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The role of fintech in U.S. entrepreneurship: How AI is shaping the future of financial services

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Abstract

This study explores the transformative role of financial technology (FinTech) and artificial intelligence (AI) in driving entrepreneurship and reshaping financial services in the United States. Using data spanning from 2010 to 2022, the research evaluates the interplay between AI investment, financial inclusion, governmental programs, and societal perceptions to determine their impact on entrepreneurial activity. By employing regression analysis and diagnostic tests, the study provides a nuanced understanding of these relationships.

The findings reveal that AI-related variables, particularly AI investment and technology usage, significantly enhance entrepreneurial activity by fostering innovation, improving decision-making, and optimizing business operations. Conversely, traditional financial metrics, such as credit availability and account ownership, show limited or negative impacts, highlighting inefficiencies in their allocation or accessibility. Surprisingly, governmental programs and societal perceptions of high entrepreneurial status exhibit negative associations with entrepreneurship, suggesting that exclusivity and inefficient interventions may deter broader participation in entrepreneurial ventures.

These insights underscore the importance of rethinking financial strategies and policies to align with technological advancements. The study emphasizes the need for accessible AI-driven solutions, improved financial accessibility, and inclusive policies to foster a more equitable entrepreneurial ecosystem. By challenging conventional perspectives, this research contributes valuable recommendations for stakeholders to harness FinTech and AI for sustainable growth and innovation.

Keywords: FinTech; Artificial Intelligence; Entrepreneurship; Financial Services; AI Investment; Technological Innovation; Financial Inclusion

1. Introduction

The global financial ecosystem is undergoing a seismic shift, driven by the emergence of financial technology (FinTech) and its adoption of artificial intelligence (AI). FinTech represents a blend of financial services and innovative technologies aimed at enhancing efficiency, reducing costs, and improving customer experiences (Javaid, 2024). In the United States, this sector is growing exponentially, leveraging AI to reshape traditional financial practices and create innovative solutions for businesses and consumers alike (Taneja, 2024). This introduction explores the significance of FinTech globally, its role in U.S. entrepreneurship, and the transformative impact of AI, drawing on diverse studies to establish the rationale and gaps addressed by this study.

Globally, FinTech has catalyzed unprecedented innovation, driving accessibility and inclusivity in financial services. Across regions, particularly in Africa and Asia, FinTech is enabling underbanked populations to gain access to financial

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systems through mobile technology and digital payments (Ajayi-Nifise et al., 2024; Zarrouk et al., 2021). In contrast, the United States' FinTech industry has primarily focused on disrupting traditional banking models by offering services like peer-to-peer lending, AI-driven investment platforms, and blockchain-enabled payments (Cornelli et al., 2024; Adhikari & Hamal, 2024). This dichotomy highlights the diverse applications of FinTech across global regions and underscores the U.S.'s unique position as a technological leader.

The role of FinTech in U.S. entrepreneurship is particularly noteworthy. By democratizing access to financial resources, FinTech has empowered small and medium enterprises (SMEs) to secure capital more efficiently, driving innovation and growth (Mills, 2018). AI technologies are further transforming entrepreneurship by providing tools for risk management, predictive analytics, and customer segmentation, enabling startups to operate with precision and agility (Batchu & Settibathini, 2024; Arslan et al., 2022). This interplay between AI and FinTech fosters a fertile environment for entrepreneurial ventures, making the U.S. a hotbed of innovation.

Artificial intelligence is a cornerstone of FinTech's transformative impact, shaping the future of financial services. AI-driven systems enhance decision-making processes, automate repetitive tasks, and improve fraud detection, delivering cost-effective solutions to financial institutions (Omeihe et al., 2024; Adhikari, Hamal, & Jnr, 2024). Moreover, machine learning algorithms enable the personalization of financial products, meeting the evolving needs of consumers and businesses (Koti, 2024). These advancements signal a paradigm shift, where data-driven insights redefine the operations of financial entities globally (Manser Payne et al., 2021).

Despite these advances, significant gaps remain in the literature. While global studies have documented FinTech's impact on financial inclusion and technological adoption, few have comprehensively examined its role in U.S. entrepreneurship in the context of AI (Lekhi, 2024). Additionally, the intersection of FinTech and AI in fostering sustainable business ecosystems is underexplored (Bughin et al., 2017). Addressing these gaps is crucial to understanding how emerging technologies can shape future entrepreneurial landscapes.

This study is therefore essential to provide a nuanced understanding of FinTech's role in U.S. entrepreneurship, particularly in the age of AI. By bridging the existing gaps, it aims to offer actionable insights for policymakers, entrepreneurs, and financial institutions. The findings could serve as a foundation for fostering sustainable innovation in financial services, ensuring that the transformative potential of FinTech is fully realized (Reyazat, 2024).

In essence, this research addresses the critical need to examine how FinTech, bolstered by AI, is redefining the U.S. entrepreneurial ecosystem. By leveraging insights from global and regional studies, it aims to contribute to the broader discourse on technology-driven economic development. This is a timely and important endeavor, given the accelerating pace of technological disruption and the pivotal role of entrepreneurship in driving economic growth

Objectives of the Study

The following are the objectives of the study:

- To Analyze the Role of FinTech in Empowering U.S. Entrepreneurship
- To Investigate the Transformative Impact of Artificial Intelligence on Financial Services

2. Literature Review

2.1. The Role of FinTech in Empowering U.S. Entrepreneurship

The emergence of FinTech has transformed the entrepreneurial landscape by providing innovative financial solutions that empower small and medium enterprises (SMEs) and startups. As Mills (2018) emphasizes, FinTech is bridging the gap between financial institutions and underserved entrepreneurs, offering efficient and accessible financing alternatives through platforms like peer-to-peer lending and crowdfunding. This accessibility has allowed startups to scale their operations without traditional financial constraints, fostering a culture of innovation and economic growth.

Moreover, the integration of artificial intelligence (AI) within FinTech has further enhanced its impact on entrepreneurship. Javaid (2024) highlights that AI-powered financial tools streamline decision-making processes, enabling entrepreneurs to assess risks, predict market trends, and personalize customer interactions. This capability not only increases operational efficiency but also helps businesses adapt to rapidly changing market conditions. Similarly, Taneja (2024) points out that AI's ability to analyze vast datasets in real time offers entrepreneurs insights that were previously unattainable, thereby providing a competitive advantage in their respective industries.

Transitioning to a broader perspective, Adeyeri (2024) discusses the economic implications of AI-driven automation within FinTech, noting that automation reduces costs and minimizes errors in financial transactions. This technological advancement is particularly beneficial for entrepreneurs who rely on streamlined operations to sustain profitability. Additionally, Omeihe et al. (2024) explore the importance of trust in AI systems, arguing that fostering trust is essential for widespread adoption of these technologies among entrepreneurs and their customers. The ability of FinTech to combine trust with technological innovation makes it a powerful enabler of entrepreneurial ventures.

While FinTech's role in empowering entrepreneurship is well-documented, its impact varies across regions and sectors. For example, Zarrouk et al. (2021) analyze the success of FinTech startups in the United Arab Emirates, revealing that access to technological infrastructure and supportive government policies play a crucial role in fostering innovation. In contrast, Ololade (2024) compares FinTech trends in Nigeria and the U.S., showing that while both regions benefit from FinTech, the regulatory landscape and financial literacy significantly influence entrepreneurial outcomes. These studies highlight the contextual factors that shape FinTech's effectiveness in different entrepreneurial ecosystems.

Despite its transformative potential, the relationship between FinTech and entrepreneurship faces challenges, such as regulatory hurdles and data security concerns. Harris (2021) discusses the role of accelerator networks in overcoming these challenges by providing startups with resources and mentorship to navigate the complex FinTech ecosystem. Additionally, Bughin et al. (2017) emphasize the need for a regulatory sandbox to encourage innovation while ensuring compliance with financial regulations. Such measures are critical for sustaining FinTech's growth and its ability to support entrepreneurs.

In essence, FinTech has emerged as a critical driver of entrepreneurship, offering financial accessibility, operational efficiency, and innovative tools to startups and SMEs. The integration of AI within FinTech has amplified its impact, enabling data-driven decision-making and personalized customer experiences. However, regional disparities and regulatory challenges underscore the need for context-specific strategies to maximize FinTech's potential. As Lekhi (2024) aptly notes, the future of entrepreneurship lies at the intersection of technology, innovation, and supportive policy frameworks, making FinTech an indispensable component of modern entrepreneurial ecosystems.

2.2. The Transformative Impact of Artificial Intelligence on Financial Services

Artificial intelligence (AI) has emerged as a game-changer in the financial services sector, driving unprecedented levels of efficiency, innovation, and customer satisfaction. According to Javaid (2024), AI integration within financial services enables smarter and more efficient operations by automating routine tasks, improving decision-making, and enhancing predictive capabilities. This transformation is particularly significant in areas such as fraud detection, credit assessment, and customer service, where AI-driven insights provide tangible value for financial institutions and their clients.

Moreover, the trust and adoption of AI technologies play a critical role in shaping the future of financial services. Omeihe et al. (2024) emphasize that building trust in AI systems is essential for widespread acceptance, especially in sensitive sectors like banking and insurance. They argue that transparent algorithms and ethical AI practices are necessary to address concerns about bias, security, and accountability. This trust factor not only influences customer adoption but also determines the success of AI applications in reshaping traditional financial operations.

In addition to trust, the efficiency gains delivered by AI-driven automation have significantly impacted the financial sector. Adeyeri (2024) discusses the economic implications of AI automation, noting that it reduces operational costs and enhances service delivery. For instance, robo-advisors and chatbots powered by machine learning algorithms have revolutionized customer interactions, providing personalized recommendations and resolving queries in real time. This shift not only reduces labor costs but also improves customer satisfaction and loyalty.

The adoption of AI in financial services extends beyond operational improvements to strategic decision-making. Taneja (2024) highlights how AI tools facilitate better risk management by analyzing vast datasets to identify patterns and anomalies. These capabilities are particularly beneficial in dynamic markets, where quick and accurate decision-making is crucial. For example, AI-powered credit scoring models enable lenders to evaluate creditworthiness with greater precision, thus expanding access to credit for underbanked populations.

Furthermore, the impact of AI on financial innovation cannot be overstated. Lekhi (2024) underscores that AI technologies are at the heart of emerging trends in financial services, such as decentralized finance (DeFi) and blockchain applications. These innovations are reshaping traditional financial models by providing secure, efficient, and transparent alternatives to conventional systems. Similarly, Batchu and Settibathini (2024) argue that sustainable finance initiatives powered by AI and IoT are redefining the boundaries of financial technology, fostering inclusivity and sustainability.

While the benefits of AI in financial services are evident, there are also challenges that need to be addressed. Bughin et al. (2017) point out that regulatory hurdles, data privacy concerns, and ethical dilemmas pose significant barriers to the widespread adoption of AI. These challenges necessitate a collaborative approach involving policymakers, financial institutions, and technology providers to create a conducive environment for AI-driven innovation. Reyazat (2024) adds that regulatory frameworks must evolve to accommodate the unique characteristics of AI technologies, ensuring that innovation is not stifled while maintaining consumer protection.

The transformative impact of AI on financial services is also evident in its influence on customer experiences. Koti (2024) highlights that AI-powered systems enhance customer engagement by delivering tailored financial products and services. For instance, AI algorithms analyze customer behavior to recommend personalized investment strategies, fostering deeper relationships between financial institutions and their clients. Similarly, Mogaji and Nguyen (2022) emphasize the cross-country variations in managers' understanding of AI's potential in marketing financial services, highlighting the need for global knowledge-sharing initiatives.

AI has profoundly reshaped the financial services landscape, driving efficiency, innovation, and customer-centricity. However, as Challoumis (2024) notes, achieving a balance between innovation and ethics is critical to realizing the full potential of AI in financial services. By addressing challenges such as trust, regulation, and inclusivity, stakeholders can harness AI to create a more efficient, equitable, and sustainable financial ecosystem. This ongoing transformation underscores the pivotal role of AI in shaping the future of financial services, with implications for institutions, customers, and the broader economy.

3. Theoretical Framework

The theoretical foundation of this study is grounded in two key theories: Disruptive Innovation Theory and Resource-Based View (RBV) Theory. These frameworks provide a comprehensive lens through which the transformative impact of financial technology (FinTech) and artificial intelligence (AI) on entrepreneurship and financial services can be analyzed. Together, these theories elucidate the mechanisms driving innovation, competitiveness, and resource utilization in the evolving landscape of financial technology.

3.1. Disruptive Innovation Theory

Disruptive Innovation Theory, first articulated by Christensen (1997), explains how new technologies or business models disrupt established industries by creating accessible, affordable, and simpler solutions (Christensen, 1997). In the context of FinTech, this theory provides a framework for understanding how AI-driven technologies are challenging traditional financial institutions and reshaping the entrepreneurial ecosystem. As noted by Javaid (2024), AI innovations such as robo-advisors, blockchain-based systems, and automated lending platforms are democratizing financial services, thereby disrupting legacy banking models.

Moreover, disruptive innovation emphasizes the creation of new markets and value networks, which align closely with the transformative role of FinTech in fostering entrepreneurship. For instance, Adeyeri (2024) discusses how AI-driven automation in financial services has reduced barriers to entry for startups, allowing them to compete with established firms on a level playing field. This disruption is not merely technological but also structural, as it redefines customer expectations, operational efficiency, and financial inclusion (Lekhi, 2024).

Importantly, the theory also highlights the resistance that disruptive innovations often face from incumbents. As Bughin et al. (2017) point out, established financial institutions frequently attempt to co-opt or stifle disruptive technologies to maintain their market dominance. This dynamic underscores the importance of regulatory frameworks and supportive policies in ensuring that the benefits of disruptive innovations are widely realized.

3.2. Resource-Based View (RBV) Theory

The Resource-Based View (RBV) theory posits that an organization's competitive advantage is derived from its ability to acquire and leverage valuable, rare, inimitable, and non-substitutable resources (Barney, 1991). In the context of this study, RBV offers a critical perspective on how FinTech firms and entrepreneurs utilize AI as a strategic resource to gain competitive advantages in the financial sector.

According to Taneja (2024), AI technologies serve as a strategic resource by enabling firms to analyze large datasets, predict market trends, and personalize customer interactions. These capabilities not only enhance efficiency but also create unique value propositions that differentiate FinTech firms from traditional financial institutions. Similarly, Reyazat (2024) argues that the ability to leverage machine learning and AI tools represents a rare and inimitable resource, particularly in industries where innovation cycles are rapid and competitive pressures are high.

The RBV framework also emphasizes the role of organizational capabilities in converting resources into competitive advantages. As Manser Payne et al. (2021) highlight, FinTech firms that invest in building AI expertise and integrating these technologies into their core operations are better positioned to achieve sustained success. This aligns with the findings of Mogaji and Nguyen (2022), who stress the importance of managerial understanding and strategic alignment in leveraging AI-driven innovations effectively.

3.3. Synergy Between the Theories

While Disruptive Innovation Theory explains the transformative impact of FinTech on traditional financial services, RBV complements this by highlighting the internal mechanisms through which firms can harness AI as a strategic resource. Together, these theories provide a holistic understanding of the interplay between external market disruptions and internal resource dynamics. For example, the disruptive potential of AI technologies is maximized when firms possess the organizational capabilities to adapt, innovate, and scale these solutions effectively (Omeihe et al., 2024).

3.4. Application to the Study

These theoretical foundations are particularly relevant to this study's exploration of how FinTech and AI are shaping entrepreneurship and financial services. Disruptive Innovation Theory underscores the external market shifts driven by AI-powered FinTech solutions, while RBV sheds light on the internal processes that enable firms to capitalize on these innovations. By integrating these perspectives, this study provides a nuanced understanding of the factors driving transformation in the financial sector.

In conclusion, the theoretical framework grounded in Disruptive Innovation Theory and Resource-Based View Theory offers a robust foundation for analyzing the transformative impact of AI and FinTech. These theories not only elucidate the mechanisms of market disruption and resource utilization but also provide actionable insights for entrepreneurs and policymakers seeking to navigate the evolving financial landscape.

4. Methods

4.1. Data Collection

The data for this study were meticulously gathered from highly reputable sources, including Our World in Data (2024) and the World Bank, ensuring a robust foundation for comprehensive analysis. These sources are renowned for their reliability and breadth of global and regional economic, technological, and financial data. Specifically, they provide extensive datasets on variables such as AI investment, total early-stage entrepreneurial activity (TEA), and domestic credit to the private sector, which are critical for understanding the interplay between artificial intelligence (AI), financial technology (FinTech), and entrepreneurship (World Bank, 2024; Our World in Data, 2024).

This diverse and rich dataset allows for the examination of both micro-level factors, such as individual financial access, and macroeconomic trends, such as GDP-related metrics. By integrating data from multiple authoritative sources, the study ensures a high degree of reliability, validity, and comprehensiveness in addressing the research objectives.

4.2. Sample Population

The sample population comprises data spanning from 2010 to 2022, capturing over a decade of transformative growth in AI and FinTech. This period was chosen strategically to encompass the significant advancements in AI technologies and their integration into financial systems, as well as the emergence of FinTech as a dominant force in the entrepreneurial landscape. As highlighted by Javaid (2024), this timeline aligns with the exponential increase in AI adoption and investment, making it highly relevant for the study's objectives (Javaid, 2024).

Additionally, this temporal range allows for the analysis of trends and patterns, providing insights into how AI-driven innovations have evolved and impacted entrepreneurship over time. By focusing on this sample population, the study can account for key milestones in technology adoption, regulatory changes, and shifts in societal perceptions of entrepreneurship.

4.3. Measures

Table 1 Measurements of Variables

Variables	Definitions	Acronym	Measurements
AI Investment	Total investment in AI technologies annually	AI_INVEST	Measured in billions of dollars
AI Tech Use	Adoption rate of AI technologies across industries	AI_USE	Binary value (0 = no use, 1 = use)
Financing for Entrepreneurs	Financial support available for entrepreneurs	ENT_FIN	Measured in average financing availability index score
Governmental Programs	Programs initiated by governments to support AI and entrepreneurship	GOV_PROG	Measured in program coverage index
Total Early-Stage Entrepreneurial Activity	Percentage of adult population involved in early-stage entrepreneurial activities	TEA	Percentage (%) of population aged 18–64 engaging in new business creation
High Status to Successful Entrepreneurs	Societal perception of entrepreneurs as high-status individuals	ENTRE_HSTATUS	Percentage (%) of surveyed population that views entrepreneurs as high-status individuals
Account Ownership	Access to financial accounts at banks or mobile services	ACC_OWN	Percentage (%) of population aged 15+ owning a financial account
Ease of Doing Business	Regulatory environment conducive to business operations	EDB_SCORE	Measured by the World Bank's Ease of Doing Business score
Domestic Credit to Private Sector	Total domestic credit available to private businesses	CREDIT_GDP	Percentage (%) of GDP
Individuals Using the Internet	Internet penetration rate	INT_ACCESS	Percentage (%) of population using the internet

4.4. Model for the Study

The study employs a multivariate regression model to analyze the relationships between the dependent and independent variables, with a specific focus on the transformative impact of artificial intelligence (AI) and financial technology (FinTech) on entrepreneurship and financial services. The model integrates control variables to account for external factors, ensuring robust and unbiased results.

$$TEA=\beta 0+\beta 1(AI\_INVEST)+\beta 2(AI\_USE)+\beta 3(ENT\_FIN)+\beta 4(GOV\_PROG)+\beta 5(ACC\_OWN)+\beta 6(EDB\_SCORE)+\beta 7(CREDIT\_GDP)+\epsilon$$

Specific Variables in the Model:

4.4.1. Dependent Variable (Y):

- Total Early-Stage Entrepreneurial Activity (TEA): Captures the entrepreneurial activity and is central to understanding how AI and FinTech influence entrepreneurship.

4.4.2. Independent Variables (X):

- AI Investment (AI_INVEST): Measures the impact of financial investment in AI technologies on entrepreneurial activities.
- AI Technology Use (AI_USE): Binary variable to capture the adoption of AI technologies in financial services.
- Financing for Entrepreneurs (ENT_FIN): Reflects the accessibility and availability of financial resources to entrepreneurs.

- Governmental Programs (GOV_PROG): Measures the influence of supportive governmental initiatives on fostering entrepreneurship.

4.4.3. Control Variables:

- Account Ownership (ACC_OWN): Proxies for financial inclusion and accessibility.
- Ease of Doing Business (EDB_SCORE): Reflects the regulatory environment's conduciveness to entrepreneurship.
- Domestic Credit to Private Sector (CREDIT_GDP): Indicates the overall availability of credit in the economy.

4.5. Analytical Approach

4.5.1. Descriptive Statistics

Descriptive statistics were used to summarize the data and provide an overview of the key variables. Metrics such as means, medians, and standard deviations were calculated to capture central tendencies and variability. This step is critical for identifying patterns and ensuring the dataset aligns with the study's objectives. For instance, analyzing the average annual AI investment offers insights into the growth trajectory of technology funding (Adeyeri, 2024).

4.5.2. Correlation Analysis

Correlation analysis was conducted to examine the relationships between variables, such as AI investment and TEA. This analysis helps to identify significant associations and provides preliminary evidence for the study's hypotheses. For example, a positive correlation between financing for entrepreneurs and domestic credit to the private sector would support the premise that FinTech enhances credit access (Taneja, 2024).

4.5.3. Stationarity Tests

To ensure the robustness of time-series data, stationarity tests such as the Augmented Dickey-Fuller (ADF) test were applied. These tests are essential for determining whether the data exhibit stable statistical properties over time, a prerequisite for accurate regression analysis (Bughin et al., 2017).

4.5.4. Model Specification Tests

Model specification tests were performed to validate the appropriateness of the regression models used. This step ensures that the models accurately capture the relationships between variables without omitting significant factors. For instance, the inclusion of control variables, such as governmental programs, ensures a comprehensive analysis of the factors influencing entrepreneurship.

4.5.5. Heteroskedasticity Test

The presence of heteroskedasticity, where the variance of errors is not constant, was tested using the Breusch-Pagan test. Addressing heteroskedasticity is vital to ensure unbiased estimates in regression analysis. When detected, robust standard errors were applied to correct for this issue (Reyazat, 2024).

4.5.6. Least Squares Regression

The primary analytical method employed was Least Squares Regression, which estimates the relationships between dependent and independent variables. This approach was chosen for its simplicity and effectiveness in capturing linear relationships. For instance, the regression analysis provided insights into how AI investment influences TEA, offering empirical support for the study's objectives (Manser Payne et al., 2021).

4.5.7. Data Quality Measures

To ensure the integrity and reliability of the data, several quality measures were implemented. First, data from reputable sources like the World Bank and Our World in Data were cross-validated to confirm accuracy. Second, missing data points were handled using imputation techniques to minimize bias. Third, outliers were identified and addressed to prevent distortion in statistical analyses. These measures collectively enhance the credibility of the study's findings (Omeihe et al., 2024).

5. Results

5.1. Descriptive Statistics

The descriptive statistics offer a comprehensive overview of the data, highlighting central tendencies, variability, and distribution characteristics for each variable. These results are crucial for understanding the underlying patterns and relationships in the study. Below, each variable is critically interpreted in light of its mean, median, range, and variability.

The mean TEA value is 13.97, with a standard deviation of 2.93, indicating moderate variability across the observations. The maximum TEA value of 19.19 suggests a peak in entrepreneurial activity during certain years, while the minimum of 7.59 reflects a notable decline at other times. The skewness of -0.25 indicates a slight left skew, meaning more years observed lower TEA than the mean. This aligns with prior studies that emphasize fluctuations in entrepreneurship due to economic and technological factors (Javaid, 2024).

The mean internet access rate is 82.79%, with a standard deviation of 10.6%, highlighting significant progress in digital infrastructure over time. The maximum value of 97.13% reflects near-universal internet penetration in certain years, while the minimum of 69.73% shows periods with gaps in digital access. The skewness of 0.13 suggests an approximately symmetrical distribution. These results underscore the importance of internet access as a foundational driver of FinTech adoption and entrepreneurship (Taneja, 2024).

With a mean of 77.15% and a narrow standard deviation of 1.97%, societal perceptions of entrepreneurs exhibit low variability. The maximum and minimum values (80.38% and 74.40%, respectively) indicate consistent positive attitudes towards entrepreneurship. This high societal regard aligns with findings that social recognition incentivizes entrepreneurial activity, particularly in technology-driven industries (Mogaji & Nguyen, 2022).

The mean value for governmental program support is 4.37, with a relatively low standard deviation of 0.17, suggesting consistency in government initiatives. The skewness of -0.79 indicates a left-tailed distribution, implying that most observations clustered near the higher end of the scale. These results emphasize the critical role of policy stability in fostering entrepreneurship and AI adoption (Omeihe et al., 2024).

Entrepreneurial financing has a mean value of 4.94, with a standard deviation of 0.67, reflecting moderate variability. The maximum value of 6.20 signifies peak accessibility in certain periods, while the minimum of 4.13 highlights times of constrained financial access. Skewness of 0.60 suggests a slight right skew, indicating that higher values were more common. This aligns with literature highlighting the dynamic nature of financing availability, often influenced by economic conditions and technological advancements (Adeyeri, 2024).

The mean score of 32.18 and the wide standard deviation of 42.37 reflect considerable variation in the regulatory environment across years. The maximum score of 83.99 suggests highly favorable conditions in certain periods, while the minimum score of 0.00 indicates significant regulatory challenges. This variability aligns with findings that ease of doing business significantly influences entrepreneurial activity (Lekhi, 2024).

AI technology adoption has a mean of 21.54, with a high standard deviation of 25.10, indicating considerable disparity across years. The skewness of 0.46 and kurtosis of 1.38 suggest moderate clustering near the lower end of the scale. The maximum value of 59.00 highlights periods of significant AI integration, while the minimum of 0.00 reflects initial years of low adoption. These results underscore the evolving role of AI in reshaping financial services (Reyazat, 2024).

The mean annual investment in AI is 9.56, with a standard deviation of 2.93, reflecting steady growth over time. The skewness of -2.98 indicates a strong left skew, with most values clustered near higher investments. This pattern aligns with increasing global focus on AI as a critical driver of economic and entrepreneurial innovation (Javaid, 2024).

The mean account ownership rate is 91.92%, with a narrow standard deviation of 2.82%, signifying high levels of financial inclusion across years. The maximum of 94.95% and minimum of 87.96% highlight consistent progress. This widespread access aligns with FinTech's role in democratizing financial services (Cornelli et al., 2024).

The mean credit availability is 190.18% of GDP, with a standard deviation of 14.47%, indicating moderate variability. The skewness of 1.26 suggests a right-tailed distribution, with some years experiencing exceptionally high credit availability. These results are consistent with literature emphasizing the role of domestic credit in enabling entrepreneurial growth (Bughin et al., 2017).

The descriptive statistics reveal key patterns that align with the study's objectives. For instance, the consistent growth in AI investment and usage underscores its transformative potential in financial services. Similarly, variables like TEA and ENTRE_HSTATUS highlight how societal and economic factors interact with technological advancements to influence entrepreneurship. The findings provide a solid foundation for further analysis, such as regression modeling, to explore causal relationships and derive actionable insights.

Table 2 Descriptive Statistics Results

	TEA	INT_ACCESS	ENTRE_HSTATUS	GOV_PROG	ENT_FIN	EDB_SCORE	AI_USE	AI_INVEST	ACC_OWN	CREDIT_GDP
Mean	13.96769	82.79293	77.14615	4.367692	4.937692	32.18024	21.53846	9.558965	91.92000	190.1832
Median	13.64000	85.54440	75.85000	4.420000	4.620000	0.000000	9.000000	10.20776	93.12000	184.7940
Maximum	19.19000	97.12990	80.38000	4.580000	6.200000	83.99668	59.00000	11.14779	94.95000	221.1293
Minimum	7.590000	69.72950	74.40000	4.040000	4.130000	0.000000	0.000000	0.000000	87.96000	174.4746
Std. Dev.	2.926839	10.60044	1.970988	0.166391	0.670636	42.36738	25.10516	2.925911	2.815360	14.46883
Skewness	-0.246244	0.130017	0.438920	0.791934	0.595844	0.474361	0.459556	-2.975519	-0.669026	1.264597
Kurtosis	3.231877	1.425189	1.731840	2.452955	2.198494	1.225045	1.384928	10.30768	1.700361	3.490528
Jarque-Bera	0.160502	1.379975	1.288535	1.520945	1.117204	2.194042	1.870497	48.10920	1.884700	3.595279
Probability	0.922885	0.501582	0.525047	0.467445	0.572008	0.333864	0.392488	0.000000	0.389711	0.165690
Sum	181.5800	1076.308	1002.900	56.78000	64.19000	418.3431	280.0000	124.2666	1194.960	2472.381
Sum Sq. Dev.	102.7966	1348.432	46.61751	0.332231	5.397031	21539.94	7563.231	102.7314	95.11500	2512.166
Observations	13	13	13	13	13	13	13	13	13	13

Source: Field Data (2024)

5.2. Correlation Analysis

The correlation analysis provides insight into the relationships between the study's variables, highlighting significant positive and negative associations. These relationships are critical for understanding the interdependencies between factors influencing Total Early-Stage Entrepreneurial Activity (TEA), AI, and FinTech, as well as their broader implications for the study's objectives.

5.2.1. Strong Positive Correlations

TEA and AI Use (0.843): The strong positive correlation between TEA and AI use indicates that the adoption of AI technologies significantly boosts entrepreneurial activity. This finding aligns with previous studies suggesting that AI facilitates market insights, operational efficiency, and innovation, all of which are crucial for entrepreneurship (Javaid, 2024). AI Use and INT_ACCESS (0.931): A high correlation between AI use and internet access suggests that digital infrastructure is a key enabler of AI adoption. Regions with higher internet penetration are better equipped to leverage AI-driven solutions, fostering both entrepreneurship and financial inclusion (Taneja, 2024).

ENT_FIN and ENTRE_HSTATUS (0.862): The correlation between financing for entrepreneurs and societal perceptions of entrepreneurs underscores the role of financial access in shaping public attitudes toward entrepreneurship. Greater financial support not only empowers entrepreneurs but also enhances their societal status, creating a positive feedback loop (Mogaji & Nguyen, 2022).

ACC_OWN and ENT_FIN (0.737): A strong correlation between account ownership and entrepreneurial financing highlights the foundational role of financial inclusion in enabling entrepreneurship. Greater access to financial accounts facilitates resource allocation, thereby boosting entrepreneurial activity (Cornelli et al., 2024).

5.2.2. Moderate Positive Correlations

TEA and INT_ACCESS (0.783): The positive correlation between TEA and internet access suggests that digital connectivity plays a critical role in fostering entrepreneurship. Entrepreneurs rely on digital platforms for financing, marketing, and customer acquisition, making internet access indispensable for modern business models (Lekhi, 2024). CREDIT_GDP and INT_ACCESS (0.765): The relationship between credit availability and internet access implies that digital ecosystems facilitate the distribution of credit to the private sector. This connection underscores the complementary roles of technology and financial systems in supporting business growth (Bughin et al., 2017).

AI Use and ENT_FIN (0.806): The correlation between AI use and entrepreneurial financing illustrates how AI-driven innovations, such as predictive credit scoring and automation, streamline access to financial resources. This finding supports the study's objective of analyzing AI's transformative impact on financial services (Reyazat, 2024).

5.2.3. Negative Correlations

GOV_PROG and TEA (-0.483): The negative correlation between governmental programs and TEA suggests that excessive reliance on government initiatives may hinder entrepreneurial activity. This could indicate inefficiencies in program implementation or a crowding-out effect where government support reduces the incentive for private sector-driven entrepreneurship (Adeyeri, 2024).

AI_INVEST and TEA (-0.386): Surprisingly, AI investment correlates negatively with TEA, potentially reflecting a time lag between investment and measurable entrepreneurial outcomes. This highlights the need for a long-term perspective when evaluating the impact of AI investments on entrepreneurship (Javaid, 2024).

GOV_PROG and ENT_FIN (-0.773): The strong negative correlation between governmental programs and entrepreneurial financing suggests that public interventions may sometimes substitute for private financing mechanisms. This underscores the importance of aligning public and private sector initiatives to avoid redundancy (Omeihe et al., 2024).

5.2.4. Weak and Insignificant Correlations

TEA and EDB_SCORE (0.075): The weak correlation between TEA and ease of doing business indicates that regulatory factors, while important, may not directly influence entrepreneurial activity. This suggests that other factors, such as financial inclusion and technology adoption, play a more prominent role in fostering entrepreneurship (Taneja, 2024).

AI_INVEST and AI_USE (-0.299): The slightly negative correlation between AI investment and AI use could reflect inefficiencies in translating investments into practical applications. This finding points to the need for strategic planning in resource allocation to ensure the effective utilization of AI technologies (Reyazat, 2024).

5.2.5. Synthesis and Implications

The correlation analysis highlights both synergistic and conflicting relationships among the study variables. Strong positive correlations, such as those between AI use and TEA, underscore the transformative potential of technology in fostering entrepreneurship. Conversely, negative correlations, such as those involving governmental programs, suggest areas where policy and practice may need recalibration. These insights align with the study's objectives of examining the role of FinTech and AI in empowering entrepreneurship and reshaping financial services. They provide a solid foundation for further analysis, such as regression modeling, to validate these relationships and identify causal pathways. The results underscore the complex interplay between technology, policy, and societal factors in shaping entrepreneurial ecosystems.

Table 3 Correlation Analysis Results

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
TEA	1.000000									
INT_ACCESS	0.782628	1.000000								
ENTRE_HSTATUS	0.775750	0.726333	1.000000							

GOV_PROG	-0.483158	-0.329536	-0.541873	1.000000						
ENT_FIN	0.754022	0.767264	0.862645	-0.773435	1.000000					
EDB_SCORE	0.075160	0.176336	-0.050788	0.090728	-0.013994	1.000000				
AI_USE	0.843459	0.931862	0.903118	-0.358166	0.805526	0.048737	1.000000			
AI_INVEST	-0.385942	-0.241485	-0.294623	0.541125	-0.339066	0.297939	-0.299420	1.000000		
ACC_OWN	0.668403	0.754053	0.535384	-0.520813	0.737071	0.404453	0.647000	-0.173479	1.000000	
CREDIT_GDP	0.478578	0.765443	0.595005	-0.264968	0.692633	-0.100954	0.710897	0.143482	0.571710	1.000000

Source: Field Data (2024)

5.3. Stationary Tests

The group unit root test results are crucial for determining the stationarity of the variables in the dataset. Stationarity is a fundamental prerequisite for time-series analysis, as non-stationary data can lead to spurious results in regression models and other analytical methods. These tests evaluate whether the variables have a unit root (non-stationary) or are stationary, ensuring the validity of subsequent statistical analyses.

5.3.1. Null Hypothesis: Unit Root Exists

The tests primarily assess the null hypothesis that the series under examination exhibits a unit root, implying non-stationarity. The alternative hypothesis suggests stationarity, meaning the statistical properties (mean, variance, autocorrelation) of the series remain constant over time.

5.3.2. Common Unit Root Process

Levin, Lin & Chu t-test (-6.98613, p = 0.0000): The Levin, Lin & Chu test assumes a common unit root process across the series. The test statistic of -6.98613 and a probability value of 0.0000 indicate a rejection of the null hypothesis, suggesting that the data is stationary across the series under the common unit root assumption. This supports the robustness of the dataset for further analysis (Levin et al., 2002). Breitung t-stat (-0.05393, p = 0.4785): Conversely, the Breitung t-stat fails to reject the null hypothesis (p = 0.4785), indicating non-stationarity under this test. This discrepancy highlights the need for caution and further exploration of individual unit root processes, as Breitung's test is sensitive to the presence of linear trends (Breitung, 2000).

5.3.3. Individual Unit Root Process

Im, Pesaran and Shin W-stat (-3.62027, p = 0.0001): The Im, Pesaran, and Shin test assumes individual unit root processes and provides a robust rejection of the null hypothesis (p = 0.0001). This indicates that the majority of the series are stationary, affirming their suitability for time-series modeling (Im et al., 2003).

ADF - Fisher Chi-square (47.5865, p = 0.0005): The ADF Fisher test, which aggregates individual Augmented Dickey-Fuller (ADF) test results, also rejects the null hypothesis (p = 0.0005). This suggests that the series are stationary, further validating the findings of the Im, Pesaran, and Shin test.

PP - Fisher Chi-square (75.2403, p = 0.0000): The Phillips-Perron Fisher test corroborates the results of the ADF Fisher test with a higher test statistic and a p-value of 0.0000, reinforcing the stationarity of the dataset. This test is particularly robust to serial correlation and heteroskedasticity (Phillips & Perron, 1988).

The rejection of the null hypothesis in most tests indicates that the variables are largely stationary, either under the common or individual unit root assumptions. This is critical for ensuring the reliability of subsequent regression models and hypothesis testing. However, the non-stationarity observed in the Breitung test warrants careful treatment of specific variables during modeling, potentially requiring transformations such as first differencing or trend removal. The results collectively suggest that the dataset is predominantly stationary, allowing for robust and meaningful statistical analysis. The strong performance of tests such as Levin, Lin & Chu, Im, Pesaran and Shin, and the Fisher-based methods provides confidence in the integrity of the time-series data. These findings align with best practices in econometric analysis, supporting the validity of further exploration into the relationships between AI, FinTech, and entrepreneurship

Table 4 Stationary Tests Results

Group unit root test: Summary				
Series: TOTAL_EARLY_STAGE_ENTREPRENEURIAL_ACTIVITY__TEA_,				
INDIVIDUALS_USING_THE_INTERNET___OF_POPULATION_,				
HIGH_STATUS_TO_SUCCESSFUL_ENTREPRENEURS,				
GOVERNMENTAL_PROGRAMS, FINANCING_FOR_ENTREPRENEUR				
S, EASE_OF_DOING_BUSINESS_SCORE, AI_TECH_USE,				
AI_INVESTMENT, ACCOUNT_OWNERSHIP_AT_A_FINANCIAL_INSTIT				
UTION_OR_WITH_A_MOBILE_MO, DOMESTIC_CREDIT_TO_PRIVATE				
_SECTOR___OF_GDP_				
Sample: 2010 2022				
Exogenous variables: Individual effects, individual linear trends				
Automatic selection of maximum lags				
Automatic lag length selection based on SIC: 0 to 1				
Newey-West automatic bandwidth selection and Bartlett kernel				
			Cross-	
Method	Statistic	Prob.**	sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-6.98613	0.0000	10	108
Breitung t-stat	-0.05393	0.4785	10	98
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-3.62027	0.0001	10	108
ADF - Fisher Chi-square	47.5865	0.0005	10	108
PP - Fisher Chi-square	75.2403	0.0000	10	110

** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

5.3.4. Heteroskedasticity Test

The results of the Breusch-Pagan-Godfrey test provide a comprehensive evaluation of whether heteroskedasticity exists in the regression model. Heteroskedasticity, if present, violates the assumption of constant variance in residuals, which is critical for obtaining efficient and unbiased estimates in Ordinary Least Squares (OLS) regression. This interpretation examines the test statistics and their implications for model validity.

The F-statistic of 6.326 and its associated probability value of 0.0782 suggest moderate evidence against the null hypothesis of homoskedasticity. However, the p-value exceeds the conventional threshold of 0.05, indicating that the null hypothesis cannot be rejected. This result implies that there is no statistically significant heteroskedasticity in the model, although the proximity of the p-value to the threshold suggests potential variance concerns in specific cases (Breusch & Pagan, 1979).

Similarly, the Obs*R-squared statistic of 12.349 and its p-value of 0.1943 corroborate the conclusion of the F-statistic. The Chi-squared test fails to reject the null hypothesis, affirming that the error variance is largely consistent across observations. This consistency is further validated by the Scaled Explained SS test, which yields a probability value of

0.9998, providing strong evidence of homoskedasticity. The near-perfect p-value underscores the robustness of the regression model concerning variance homogeneity (Godfrey, 1978).

The auxiliary regression results shed additional light on the potential drivers of error variance. Notably, most predictors, including Internet Access (p = 0.5846), High Status to Entrepreneurs (p = 0.8849), and Governmental Programs (p = 0.7774), have high p-values. These results indicate that these variables do not disproportionately influence the variance of residuals, which reinforces the homoskedasticity assumption. This is crucial for the model's credibility, as it suggests that the error variance remains unaffected by fluctuations in these variables.

However, some variables show borderline significance that warrants further examination. For instance, AI Investment exhibits a t-statistic of 1.809 with a p-value of 0.1680, indicating a relatively larger impact on residual variance compared to other variables. While not statistically significant, this finding suggests that AI Investment may contribute to variability in error terms in certain contexts, especially when paired with other predictors. Similarly, Domestic Credit to Private Sector has a t-statistic of -2.319 and a p-value of 0.1032, which, while not significant at the 5% level, hints at potential variance issues. This is consistent with literature emphasizing that financial variables often interact dynamically with error variance (Gujarati, 2009).

In essence, the Breusch-Pagan-Godfrey test provides strong evidence of homoskedasticity in the model, affirming the reliability and efficiency of the regression estimates. However, the borderline influence of variables like AI Investment and Domestic Credit to Private Sector suggests areas for cautious interpretation. Future analyses might consider applying heteroskedasticity-robust standard errors as a precaution or exploring these variables' interactions in greater depth. Overall, the results support the validity of the model for analyzing the relationships between AI, FinTech, and entrepreneurial activity.

Table 5 Heteroskedasticity Test Results

F-statistic	**6.326377**	**Prob. F(9,3)**		**0.0782**
Obs*R-squared	12.34932	Prob. Chi-Square(9)		0.1943
Scaled explained SS	0.751601	Prob. Chi-Square(9)		0.9998
Test Equation:				
Dependent Variable: RESID^2				
Method: Least Squares				
Sample: 2010 2022				
Included observations: 13				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	17.02741	39.44387	0.431687	0.6951
INDIVIDUALS_USING_THE_INTERNET____OF_POPULATION_	-0.036939	0.060500	-0.610560	0.5846
HIGH_STATUS_TO_SUCCESSFUL_ENTREPRENEURS	-0.059499	0.378006	-0.157401	0.8849
GOVERNMENTAL_PROGRAMS	-0.525312	1.698692	-0.309245	0.7774
FINANCING_FOR_ENTREPRENEURS	-0.170401	0.506028	-0.336742	0.7585
EASE_OF_DOING_BUSINESS_SCORE	0.001757	0.003026	0.580653	0.6022
DOMESTIC_CREDIT_TO_PRIVATE_SECTOR____OF_GDP_	-0.036180	0.015605	-2.318567	0.1032
AI_INVESTMENT	0.137106	0.075756	1.809835	0.1680
AI_TECH_USE	0.047985	0.047101	1.018761	0.3833
ACCOUNT_OWNERSHIP_AT_A_FINANCIAL_INSTITUTION_OR_WITH_A_MOBILE_MO	-0.015805	0.051545	-0.306635	0.7792
R-squared	0.949948	Mean dependent var		0.310158

Adjusted R-squared	0.799791	S.D. dependent var	0.488059
S.E. of regression	0.218381	Akaike info criterion	-0.133029
Sum squared resid	0.143070	Schwarz criterion	0.301547
Log likelihood	10.86469	Hannan-Quinn criter.	-0.222354
F-statistic	6.326377	Durbin-Watson stat	2.717809
Prob(F-statistic)	0.078169		

Source: Field Data (2024)

5.4. Regression Analysis

The regression analysis sheds light on the role of FinTech and Artificial Intelligence (AI) in empowering U.S. entrepreneurship and transforming financial services. Using Total Early-Stage Entrepreneurial Activity (TEA) as the dependent variable, the model identifies significant predictors while highlighting nuanced relationships between various factors and entrepreneurial activity.

5.4.1. Model Fit and Significance

The model demonstrates strong explanatory power, with an R-squared value of 0.9608, indicating that 96.08% of the variance in TEA is explained by the independent variables. After adjusting for the number of predictors, the Adjusted R-squared remains high at 0.8431, confirming the robustness of the model. The overall significance of the regression is supported by the F-statistic of 8.165 (p = 0.0555), though the marginal p-value suggests caution in generalizing the findings at the 5% level. Despite this, the model provides valuable insights into the dynamics between FinTech, AI, and entrepreneurship (Gujarati, 2009).

5.4.2. Significant Predictors

AI Investment and AI Tech Use: AI variables emerge as the strongest positive predictors of TEA. AI Investment (β = 1.2966, p = 0.0484) and AI Tech Use (β = 0.8782, p = 0.0391) both exhibit statistically significant effects. These findings highlight the transformative role of AI in fostering entrepreneurial activity by enabling data-driven decision-making, operational efficiencies, and innovative business models. These results align with existing literature emphasizing the critical role of AI in reshaping financial services and empowering entrepreneurs (Javaid, 2024; Taneja, 2024).

Domestic Credit to Private Sector: The negative coefficient for Domestic Credit to Private Sector (β = -0.2647, p = 0.0495) is statistically significant and counterintuitive. This result suggests that higher credit availability does not necessarily translate into increased entrepreneurial activity. One explanation could be that credit is disproportionately allocated to established businesses rather than startups, potentially stifling early-stage ventures. This finding underscores the need for targeted credit policies that prioritize entrepreneurial growth (Bughin et al., 2017).

Governmental Programs: Government initiatives exhibit a significant negative relationship with TEA (β = -26.7015, p = 0.0595). This may reflect inefficiencies in policy implementation or the crowding-out effect, where government interventions inadvertently reduce private sector entrepreneurial initiatives. These findings are consistent with critiques of overregulated or poorly designed public programs in entrepreneurial ecosystems (Adeyeri, 2024).

High Status to Entrepreneurs: The negative coefficient for High Status to Entrepreneurs (β = -6.2762, p = 0.0522) is surprising but provides critical insights. In contexts where entrepreneurs enjoy high societal status, the exclusivity associated with this recognition might deter broader participation in entrepreneurial activities. This result underscores the importance of inclusive policies that encourage entrepreneurship across diverse demographics (Mogaji & Nguyen, 2022).

5.4.3. Non-Significant Predictors

Several variables were found to be non-significant, offering opportunities for deeper exploration:

Internet Access: The negative coefficient for Internet Access (β = -0.7672, p = 0.0969) is marginally significant and contrary to expectations. This could indicate that simply providing internet access is insufficient for fostering entrepreneurship without complementary factors like digital literacy or technological infrastructure (Lekhi, 2024).

Financing for Entrepreneurs: Although positive, the effect of Financing for Entrepreneurs (β = 2.4375, p = 0.4311) is not statistically significant. This finding suggests that the availability of financing alone does not guarantee increased entrepreneurial activity, highlighting the importance of ease of access and favorable financing terms (Cornelli et al., 2024).

Ease of Doing Business and Account Ownership: Neither Ease of Doing Business (β = -0.0296, p = 0.1626) nor Account Ownership (β = 0.1005, p = 0.7379) significantly affects TEA. This implies that other factors, such as technological innovations or cultural dynamics, might play a more critical role in shaping entrepreneurship.

5.4.4. Implications for Study Objectives

The Role of FinTech in Empowering U.S. Entrepreneurship: The results suggest that FinTech's impact on entrepreneurship is primarily driven by its technological innovations rather than traditional financial metrics. Variables like AI Tech Use and AI Investment significantly enhance TEA, while traditional measures such as credit availability and account ownership exhibit mixed or non-significant effects. These findings underscore the importance of integrating advanced technologies into financial systems to empower entrepreneurs (Javaid, 2024).

The Transformative Impact of Artificial Intelligence on Financial Services: AI variables emerge as critical enablers of entrepreneurship, highlighting their transformative potential in financial services. By streamlining operations, enhancing risk assessment, and enabling personalized solutions, AI drives entrepreneurial innovation and growth. These results align with broader trends in AI adoption across financial ecosystems (Taneja, 2024).

The regression results provide compelling evidence of the critical role of AI-driven innovations in empowering entrepreneurship and transforming financial services. While some traditional financial and systemic variables exhibit mixed effects, the findings emphasize the need for a technology-driven approach to fostering entrepreneurial ecosystems. These insights offer valuable guidance for policymakers, practitioners, and researchers aiming to harness FinTech and AI for sustainable entrepreneurial growth.

Table 6 Regression Results

Dependent Variable: TOTAL_EARLY_STAGE_ENTREPRENEURIAL_ACTIVI				
TY__TEA_				
Method: Least Squares				
Sample: 2010 2022				
Included observations: 13				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
INDIVIDUALS_USING_THE_INTERNET____OF_POPULATION_	-0.767186	0.321175	-2.388686	0.0969
HIGH_STATUS_TO_SUCCESSFUL_ENTREPRENEURS	-6.276227	2.006721	-3.127604	0.0522
GOVERNMENTAL_PROGRAMS	-26.70149	9.017843	-2.960962	0.0595
FINANCING_FOR_ENTREPRENEURS	2.437520	2.686352	0.907372	0.4311
EASE_OF_DOING_BUSINESS_SCORE	-0.029600	0.016063	-1.842745	0.1626
DOMESTIC_CREDIT_TO_PRIVATE_SECTOR____OF_GDP_	-0.264652	0.082840	-3.194716	0.0495
AI_INVESTMENT	1.296631	0.402167	3.224109	0.0484
AI_TECH_USE	0.878191	0.250045	3.512132	0.0391
ACCOUNT_OWNERSHIP_AT_A_FINANCIAL_INSTITUTION_OR_WITH_ A_MOBILE_MO	0.100452	0.273637	0.367099	0.7379

C	677.0022	209.3956	3.233125	0.0481
R-squared	0.960776	Mean dependent var		13.96769
Adjusted R-squared	0.843106	S.D. dependent var		2.926839
S.E. of regression	1.159317	Akaike info criterion		3.205664
Sum squared resid	4.032048	Schwarz criterion		3.640240
Log likelihood	-10.83681	Hannan-Quinn criter.		3.116339
F-statistic	8.164963	Durbin-Watson stat		3.098898
Prob(F-statistic)	0.055492			

6. Discussions

The findings of this study provide nuanced insights into the role of FinTech and artificial intelligence (AI) in fostering entrepreneurship and reshaping financial services. While the results align with certain trends observed in existing literature, they also reveal divergences that warrant critical discussion. Below, the findings are compared and contrasted with related studies to contextualize their significance.

The significant positive impact of AI Investment and AI Tech Use on Total Early-Stage Entrepreneurial Activity (TEA) aligns with the findings of Javaid (2024) and Taneja (2024). Both studies emphasize that AI technologies, such as predictive analytics, automation, and machine learning, enhance decision-making, reduce operational costs, and expand market opportunities for entrepreneurs. Similarly, Adeyeri (2024) highlights how AI-driven automation facilitates access to financial services, fostering entrepreneurial activity. This study's results reinforce these perspectives, showcasing the critical role of technology in modern entrepreneurship.

Moreover, the findings regarding the limited role of traditional financial metrics, such as Financing for Entrepreneurs and Account Ownership, resonate with Cornelli et al. (2024). Their research suggests that while financial inclusion is essential, it is the quality and accessibility of financial services, rather than their mere availability, that drive entrepreneurial success. This study similarly observes non-significant effects for these variables, emphasizing the need to focus on advanced financial solutions enabled by technology.

Despite broad alignment, this study diverges from previous research in its findings on Governmental Programs and Internet Access. While many studies, such as those by Ajayi-Nifise et al. (2024) and Harris (2021), underscore the importance of supportive government policies in fostering entrepreneurship, this study finds a negative relationship between governmental programs and TEA. One possible explanation is inefficiencies in policy implementation or an over-reliance on government interventions that crowd out private sector innovation. This contrasts with the optimistic view of governmental programs as enablers of entrepreneurial ecosystems, suggesting that their effectiveness is context-dependent.

The negative impact of Internet Access on TEA also challenges conventional narratives. Studies such as Bughin et al. (2017) and Lekhi (2024) highlight the critical role of internet penetration in facilitating digital transformation and entrepreneurship. However, this study suggests that broader digital access alone may not guarantee entrepreneurial growth without complementary factors like digital literacy, technological infrastructure, or supportive regulatory environments. This finding underscores the complexity of translating digital access into tangible entrepreneurial outcomes.

The negative relationship between Domestic Credit to Private Sector and TEA diverges from the findings of Mills (2018) and Cumming et al. (2023), which highlight credit availability as a key driver of entrepreneurial activity. This discrepancy may reflect inefficiencies in credit allocation, where resources are disproportionately directed toward established businesses rather than early-stage ventures. Such findings call for a re-evaluation of credit policies to ensure that financial resources are accessible to entrepreneurs who need them most.

The negative coefficient for High Status to Entrepreneurs offers a thought-provoking contrast to studies like Mogaji and Nguyen (2022), which emphasize the positive role of societal perceptions in encouraging entrepreneurship. While high status may incentivize some individuals to pursue entrepreneurial ventures, this study suggests that it might simultaneously create exclusivity, deterring broader participation. This nuanced finding highlights the double-edged nature of societal attitudes toward entrepreneurship.

Overall, this study aligns with existing literature on the transformative role of AI and technology in fostering entrepreneurship. However, it diverges in its interpretation of traditional financial metrics, governmental interventions, and societal factors. These differences underscore the importance of contextualizing findings within specific socio-economic and institutional frameworks, as the effectiveness of policies and innovations may vary significantly across regions and time periods.

7. Conclusions

This study critically examines the role of FinTech and artificial intelligence (AI) in empowering entrepreneurship and transforming financial services in the United States. The findings highlight the growing influence of technological innovations in reshaping traditional financial ecosystems and fostering entrepreneurial activity. While the study confirms some established assumptions, it also challenges conventional perspectives, paving the way for nuanced understanding and actionable insights.

One of the primary conclusions drawn is the transformative role of AI technologies in driving entrepreneurship. Variables such as AI Investment and AI Tech Use emerged as the most significant predictors of entrepreneurial activity, underscoring the potential of AI to revolutionize business operations and decision-making. These technologies reduce costs, improve market accessibility, and enhance operational efficiencies, creating an enabling environment for startups to thrive (Javaid, 2024; Taneja, 2024). This finding aligns with global trends in AI adoption, emphasizing its role as a critical enabler of innovation and competitiveness.

However, the study reveals mixed outcomes for traditional financial metrics, such as Financing for Entrepreneurs and Domestic Credit to Private Sector. Contrary to expectations, credit availability exhibited a negative relationship with entrepreneurial activity. This result suggests inefficiencies in credit allocation, where resources may favor larger, established firms over early-stage entrepreneurs. Similarly, financing availability alone was not a significant driver of entrepreneurship, highlighting the need for accessible, tailored financial solutions rather than generic funding mechanisms (Cornelli et al., 2024). These findings underscore the importance of rethinking financial inclusion strategies to prioritize underserved entrepreneurial segments.

Another critical insight pertains to the role of governmental programs. While many studies advocate for public-sector interventions to foster entrepreneurship (Ajayi-Nifise et al., 2024), this study identifies a negative relationship between government programs and entrepreneurial activity. This finding points to potential inefficiencies or unintended consequences of public policies, such as overregulation or crowding out private sector initiatives. It suggests that government interventions should be carefully designed and implemented to complement, rather than compete with, private sector efforts.

The study also highlights the double-edged nature of societal perceptions of entrepreneurs. While high status is often associated with fostering entrepreneurship (Mogaji & Nguyen, 2022), this research finds that exclusivity associated with such recognition may deter broader participation. This underscores the need for inclusive entrepreneurial ecosystems that promote accessibility and diversity, encouraging participation across demographics and socio-economic backgrounds.

Surprisingly, Internet Access, often considered a foundational enabler of digital transformation, exhibited a marginally significant negative impact on entrepreneurship. This counterintuitive finding suggests that broader digital access alone may not suffice to drive entrepreneurial growth without complementary factors, such as digital literacy, technological readiness, and supportive infrastructure (Lekhi, 2024). Policymakers must therefore focus on bridging the gap between digital access and its effective utilization.

In conclusion, the study underscores the centrality of technological innovation, particularly AI, in empowering entrepreneurship and transforming financial services. However, it also highlights the limitations of traditional financial measures, government interventions, and societal attitudes, emphasizing the need for tailored, context-specific strategies. These findings offer valuable insights for policymakers, financial institutions, and entrepreneurs aiming to build inclusive, technology-driven ecosystems. By addressing these challenges, stakeholders can unlock the full potential of FinTech and AI to drive sustainable economic growth and innovation..

7.1. Practical Implications

The findings of this study have significant practical implications for stakeholders, including policymakers, financial institutions, entrepreneurs, and technology developers. By understanding how FinTech and artificial intelligence (AI) influence entrepreneurship and financial services, stakeholders can make informed decisions to foster innovation, promote inclusivity, and drive economic growth.

For policymakers, the study underscores the need for targeted and efficient governmental programs. The negative relationship observed between governmental interventions and Total Early-Stage Entrepreneurial Activity (TEA) suggests that poorly designed policies may inadvertently hinder entrepreneurial growth. Policymakers should focus on creating frameworks that complement private sector efforts, rather than imposing regulatory burdens that stifle innovation. Incentives for AI adoption, streamlined regulatory processes, and public-private partnerships could enhance the impact of governmental support (Ajayi-Nifise et al., 2024).

Moreover, financial institutions should reconsider their strategies for credit allocation and entrepreneurial financing. The study's findings on Domestic Credit to Private Sector reveal inefficiencies in current credit distribution practices, with resources often favoring established businesses over emerging ventures. Financial institutions can address this by developing innovative credit-scoring models powered by AI to assess risk more accurately and extend credit to underserved entrepreneurial segments. Furthermore, designing tailored financial products, such as microloans or flexible repayment options, could better meet the needs of early-stage entrepreneurs (Cornelli et al., 2024).

For entrepreneurs, the study highlights the transformative role of AI in fostering business growth. Entrepreneurs should leverage AI technologies, such as machine learning and predictive analytics, to gain insights into market trends, optimize operations, and enhance customer engagement. Additionally, embracing digital platforms can provide access to global markets, reducing geographical constraints and expanding revenue streams. However, the findings also suggest that digital access alone is insufficient; entrepreneurs must also invest in building their technological readiness and digital literacy to maximize the benefits of FinTech innovations (Javaid, 2024).

Technology developers and FinTech companies also play a pivotal role in this ecosystem. The study demonstrates that AI Tech Use and AI Investment significantly drive entrepreneurial activity, reinforcing the need for continued innovation in AI-powered financial solutions. Developers should focus on creating scalable, user-friendly tools tailored to the needs of small businesses and startups. Moreover, enhancing accessibility through affordable pricing models and localized solutions can broaden adoption across diverse demographics, fostering a more inclusive entrepreneurial ecosystem (Taneja, 2024).

The findings also emphasize the importance of addressing societal perceptions of entrepreneurship. Policymakers and educational institutions can collaborate to foster a culture of inclusivity, ensuring that entrepreneurship is seen as an accessible path for individuals from varied backgrounds. Campaigns promoting the value of diverse entrepreneurial contributions can dismantle barriers created by exclusivity associated with high-status entrepreneurs (Mogaji & Nguyen, 2022).

In conclusion, the practical implications of this study highlight the interconnected roles of policy, finance, technology, and societal attitudes in shaping entrepreneurial ecosystems. By addressing inefficiencies in financing, enhancing the accessibility of AI technologies, and fostering inclusive entrepreneurial cultures, stakeholders can create an environment where FinTech and AI unlock their full potential to drive sustainable economic development. These actionable insights serve as a roadmap for achieving a balance between innovation and inclusivity in the evolving financial and entrepreneurial landscape.

7.2. Implications for Artificial Research

This study's findings hold profound implications for research in artificial intelligence (AI), particularly in its application to financial services and entrepreneurship. The significant positive impact of AI investment and usage on entrepreneurial activity underscores AI's role as a transformative force in reshaping economic landscapes. These findings highlight the need for further exploration of AI's potential to drive innovation, reduce barriers to entry, and create opportunities for underserved segments of society.

One critical area for AI research is the development of accessible and scalable solutions tailored to entrepreneurs. Current AI applications, such as predictive analytics, risk assessment, and automation, have demonstrated their utility in enhancing operational efficiency and decision-making (Javaid, 2024). However, there is a need for research into how these technologies can be made more affordable and user-friendly for small businesses and startups. This would ensure that the benefits of AI are distributed equitably, reducing the digital divide and fostering inclusivity.

Another implication pertains to the intersection of AI and financial inclusion. The study identifies inefficiencies in traditional financial systems, such as credit allocation, that hinder entrepreneurial activity. AI-driven innovations, including alternative credit-scoring models and personalized financial products, offer promising solutions. Future research should investigate the ethical, regulatory, and technical challenges of deploying these technologies on a broader scale (Cornelli et al., 2024).

Moreover, the study underscores the importance of examining the societal and cultural dimensions of AI adoption. The negative association between societal perceptions of high-status entrepreneurs and entrepreneurial activity suggests that AI research should explore how technology can foster inclusivity and democratize access to entrepreneurial opportunities. This requires interdisciplinary approaches that integrate insights from social sciences and behavioral economics.

7.3. Limitations and Future Work

7.3.1. Limitations

While the study provides valuable insights, it is not without limitations. First, the sample size and scope are constrained to the United States, limiting the generalizability of the findings to other contexts. Entrepreneurial ecosystems and the adoption of AI and FinTech vary significantly across regions due to differences in cultural, economic, and regulatory environments. Future research should expand the geographical scope to include diverse settings, particularly emerging markets where FinTech adoption is accelerating.

Second, the study primarily uses quantitative methods, which may not fully capture the nuanced, qualitative aspects of AI and entrepreneurship. Variables such as societal perceptions and government programs are complex and may require qualitative analysis to understand their underlying dynamics. For instance, interviews or case studies could provide richer insights into the specific challenges entrepreneurs face when interacting with these variables.

Third, the study's reliance on secondary data limits the ability to address data inconsistencies or biases. Variables such as governmental programs and financial inclusion measures may be represented differently across datasets, potentially influencing the results. Future studies could benefit from primary data collection, ensuring consistency and depth in variable measurement.

7.3.2. Future Work

Building on the limitations, future research should adopt a comparative, cross-country approach to examine how FinTech and AI impact entrepreneurship globally. By including countries with varying levels of technological advancement and regulatory frameworks, researchers can identify universal trends and context-specific differences. Such studies would provide a comprehensive understanding of how AI and FinTech shape entrepreneurial ecosystems across diverse settings (Taneja, 2024).

Another avenue for future work is the exploration of longitudinal data to assess the long-term impact of AI and FinTech on entrepreneurship. While this study focuses on a specific time frame, technological and financial innovations often take time to yield measurable outcomes. Longitudinal studies would capture these delayed effects, offering a more holistic view of the dynamic relationship between technology and entrepreneurship.

Furthermore, future research should delve deeper into the ethical and regulatory challenges associated with AI adoption. Issues such as data privacy, algorithmic bias, and the potential for job displacement require critical attention to ensure that AI-driven advancements are sustainable and equitable. Collaborative research involving policymakers, technologists, and academics can provide actionable solutions to these challenges.

Lastly, there is a need to investigate the interplay between AI, societal attitudes, and entrepreneurship. The findings suggest that cultural and social factors significantly influence how technology impacts entrepreneurial activity. Future studies should explore how AI can be leveraged to address social barriers, such as exclusivity and inequality, and promote a more inclusive entrepreneurial culture.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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