating that higher GAI financing contributes to increased financial development. This suggests that GAI startups play a crucial role in enhancing the financial development of the countries in the sample. The models also show that NOE has a negative and significant effect on FD, implying that larger GAI startups (in terms of employees) may not necessarily boost financial development. On the other hand, AGE and IT spending show no significant influence on financial development.

The control variables FDI and NI have significant effects on financial development. FDI consistently shows a negative and significant relationship with FD, while national income has a strong positive impact across all years, highlighting the role of broader economic factors in shaping financial development. The high R-squared values (0.594–0.620) across the models indicate that the independent variables explain a substantial portion of the variation in financial development. These findings underscore the importance of both GAI financing and macroeconomic variables in determining financial development, while also pointing to potential areas for further investigation, such as the role of IT spending and firm characteristics.

3.3. Robustness analysis

The outcomes of the 2SLS approach presented in Table 4 indicate the robustness of the relationship between GAIF and FD while addressing potential endogeneity. In the first stage, Publicity Exposure (PE) is used as an instrumental variable for GAIF, showing a

Table 2
Descriptive statistics.

Variable	Observation	Mean	Std. Dev.	Min	Max
FD_{2020}	384	0.839	0.132	0.280	0.950
FD_{2021}	384	0.840	0.136	0.252	0.939
FD_{2022}	384	0.841	0.141	0.225	0.929
GAIF	384	6.590	1.033	3.653	10.053
NOE	383	2.117	1.234	1.000	8.000
AGE	384	4.521	2.744	1.000	14.000
Itspend	384	2.321	2.767	0.000	7.109
FDI_{2020}	384	0.197	0.976	−1.219	3.140
FDI_{2021}	384	0.629	0.972	−2.634	3.454
FDI_{2022}	384	0.586	0.859	−4.048	3.884
NI_{2020}	384	29.438	1.464	23.960	30.514
NI_{2021}	384	29.543	1.443	24.121	30.606
NI_{2022}	384	29.637	1.427	24.260	30.691

Table 3
Benchmark regression.

Models	(M1)	(M2)	(M3)	(M4)	(M5)	(M6)
Variables	FD_{2020}	FD_{2020}	FD_{2021}	FD_{2021}	FD_{2022}	FD_{2022}
GAIF	0.028***	0.018***	0.029***	0.023***	0.031***	0.023***
	(4.331)	(3.308)	(4.444)	(4.150)	(4.538)	(4.007)
NOE		−0.016***		−0.019***		−0.019***
		(−3.311)		(−3.800)		(−3.726)
AGE		−0.001		−0.000		−0.000
		(−0.333)		(−0.190)		(−0.034)
Itspend		0.003		0.002		0.002
		(1.526)		(1.318)		(1.147)
FDI_{2020}		−0.031***				
		(−4.587)				
NI_{2020}		0.050***				
		(10.794)				
FDI_{2021}				−0.025***		
				(−5.481)		
NI_{2021}				0.067***		
				(20.923)		
FDI_{2022}						−0.022***
						(−3.967)
NI_{2022}						0.068***
						(18.870)
Constant	0.657***	−0.702***	0.647***	−1.235***	0.637***	−1.265***
	(15.455)	(−5.139)	(14.753)	(−13.211)	(14.057)	(−11.995)
N	384	384	384	384	384	384
R^2	0.047	0.600	0.049	0.620	0.051	0.614
adj. R^2	0.044	0.594	0.047	0.613	0.049	0.608

Note: Significant at* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

strong and significant positive effect on GAIF across all models, with coefficients around 0.80. This demonstrates that PU is a strong instrument for predicting GAI financing. In the second stage, GAIF continues to have a positive and significant impact on FD in all three years (2020, 2021, and 2022). The coefficients range from 0.029 to 0.034, confirming that higher GAI financing positively influences financial development, even after accounting for endogeneity. The under-identification test (Kleibergen-Paap) shows that the models are well-identified, and the weak identification test confirms the strength of the instrument. Additionally, the Hansen J statistic for overidentification does not reject the null hypothesis, indicating that the instruments are valid. Thus, the 2SLS results reinforce the findings from the benchmark model, showing that GAI financing significantly enhances financial development, and the instrumental variable approach effectively addresses potential bias.

3.4. Heterogeneity analysis

The heterogeneity analysis examines the varying impacts of GAIF on FD across different subcontinental regions, as outlined in Table 5. In Panel A (Asian vs. non-Asian countries), GAIF has a significant and positive impact on FD in Asian countries across all years, with coefficients ranging from 0.043 to 0.056. However, in non-Asian countries, GAIF's impact is much weaker, with coefficients close to zero and statistical significance only in 2021 (0.008, $p < 0.1$). This suggests that GAI financing plays a more critical role in driving financial development in Asian countries compared to non-Asian regions.

Panel B (European vs. non-European countries) shows a similar divergence. In non-European countries, GAIF has a positive and

Table 4
The estimation using an IV approach is conducted through a 2SLS method.

Models	(M1)	(M2)	(M3)	(M4)	(M5)	(M6)
Variables	GAIF	FD_{2020}	GAIF	FD_{2021}	GAIF	FD_{2022}
PE	0.796***		0.802***		0.799***	
	(13.560)		(13.770)		(13.680)	
GAIF		0.029**		0.031**		0.034***
		(2.690)		(2.920)		(3.350)
Constant	3.417***	−0.738**	2.597***	−1.251***	2.228***	−1.284***
	(3.320)	(−2.670)	(3.730)	(−9.240)	(2.940)	(−12.110)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
N	384	384	384	384	384	384
Under identification test		56.052***		57.043***		56.639***
Weak identification test		183.901		189.503		187.238
Hansen J statistic		0.000		0.000		0.000

Note: Significant at* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5
Heterogeneity analysis subcontinent wise.

Panel A: Asian and non-Asian countries.						
Models	Asian	Non-Asian	Asian	Non-Asian	Asian	Non-Asian
Variables	FD_{2020}	FD_{2020}	FD_{2021}	FD_{2021}	FD_{2022}	FD_{2022}
GAIF	0.056**	0.005	0.052**	0.008*	0.043*	0.008
	(2.379)	(1.068)	(2.181)	(1.695)	(1.959)	(1.531)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Constant	1.072	−0.610***	0.543	−1.154***	0.396	−1.123***
	(1.393)	(−4.972)	(0.651)	(−13.789)	(0.423)	(−12.247)
N	40	343	40	343	40	343
R^2	0.338	0.600	0.226	0.665	0.249	0.667
adj. R^2	0.218	0.593	0.085	0.659	0.112	0.661
Panel B: European (EURO) and non-European (NEURO) countries.						
Models	EURO	NEURO	EURO	NEURO	EURO	NEURO
Variables	FD_{2020}	FD_{2020}	FD_{2021}	FD_{2021}	FD_{2022}	FD_{2022}
GAIF	0.012	0.020***	0.029*	0.016***	0.028	0.015***
	(0.710)	(3.644)	(1.886)	(2.913)	(1.565)	(2.732)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−1.407***	−0.497**	−0.696**	−1.719***	−1.675***	−2.480***
	(−5.041)	(−2.154)	(−2.327)	(−13.504)	(−5.367)	(−13.873)
N	85	298	85	298	85	298
R^2	0.563	0.607	0.664	0.642	0.593	0.667
adj. R^2	0.529	0.599	0.638	0.635	0.561	0.660
Panel C: Latin & north America (L&NA) and others.						
Models	L&NA	Others	L&NA	Others	L&NA	Others
Variables	FD_{2020}	FD_{2020}	FD_{2021}	FD_{2021}	FD_{2022}	FD_{2022}
GAIF	0.002	0.061***	0.001	0.064***	0.001	0.070***
	(0.500)	(4.197)	(0.402)	(4.839)	(0.340)	(4.572)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−3.990***	−0.959***	−2.801***	−0.076	−1.466***	−0.920***
	(−14.387)	(−3.137)	(−43.830)	(−0.233)	(−4.192)	(−2.685)
N	253	130	253	130	253	130
R2	0.704	0.378	0.934	0.495	0.581	0.348
adj. R2	0.697	0.348	0.932	0.470	0.571	0.316

Note: Significant at* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

significant effect on FD in all three years, with coefficients ranging from 0.015 to 0.020. In contrast, the impact of GAIF in European countries is less significant, showing moderate effects only in 2021 (0.029, $p < 0.1$). In Panel C (Latin & North America vs. other countries), GAIF has a consistently strong and significant impact on FD in "Other" regions, with coefficients around 0.061 to 0.070 across all years. In Latin & North America, however, GAIF shows no significant effect on FD. Overall, the heterogeneity analysis highlights regional differences, with GAIF showing a stronger impact on financial development in Asian and non-European countries compared to other regions.

4. Conclusion

Our study underscores the significant role of GAIF in advancing financial development across 2020, 2021, and 2022, with robust evidence from 2SLS analysis affirming GAIF's positive impact on FD. Notably, we observe substantial regional heterogeneity, as GAIF exerts a stronger influence on FD in Asian and non-European countries compared to Europe and the Americas. This regional disparity suggests that GAIF is more effective in enhancing financial systems in some areas, while other factors may drive FD in others. These findings have multifaceted policy implications. Policymakers, banks, financial institutions, and financial regulators should collaborate to create conducive environments for GAI startups to enhance financial development. In Asian and developing regions, regulatory bodies should foster favorable conditions by providing financial incentives, enhancing infrastructure, and establishing supportive regulatory frameworks. Additionally, financial institutions and banks should actively invest in and collaborate with GAI startups to drive innovation in financial services. For European, Latin American, and North American markets, financial regulators should focus on integrating GAI into existing financial frameworks, encouraging partnerships between GAI firms and traditional financial entities. This approach could help overcome limitations in these regions where GAIF has less impact. Furthermore, banks and financial institutions in these areas can play a pivotal role by offering targeted financial products and services that align with GAI-driven innovations. Finally, financial regulators across all regions should address ethical concerns—such as biases in AI-driven decision-making, privacy risks, and potential job displacement—by developing frameworks that promote fairness and transparency. Public campaigns and initiatives to promote GAI can also increase visibility and attract investors, helping drive sustainable financial development across diverse contexts. Limitations of this study and recommendations for future research are outlined in Table A2 (see appendix).

CRediT authorship contribution statement

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

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.

Appendix

Table A1(a)
Pairwise correlation (for the year 2020).

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) FD_{2020}	1.000						
(2) GAIF	0.216***	1.000					
(3) NOE	0.026	0.639***	1.000				
(4) AGE	−0.031	0.346***	0.472***	1.000			
(5) Itspend	0.200***	0.202***	0.181***	0.316***	1.000		
(6) FDI_{2020}	−0.665***	−0.182***	−0.072	0.003	−0.146**	1.000	
(7) NI_{2020}	0.747***	0.219***	0.116**	−0.025	0.210***	−0.753***	1.000

Note: Significant at* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A1(b)
Pairwise correlation (for the year 2021).

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) FD_{2021}	1.000						
(2) GAIF	0.222***	1.000					
(3) NOE	0.031	0.639***	1.000				
(4) AGE	−0.027	0.346***	0.472***	1.000			
(5) Itspend	0.201***	0.202***	0.181***	0.316***	1.000		
(6) FDI_{2021}	−0.244***	0.053	0.011	−0.007	−0.024	1.000	
(7) NI_{2021}	0.754***	0.219***	0.117**	−0.025	0.209***	−0.106**	1.000

Note: Significant at* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A1(c)
Pairwise correlation (for the year 2022).

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) FD_{2022}	1.000						
(2) GAIF	0.226***	1.000					
(3) NOE	0.035	0.639***	1.000				
(4) AGE	−0.023	0.346***	0.472***	1.000			
(5) Itspend	0.201***	0.202***	0.181***	0.316***	1.000		
(6) FDI_{2022}	−0.391***	−0.023	−0.031	−0.007	−0.102**	1.000	
(7) NI_{2022}	0.760***	0.219***	0.118**	−0.024	0.208***	−0.367***	1.000

Note: Significant at* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A(2)
Study limitations and directions for future studies.

Study Limitations	Recommendations for Future Studies
Our analysis is based on cross-sectional data, which limits the ability to infer causality and observe dynamic changes over time.	Future research should employ longitudinal data to capture the dynamic effects of GAI financing on financial development over time.
The study reveals significant regional heterogeneity in the impact of GAI financing but does not deeply explore the underlying causes.	Future studies should conduct in-depth regional analyses to better understand the institutional, cultural, and economic factors contributing to heterogeneity.
While the 2SLS approach addresses endogeneity, it is limited by the availability and strength of instrumental variables.	Future research could explore alternative instrumental variables or advanced econometric techniques to further mitigate endogeneity concerns.
The study includes key control variables like FDI and national income but omits other influential factors.	Future studies should incorporate governance quality, innovation policies, regulatory environments, and country-level technological infrastructure, such as broadband and cloud computing adoption, to provide a more comprehensive analysis of GAI startups' impact on financial development.

(*continued on next page*)

Table A(2) (*continued*)

Study Limitations	Recommendations for Future Studies
The study focuses exclusively on GAI financing, potentially overlooking other forms of financing that might influence financial development.	Future research could examine the role of other financing sources, such as venture capital or government funding, in fostering financial development.
The study is limited to a specific set of countries and may not generalize to others with different economic structures.	Future studies should expand the geographical scope to include a broader set of countries, including smaller or emerging economies.

Data availability

Data will be made available on request.

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