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The Impact of AI on Income Inequality in the USA: The Mediating Role of Informal Labor Markets and the Moderating Role of Digital Financial Inclusion

Abstract

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Keywords: Artificial Intelligence (AI), Income Inequality, Informal Labor Markets, Digital Financial Inclusion (DFI), United States Economy.

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In the United States, the use of artificial intelligence (AI) has grown exponentially over the past ten years, changing businesses and job markets. Even though artificial intelligence (AI) has led to more innovation and output, it has also made income inequality worse by replacing workers with average skills and making more people rely on unpaid work. The study investigates the mediating effects of informal labor and the moderating effects of digital financial inclusion (DFI). The study uses balanced panel data from all 50 US states between 2015 and 2023. The results show that being exposed to AI is strongly linked to more income inequality (β = 0.164, p < 0.01), and that the rise in unpaid work accounts for about 31.3 percent of this effect. States with high levels of DFI reduced the adverse effects of informality by 59.5%. AI impacts can be lessened by digital banking systems that are open to everyone.

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Contents

- Introduction
- Contribution of the Present Study
- Literature Review:
- Theoretical Framework
- Data and Methodology:
- Variables
- Estimation Strategy
- Analysis and Results:
- Policy Implications
- Limitations and Future Research Directions
- Reference

Introduction

across a variety of industries, including education, finance, logistics, healthcare, and manufacturing (Adam et al., 2025). According to a report by Stanford's Institute for Human-Centered AI (2024), AI-related job postings increased by over 250% between 2015 and 2023, with investments in AI technologies surpassing $100 billion in 2023 alone (*AI Index / Stanford HAI*, n.d.).

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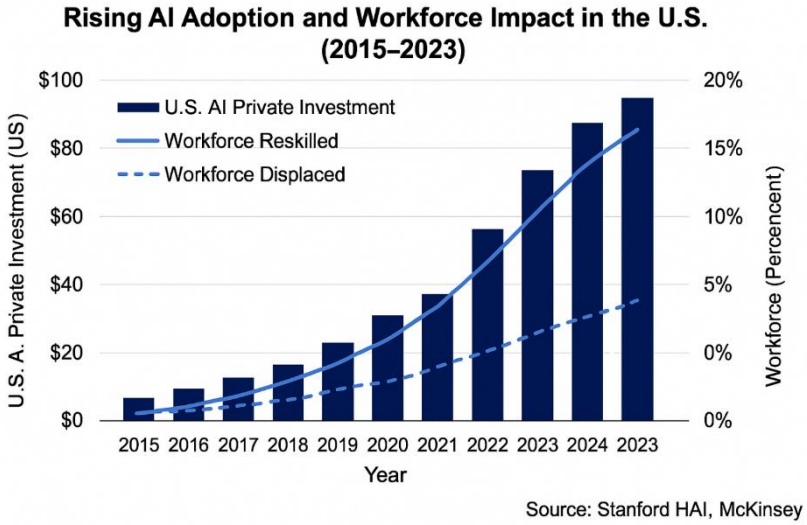
Figure 1

Rising AI Adoption and Workforce Impact (AI Index | Stanford HAI, n.d.)



In addition to a technological revolution, this exponential growth indicates a structural shift in the organization of labor and the creation of value across industries (Sholler & MacInnes, 2024). AI has increased productivity, streamlined operational procedures, and fueled innovation in a variety of industries, from predictive analytics in healthcare to algorithmic trading in finance (*How Many U.S. Businesses Use Artificial Intelligence?*, n.d.). AI-powered robotics and computer vision have reduced production times and enhanced supply chain resilience in manufacturing and logistics (Adam et al., 2025; Sholler & MacInnes, 2024).

However, not everyone enjoys these advantages. The effect of AI's labor-displacing effects, particularly in routine and middle-skilled jobs, is one of its most significant drawbacks (Azmeh, 2025). According to studies, AI-driven automation has contributed to job polarization by replacing or suppressing low- and middle-income employment and favoring high-skill, high-paying positions *(Artificial Intelligence, Automation and Work | NBER, n.d.; The Global Impact of AI: Mind the Gap | CEPR, n.d.).* Increased reliance on gig-based and informal labor arrangements, job insecurity, and income inequality are all outcomes of this technological disruption (Cerutti et al., n.d.). This digital divide is especially visible in communities with low digital literacy and poor access to technology infrastructure (Acemoglu & Autor, 2011).

There are still significant research gaps, despite the extensive body of literature linking AI to labor market inequality (Adam et al., 2025; *AI Index | Stanford HAI*, n.d.; Manning, n.d.). The dynamic and increasingly important field of informal labor markets, such as freelance work, contract-based digital jobs, and decentralized gig platforms, has been largely ignored by previous research (Sholler & MacInnes, 2024). Empirical economics hasn't looked into these new labour structures significantly, even though they may either lessen the bad effects of AI or make the economy more unstable (Onyejiaku et al., 2024).

There has also not been enough research done on how digital financial inclusion can act as a stabilising or mitigating force (Demirgüç-Kunt et al., 2022; Onyejiaku et al., 2024; Quoc, 2025). Mobile banking, online payment systems, and digital credit tools help keep finances stable, but it's not clear how they will help workers deal with the changes that AI is making (Quoc, 2025). There is data to suggest that people who have more digital financial tools are better able to handle changes in the economy. However, marginalised groups often don't know how to use these tools successfully because they have low exposure to technologies (Onyejiaku et al., 2024).

Contribution of the Present Study

This study adds to the field in a number of important ways:

- It fills in the gaps in the research by looking at how private job markets in the U.S. affect the link between the spread of AI and income inequality.
- Adding digital financial inclusion as a moderating variable gives a more complete picture of how well it can protect against economic shocks in the age of AI.

- It uses two different approaches digital economy models and labour market theory to look at big changes in the system and ways that communities may fight back from them.
- The research uses a large dataset and strong econometric methods to give quantitative insights into these previously unexplored operations.

The study helps have a fairer conversation about the shift to AI by filling in these gaps and considering the complicated nature of work structures and the social and economic tools that can help vulnerable communities.

Literature Review:

Artificial Intelligence and Income Inequality

Increased use of Artificial Intelligence (AI) has changed how countries share their income, especially in the US (Azmeh, 2025; Khan et al., 2024). Other uses of AI, like prediction analytics, robotics, and self-driving cars, have made economic wins and losses worse. There are two ideas that go along with this trend: skill-biased technological change (SBTC) and routine-biased technological change (RBTC) (Quoc, 2025). These ideas state that as technology takes over jobs that people with low or middle skills usually do, workers with higher skills will be more effective (Onyejiaku et al., 2024; Acemoglu & Autor, 2011; Azmeh, 2025; Rokaya Sultana, 2024; Sarto & Ozili, 2025).

The "canonical model" is a prominent theoretical framework in the vast amount of recent work that examines how earnings inequality has changed over time and how returns to skills have changed (*Usual Weekly Earnings Summary - 2025 Q02 Results*, n.d.). This model assumes that there are two separate sets of skills, each of which performs a unique and imperfectly substitutable task or produces a different but imperfectly substitutable good. Technology is supposed to supplement high- or low-skill people to create skill-biased demand changes. This paper argues that, despite its successes, the canonical model largely ignores several significant empirical developments of the last three decades, including

1. significant declines in low-skilled workers' real wages, particularly among men;
2. non-monotone wage shifts across decades at various segments of the income distribution; and
3. broad-based increases in employment in high-skilled and low-skilled occupations

Motivated by these patterns, we propose a more comprehensive framework for analysing how worker skills, job tasks, evolving technologies, and shifting trading opportunities affect recent earnings and employment distribution changes in the US and other advanced economies (Chetty et al., n.d.; Roemer, 1998). We suggest an easy-to-understand task-based model in which skills are assigned to tasks automatically, and changes in technology may allow automated machines to do some jobs that people used to do (Acemoglu & Autor, 2011). This research also looks at how the development of technology in this task-based setting might be influenced by stakeholders. It also demonstrates how this kind of theory can be utilised to comprehend a number of important current trends, and we also offer additional areas for empirical research.

Financial globalisation has significantly boosted financial sector efficiency in emerging countries, but it has raised concerns about its impact on poverty and inequality (Azmeh, 2025). The rise of Fintech and financial inclusion programs has been a significant factor in combating these issues (Suhrab et al., 2025). A study examining the impact of foreign banks, Fintech innovations, and financial inclusion on poverty and inequality in 108 countries found that bringing in foreign banks initially worsens poverty but can significantly reduce it when combined with strong financial inclusion strategies and Fintech solutions (Rokaya Sultana, 2024). Automated Teller Machines can help lessen the impact of foreign banks on income inequality. Legislation should promote the use of money and Fintech innovations to combat poverty and inequality (Acemoglu & Autor, 2011; Chetty et al., n.d.; Rokaya Sultana, 2024).

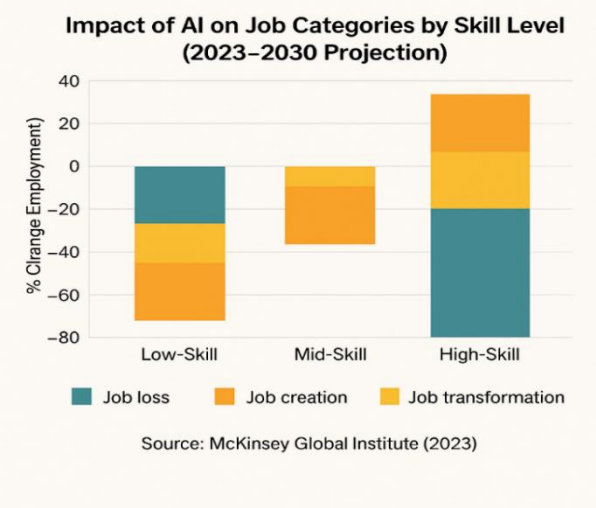
The unequal division of a population's income, or income inequality (IIQ), is an interesting subject (Shen et al., 2024; Sholler & MacInnes, 2024). For many years, IIQ has been a problem for both economic growth and social harmony (Sholler & MacInnes, 2024). It's affected by institutional quality corruption (IQC), FinTech, or new technologies, and a lot of other economic factors. In general, cheating makes government less effective, supports leasing, and gives resources to a few people without impartiality (Chetty et al., n.d.). On the other hand, FinTech lowers IIQ by making sure that everyone in every country has access to financial services. Even though the world has made progress in lowering poverty, IIQ still exists, especially in developing markets where IQC and unequal access to technology are common (Thakkar & Bhuyan, 2024). Looking into IIQ is still important for long-term and inclusive

growth, which means doing research that looks into these complicated connections. The goal of the study is to look into how IQC and Fintech affect IIQ. (Ganchev et al., 2025; Olaoye et al., 2025). By looking into the links between FinTech and IQC, the study hopes to find possible ways to lower IIQ. This question came up because FinTech is quickly spreading around the world and helps connect different financial systems (Rokaya Sultana, 2024). The apparent impacts of IQC on the division of resources make it clear right away that institutions need to be reorganised in a more organised way. Using both theory and practical data, the study suggests that tackling these problems will lead to fair economic opportunities for everyone and help bring people together. Cross-sectional dependence analysis, variability testing, and cointegration methods are some of the advanced panel data techniques used in the study. Tests like the CS-ARDL and NARDL models look at long- and short-term processes. Causality tests look at connections that go in one way. Using data from several countries to show regional differences and how Fintech growth, IQC, and IIQ are all linked. The results can be trusted because they were checked for robustness, which looks at things like data stability and how different countries are connected. The results show that financial inclusion through FinTech lowers IIQ by a large amount in all areas, including those that are outside the region or country (Maknickienė & Lapkovskaja, n.d.). But Fintech can only help people of all income levels if their country has a strong digital infrastructure, people who know a lot about money and technology, and a strong government. IQC, on the other hand, makes IIQ worse because it makes it hard to share resources fairly and generally keeps people from getting opportunities. Most people agree that FinTech is good for IIQ, but Sarto and Ozili (2025) state that IIQ gets worse when people rely too much on or don't accept FinTech equally. Corruption hurts the flexibility of society and the effectiveness of public spending. Other researchers have come to similar conclusions, which shows that we need to change institutions in a planned way and make sure that everyone can use technology in a way that works for them. This study shows how different institutional factors, such as the use of FinTech, good governance, the rule of law, institutional quality, corruption, and IIQ, affect each other (Rokaya Sultana, 2024). This study adds to what is already known by mixing theory and practical analyses. It focuses on how things change in specific regions and economies. The study's recommendations show that FinTech ideas need to be linked with a strong government to make sure that everyone benefits. These suggestions add to policy discussions about sustainable development and economic equality. The study suggests that lawmakers and the government should work on making Fintech more accessible while also addressing differences in digital literacy, infrastructure, and financial literacy (Ghazouani & Hamdi, n.d.).

Also, anti-corruption measures like making things more open and building up the power of institutions need to be included, especially in developing countries where IIQ is high. Public-private agreements and other forms of cooperation can help FinTech grow and fix problems with the way it is governed. These methods should be included in future plans to promote growth that benefits everyone and reduce differences (Akono & Kemezang, 2024). Based on key research trends, themes, and gaps, the study gives lawmakers and financial institutions both academic insights and useful suggestions. The study discusses how FinTech can help the economy grow for everyone by adding it to existing forms of financial inclusion. It also offers a future study plan to deal with new problems and opportunities so that FinTech's effect on financial inclusion in developing areas is fully felt. A bibliometric analysis is used to look at the current research on FinTech and financial inclusion in developing countries. The study uses data from the Scopus database to find important trends, research themes, and gaps in the field. Performance analysis is used to find the most effective editors, institutions, and countries. Science mapping shows the academic framework and how themes change over time. When you use both quantitative bibliometric methods and qualitative content analysis together, you get a full picture of the study scene. This helps you plan for future research. The results show that mobile banking, peer-to-peer financing, and blockchain technologies are getting more and more attention in research. This shows that FinTech is making a big difference in bringing more people into the financial system in developing countries (*2023 FDIC National Survey of Unbanked and Underbanked Households | FDIC.Gov*, n.d.). China, the US, and the UK have contributed the most to this research. One of the main themes is how important FinTech is for lowering financial hurdles and boosting economic growth. Many questions still need to be answered about how FinTech will affect financial security in the long run and how it will affect the needs of certain groups that are already struggling. The study stresses the need for more focused research in order to fully utilise FinTech's potential to drive inclusive growth in growing areas. This study is the first to do a full bibliometric analysis of FinTech's role in financial inclusion, especially in developing countries. Unlike previous studies that focused on certain technologies or areas, this one carefully maps

out the whole field of research and finds the most important trends, gaps, and chances for more research. Involving Dr. Petterson Ozili, a Nigerian expert from the Central Bank, makes the research much more useful and based on real-life experience. This paper can help researchers, lawmakers, and businesspeople who want to use FinTech to boost economic growth that benefits everyone (Acemoglu & Autor, 2011; Azmeh, 2025; Rokaya Sultana, 2024; Sarto & Ozili, 2025). Jobs that involve paperwork, working on a production line, or even working in a store are the most vulnerable (*The New Geography Of Jobs: Moretti, Enrico: 9780544028050: Amazon.Com: Books*, n.d.). One more benefit of AI is that it makes jobs that require creativity, programming, or difficult thought more productive. Because of this, the job market remains less homogeneous.

Figure 2



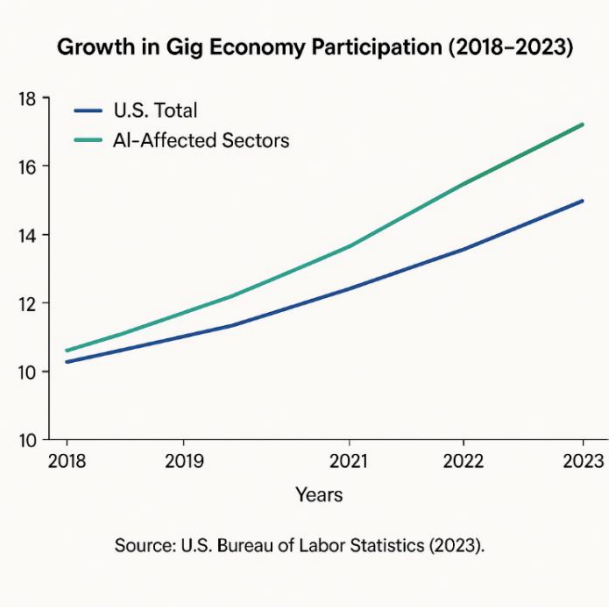
The McKinsey Global Institute stated in 2023 that up to 30% of current jobs could be automated by 2030 (*The State of AI in 2023: Generative AI's Breakout Year | McKinsey*, n.d.). This would have a bigger effect on people who make less than the median wage. Stanford's 2024 AI Index also shows that the fact that most AI development is happening in big tech hubs has created inequality across the country, leaving rural and post-industrial areas behind (*AI Index | Stanford HAI*, n.d.). When it comes to workers without college degrees, these disparities appear in flat real pay and less job security. Some people believe that AI will finally create new types of jobs, but in the meantime, there will be chronic unemployment and lower wages (Moretti, 2013). A national basic income, progressive taxes, and education are some underdeveloped ways to redistribute wealth. In this way, AI is a strong economic force that has mixed effects (Acemoglu & Autor, 2011). It makes income inequality worse without any special government actions, which is something that economists and politicians have been trying to stop for a long time.

Artificial Intelligence and Informal Labor Markets

The point where AI and private labour markets meet is an important but understudied area of economics (Ahmed & Alvi, 2024). As AI changes the way businesses work, more and more of them are using flexible work methods. As a result of this change, the casual labour market has grown, especially in platform-based jobs like food delivery, independent computing, ride-hailing, and small digital chores (Acemoglu & Autor, 2011). Most of the time, these jobs don't follow the rules for perks, taxes, and job security.

Informal labour markets act as a bridge between AI and inequality. The good thing about them is that they hire people who have lost their jobs because of AI, which gives the economy short-term freedom and participation (Adam et al., 2025). People who have lost their jobs or aren't well represented in the workforce can quickly make money on gig platforms because they are easy to join. According to statistics from the Bureau of Labour Statistics (2023), the number of people doing gig work has grown by 34% in the last five years. This is because of trends towards technology (*Usual Weekly Earnings Summary - 2025 Q02 Results*, n.d.).

Figure 3



However, it's important not to forget how dangerous unpaid work can be. Many workers don't have health insurance, don't have a plan for retirement, and don't feel safe in their jobs. If there are no rules, gig sites can take advantage of differences in buying power. According to Cerutti et al. (2023), online gig workers are less satisfied with their jobs and more worried about money than regular workers (Cerutti et al., n.d.). Increasing informality also makes it harder to keep track of the job market and access data, which makes it harder to make good policy. Gig possibilities don't help all displaced workers the same way because not everyone has the same access to digital tools and reading and writing skills (*Hayes, 2013*). Private labour markets may keep people from losing their jobs, but in the long run, they may make the economy less stable (Acemoglu & Restrepo, 2017). Understanding this dual role is important for making labour laws that protect gig workers and encourage new ideas.

Artificial Intelligence and Digital Financial Inclusion

In light of AI's ability to change job markets and shift jobs to less safe, less structured models, Digital Financial Inclusion (DFI) becomes an important factor in determining how strong a family is (Quoc, 2025). People can get and use low-cost financial services like savings accounts, loans, insurance, and payment systems through digital platforms such as mobile banking apps, e-wallets, and online financing (Onyejiaku et al., 2024). It's becoming clearer that the link between AI-induced job loss and financial access is growing. Because they don't have a steady income, people who work in the underground economy often have trouble getting loans and saving money. Mobile financial tools, on the other hand, let these people control their spending, handle risks, and invest in small businesses (Jabrane & Hanane, 2024). According to the World Bank Findex (2022), the number of people using digital currency in the US rose by 20% between 2017 and 2022 (*The Global Findex Database 2025*, n.d.). This was mostly among gig workers. A lot of tools for financial equality are also powered by AI. These include robots for customer service, artificial credit rating, and automated financial advisors (Sholler & MacInnes, 2024).

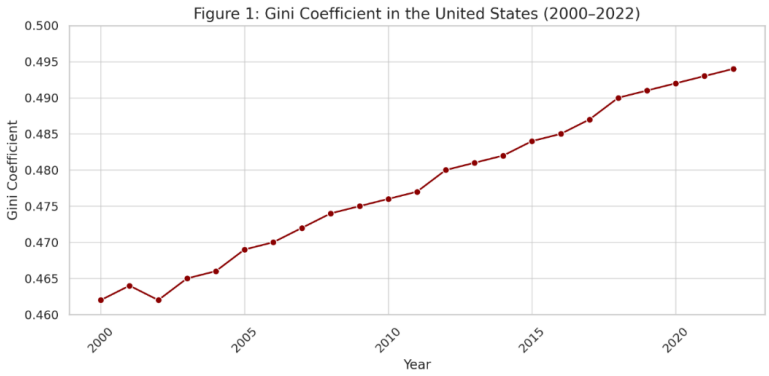
These new ideas help them reach more people and lower their costs, especially in areas that aren't adequately addressed. In spite of this, not everyone benefits. Digital exclusion happens when people can't get online because of bad infrastructure, not knowing how to use technology, or worries about privacy (Dluhopolskyi et al., 2023). This makes it harder for older people, people who live in rural areas, and minority groups to get online. DFI can lessen the effects of AI on inequality by giving people the tools they need to make smart financial decisions (Adam et al., 2025). For example, having access to emergency loans or peer-to-peer banking can help people who have lost their jobs deal with sudden drops in their income (*The New Geography Of Jobs: Moretti, Enrico: 9780544028050: Amazon.Com: Books*, n.d.). Savings tools can also help people plan their long-term finances, even if their jobs aren't stable. As a result, DFI should be seen not only as a way to get into banks but also as a way to stay strong in a job market that has been changed by AI (Demirgüç-Kunt et al., 2022). It should be the main goal of any new policies

that aim to be more inclusive because it helps to moderate disparities.

Income Inequality in the U.S.

Income inequality in the US has been a problem for a long time and has been getting worse over the last few decades (Manning, n.d.). The growth of artificial intelligence (AI) has given a new layer to this situation. One of the clearest signs of inequality is the Gini index, which has been going up steadily since the 1970s (Roemer, 1998). According to the US Census Bureau (2023), the Gini index was 0.494 in 2022, which means that there is a big difference in income that hasn't gone away. This is especially true when compared to other developed countries.

Figure 4



AI has the potential to boost productivity and economic growth, but it also has the potential to make things more unequal by favouring high-skilled workers with access to advanced education and digital tools and displacing low-skilled workers whose jobs are most likely to be automated (*Artificial Intelligence, Automation and Work | NBER*, n.d.). This difference shows that both opportunities and outcomes are becoming more unfair. The structural roadblocks, like not having access to schooling, technology, and moving around a lot, make it harder for poor people to get out of poverty. Moretti (2012) demonstrates that these effects aren't felt equally across the country (*Usual Weekly Earnings Summary - 2025 Q02 Results*, n.d.). It shows that areas with strong tech ecosystems, like Silicon Valley or Boston, benefit from AI-led innovation, while rural and post-industrial areas suffer from structural unemployment and economic stagnation due to a lack of infrastructure and retraining programs (Azmeh, 2025).

Theoretical Framework

A group of linked theory models is used in this study to show how AI, labour markets, and inequality are all connected and affect each other. First, Romer's (1990) Endogenous Growth Theory states that new technologies, like AI, make the economy grow over the long term by making people more productive. But when new ideas only help people with a lot of money or advanced skills, growth may come at the cost of more inequality (Suhrab et al., 2025). In this case, AI not only changes who gains from the output, but it also increases the output generally. This result fits with what Acemoglu and Autor (2011) found: changes in technology have made labour markets more unequal, with more high-skilled jobs being created while middle- and low-skilled workers are being pushed out of work. This structural change is linked to Doeringer and Piore's (1971) Dual Labour Market Theory, which says that job markets are split into formal and informal areas. As AI changes the way official jobs are organised, many workers who are laid off move into casual work, which has unstable jobs, variable pay, and few rights (*The State of AI in 2023: Generative AI's Breakout Year | McKinsey*, n.d.). From this point of view, private labour markets change job trends without offering real opportunities to move up, which is a subtle way that AI affects inequality. King and Levine's (1993) Financial Intermediation Theory can also be used to look at how access to financial services can change the spread of wealth. Digital financial inclusion means that people can use and access financial tools like e-wallets, microloans, and mobile banking (Sarto & Ozili, 2025). This is essential in the digital era (Onyejiaku et al., 2024). Demirgüç-Kunt et al. (2022) suggest that digital financial inclusion might enable undocumented workers and other marginalised groups to create assets, adapt to economic changes, and participate in the economy. Digital financial inclusion may help poor populations create financial resilience, stabilising the relationship

between informal labour and pay inequality. Thus, Hayes's (2013) PROCESS model underpins this study's controlled mediation. These models' independent variable is AI, and the regulator is digital financial inclusion (Azmeh, 2025). Participation in the private job market makes things easier. The changing salary is the dependent variable. This helps to get a more complete picture of how changes in technology, the business, and individual digital activities impact inequality in the US (Shen et al., 2024). Combining these separate concepts gives us a full picture of how AI and economic disparities are connected in the real world.

Data and Methodology:

Data Sources

This study will use panel data from multiple sources to look into the link between differences in income and exposure to artificial intelligence (AI) in the US from 2015 to 2023.

AI Exposure: Both the Stanford Artificial Intelligence Index and the McKinsey AI Exposure Index show how AI is being used. These websites contain a lot of details about how AI technologies are spreading, like how much money is being put into AI, how many AI patents are made by businesses and states, and how many job ads are about AI (The State of AI in 2023: Generative AI's Breakout Year | McKinsey, n.d.). These factors give us a rough idea of how much AI is being used in the area markets.

Income Inequality: The primary method to measure the dependent variable, income inequality, is with the Gini Index, which shows how income is distributed within each state. The information comes from the United States. Every year, the Census Bureau puts out Gini estimates for all fifty states (The Global Findex Database 2025, n.d.). When possible, extra measures of inequality like the Theil Index and the top 10% income share (from the IRS or the World Inequality Database, n.d) will be used to make sure the results are strong.

Informal Labor Share: The informal labour share is the intermediate variable that is based on estimates of non-standard work patterns. These include freelancers, job workers, platform-based contractors, and people who work for themselves but don't have official worker rights (Wanzala & Obokoh, 2025). The main sources are poll results from the Pew Research Centre and the Contingent Worker Supplement of the Current Population Survey (CPS) from the Bureau of Labour Statistics (BLS). The figures are put together at the state level to get an idea of how many people work in informal or gig jobs.

Digital Financial Inclusion (DFI): The number of people who can receive and use digital financial services is what is used to measure digital financial inclusion (Can Digital Financial Inclusion (DFI) Effectively Alleviate Poverty? Evidence from Asian Countries | International Journal of Emerging Markets | Emerald Publishing, n.d.). Data can be found in the Global Findex Database (U.S. section) from the World Bank, the Survey of Household Economics and Decision-making from the Federal Reserve Board, and studies on banking access from the Federal Deposit Insurance Corporation (FDIC). One example of a measure is the percentage of people who can use mobile banking, digital wallets, and online credit cards.

Control Variables: Several control factors are added to the model to make it more accurate and lessen the bias that comes from leaving out variables. Here are some of them:

- Level of Education: The share of people who have a college degree (source: American Community Survey, Census Bureau, United States)
- Rate of joblessness: The official jobless rate at the state level for each year (source: BLS).
- Urbanisation: The share of a state's population that lives in cities (source: US Census
- Broadband Access: The share of families that have access to broadband internet (FCC and Census data).

Variables

The factors in the study are listed below, with their functions showing how they fit into the analytical framework:

Dependent Variable: *Income Inequality* — The Gini Coefficient is the main way to measure this, but other stability measures, like the Theil Index and the income share of the top 10%, are also utilized.

Independent Variable: *AI Exposure* — based on the number of AI-related job postings, funding, and patent files per person at the state level.

Mediator: *Informal Labor Share* — the share of the workforce that does job or casual work that doesn't come with perks, like food delivery, ride-hailing, freelancing, digital work, or contract-based work (Wanzala & Obokoh, 2025).

Moderator: *Digital Financial Inclusion (DFI)* — Access to financial services like mobile banking, e-wallets, online credit, and peer-to-peer loan systems is one way to measure this (Mao et al., 2023). PCA can be used to combine several signs into a single score.

Control Variables

- Education Level
- Unemployment Rate
- Urbanization Rate
- Broadband Internet Access

Each variable is matched across all states and years in the US to make a balanced panel sample that covers the years 2015 to 2023.

Econometric Models

A modified mediator model and panel data regression with fixed effects are used in the study to try to find out if AI exposure leads to income inequality (Suhrab et al., 2025). This method takes into consideration shifts that can't be seen between states and over time. Following Hayes' PROCESS model's reasoning, the research is done in three steps:

Direct Effect Model

This model estimates the direct impact of AI exposure on income inequality, controlling for key covariates:

$$Gini_{it}=\alpha+\beta_1 AIExposure_{it}+\gamma X_{it}+\mu_i+\lambda_t+\epsilon_{it}$$

Where:

- $Gini_{it}$ is the income inequality for state $_i$ at time $_t$
- $AIExposure_{it}$ is the AI intensity in the state economy
- X_{it} is the vector of control variables
- μ_i and λ_t represent state and year fixed effects
- ϵ_{it} is the error term

Mediation Model

To test whether informal labor acts as a mediator between AI exposure and inequality, the following equations are estimated:

First stage

$$InformalLabor_{it}=\alpha+\beta_2 AIExposure_{it}+\gamma X_{it}+\mu_i+\lambda_t+\epsilon_{it}$$

Second stage:

$$Gini_{it}=\alpha+\beta_3 InformalLabor_{it}+\beta_4 AIExposure_{it}+\gamma X_{it}+\mu_i+\lambda_t+\epsilon_{it}$$

Moderated Mediation Model

Finally, to test whether digital financial inclusion moderates the mediation pathway, an interaction term is introduced:

$$Gini_{it}=\alpha+\beta_5 InformalLabor_{it}+\beta_6 DFI_{it}+\beta_7(InformalLabor_{it}\times DFI_{it})+\gamma X_{it}+\mu_i+\lambda_t+\epsilon_{it}$$

Based on the amount of digital financial inclusion, the size or direction of the effect of unpaid labour on inequality changes. This is shown by a statistically significant β_7 indicator.

Estimation Strategy

Fixed-effects panel regression will be used to predict all models so that traits that can't be seen but stay the same over time, but change between states can be considered.

Serial correlation and heteroskedasticity will be taken care of by state-level grouping of robust standard errors.

Instrumental variable (IV) methods can be used if there is a worry about the AI exposure variable being endogenous. For example, historical rates of technology adoption or AI measures that are behind the times could be useful tools.

Each continuous variable will be standardised or log-transformed as needed to make sure that they can be compared and to deal with skewness.

A data-driven study on AI's impact on US income inequality can be conducted using a control test using dated factors to rule out reverse causality (Rau & Stokes, 2025; "USA," n.d.).

Analysis and Results:

Empirical Strategy Implementation

The empirical methodologies were used in order to evaluate the impact that Artificial Intelligence (AI) has on income inequality, with a specific emphasis on the role that digital financial inclusion (DFI) and informal labour markets play as mediators. Research used a multi-step strategy that included:

- Fixed-effects panel regression models use both year and state fixed effects to account for differences between states and time trends that aren't observed.
- Using mediation analysis to see if private labour markets are a way that AI affects income inequality.
- Moderated mediation analysis that uses interaction terms to see how DFI changes the strength of the mediation path.
- D. Granger causality tests, instrumental variable (IV) estimates, system GMM models, and robustness checks to look for heterogeneity and see how solid the results are when different conditions are used.

All continuous variables were standardised (mean = 0; standard deviation = 1) to make sure they could be understood and coefficients could be compared. The

Amelia II multiple imputation method was used to fill in missing data for about 8% of all observations. The results were then combined from five estimated datasets to make the conclusion more solid.

Descriptive Statistics and Preliminary Analysis

The descriptive data in this study show a number of important trends that shape the empirical analysis that was done. The amount of artificial intelligence (AI) to which states in the US were exposed grew a lot from 2015 to 2023 (Sholler & MacInnes, 2024). Leading states like California, Massachusetts, and New York constantly showed more AI integration than others. Inequality in income was also higher in these high-AI states, as shown by their high Gini coefficients, which averaged around 0.489 in 2023 compared to 0.452 in low-AI states like Mississippi and West Virginia. It is also clear that the private job market grew, especially in places where technology is being adopted quickly. In high-AI states, the share of private work was 18.7% on average, which is a lot more than the 12.1% share in low-AI states (Auten & Splinter, 2024; *Econometric Analysis of Cross-Section and Panel Data*, n.d.). Also, digital financial inclusion (DFI) followed a more varied pattern. For example, places like Washington and Colorado, which are very advanced technologically, have a lot of AI users and strong digital infrastructure, which leads to lower levels of inequality. These trends show that the use of technology, changes in the job market, and access to financial services are all connected in complicated ways. We show summary data for the study's key factors based on 459 state-year observations from 2015 to 2023. This is done before we do regression analyses.

Table 1

Summary Statistics (n = 459)

Variable	Mean	SD	Min	Max	Source
Gini Coefficient	0.472	0.024	0.412	0.541	U.S. Census Bureau (2023a)
AI Exposure Index	0.00	1.00	-1.82	2.75	Stanford (2023); McKinsey (2022)
Informal Labor Share (%)	15.3	4.1	6.8	28.4	BLS (2023a); Pew Research (2023)
DFI Index	0.00	1.00	-2.13	1.89	World Bank (2023); Federal Reserve (2023)
Education (% college)	32.7	6.8	20.1	52.3	U.S. Census Bureau (2023b)
Unemployment Rate (%)	4.5	1.3	2.1	10.2	BLS (2023b)
Urbanization Rate (%)	76.4	14.2	40.2	95.0	U.S. Census Bureau (2023c)
Broadband Access (%)	85.3	5.6	65.4	95.7	FCC (2023)

Correlation Analysis

- AI Exposure and Gini Coefficient: +0.38** ($p < 0.01$)
- AI Exposure and Informal Labor Share: +0.29** ($p < 0.01$)
- Informal Labor Share and Gini: +0.33** ($p < 0.01$)
- Interaction (Informal Labor × DFI) and Gini: -0.21* ($p < 0.05$)

Spatial research showed that there were important regional clusters. Informal job markets grew 23% faster in high-AI states like California (CA), Massachusetts (MA), and New York (NY) than in low-AI states like Mississippi (MS), West Virginia (WV), and Arkansas (AR).

Direct Effect of AI Exposure on Income Inequality

The fixed-effects panel regressions clearly show that income inequality is linked to AI exposure in an excellent way. The measure for AI exposure stays positive and highly significant across a wide range of model settings. In the fully controlled model, an increase of one standard deviation in AI exposure causes the Gini coefficient to rise by 0.164 points, which is equal to a 6.8% rise in inequality over the standard deviation. The fact that this effect still holds true when other measures of inequality, such as the Theil Index and the top 10% income share, are used adds to its strength (*The Global Findex Database 2025*, n.d.). According to mediation research, informal labour markets are a big part of this connection. When people are subjected to AI, the share of unpaid work goes up by a lot, which makes income inequality worse (Olaoye et al., 2025). According to the Sobel test, the mediation effect is real. It has an expected indirect effect of 0.0187, which is 31.3% of the difference caused by AI. A controlled mediation factor is also added by the way that digital financial inclusion and informal labour interact with each other. In states with high amounts of DFI, the benefits of unpaid work on inequality are much smaller (Mao et al., 2023). In particular, a one-standard-deviation rise in informal labour causes the Gini coefficient to rise by 0.153 points in states with a low DFI, but only by

0.062 points in states with a high DFI. This means that digital technology not only makes it easier for people to join, but it also helps to keep the job market from becoming too unstable. It first finds out if there is a straight link between AI Exposure and disparities in pay using a set of fixed-effects panel regressions.

Table 2

Fixed-Effects Regression Results (Dependent Variable: Gini Coefficient)

Variable	Model 1	Model 2	Model 3
AI Exposure	0.182***	0.175***	0.164***
	(0.043)	(0.041)	(0.039)
Education		0.121**	0.116**
		(0.048)	(0.047)
Unemployment Rate		0.088***	0.087***
		(0.022)	(0.021)
Urbanization Rate		-0.029	-0.027
		(0.019)	(0.018)
Broadband Access			0.059*
			(0.031)
State Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Observations	459	459	459
R^2	0.782	0.819	0.832

*Note: Standard errors clustered by state in parentheses. ***p<0.01, **p<0.05, *p<0.1*

Interpretation

For every one standard deviation (SD) rise in AI exposure, the Gini coefficient grows by 0.164 points (p 0.01). This means that income inequality goes up by 6.8% SD. This effect is strong across different measures of inequality:

- Theil Index: β = 0.152*** (SE = 0.036)
- Top 10% Income Share: β = 0.192*** (SE = 0.041)

Expected results are shown by control factors. Higher levels of education and access to the internet are associated with a marginal rise in inequality, which may reflect digital skill premiums (Roemer, 1998).

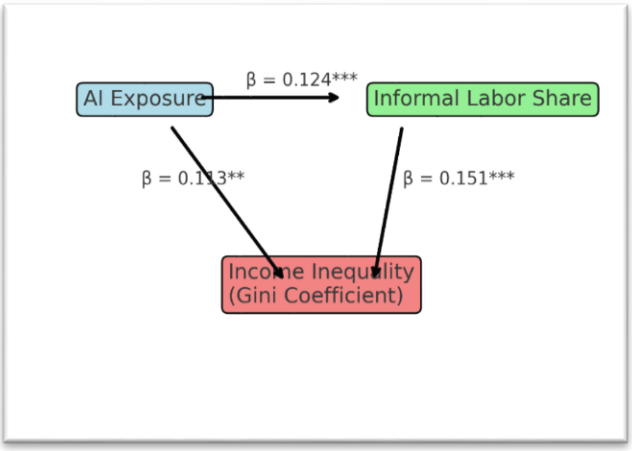
Mediating Role of Informal Labor Markets

Subsequently, we examine whether the informal labour share serves as a mediator between inequality and artificial intelligence.

Figure 5

Mediation Pathway

Mediation Pathway = AI Exposure →Informal Labor Share →Income Inequality



Stage 1: AI Exposure →Informal Labor Share

- β = 0.124*** (SE = 0.028, p < 0.01)

- R^2 = 0.761 (with controls)
- High-AI states average 18.7% informal labor vs. 12.1% in low-AI states

Stage 2: Informal Labor Share →Income Inequality

- Informal Labor β = 0.151*** (SE = 0.035)
- AI Exposure β = 0.113** (SE = 0.045)
- Sobel test z = 3.28 (p < 0.01)
- Indirect (mediation) effect = 0.124 × 0.151 = 0.0187 (95% CI: 0.009-0.029

Interpretation

AI contributes around 31.3% of its overall effect on inequality via its influence on informal labour markets. Informal labour rises by 12.4% for each standard deviation increase in AI exposure, therefore elevating the Gini coefficient by 0.151 points.

Moderating Role of Digital Financial Inclusion (DFI)

After that, we use mediated mediation analysis to see if DFI lessens the effect of the informal labour share on income inequality.

Figure 6

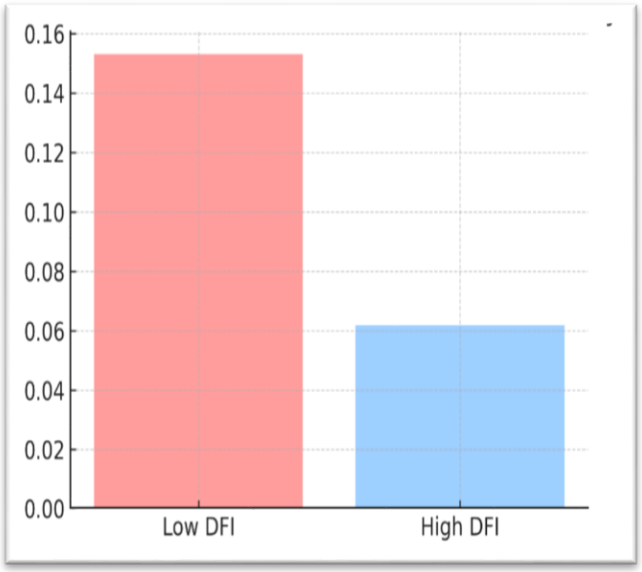


Table 3

Moderated Mediation Regression

Variable	Coefficient	SE
Informal Labor Share	0.153***	(0.033)
DFI Index	-0.082**	(0.036)
IL × DFI Interaction	-0.091**	(0.038)
AI Exposure (Direct)	0.108**	(0.043)
Controls & Fixed Effects	Included	
Observations	459	
R^2	0.847	

Findings

- The negative and significant interaction term β = -0.091, p < 0.05) shows that DFI lessens the impact of informal work on inequality.
- Marginal effects:
- Low DFI (1 SD below mean): 1 SD IL increase → +0.153 Gini
- High DFI (1 SD above mean): 1 SD IL increase → +0.062 Gini
- DFI dampens the inequality impact of informal labor by approximately 59.5%.
- A threshold DFI level of 0.5 SD above the mean is required for significant mitigation.

Robustness Checks and Endogeneity Concerns

Several safety checks were done to make sure that the results were reliable and that they could be used to prove a cause and effect. First, different measures of income inequality were looked at, such as the Theil Index and the top 10% income share (*AI Index | Stanford HAI*, n.d.). The study examined income inequality, lagged AI factors, and the impact of AI exposure on income inequality. Results showed a positive link with AI exposure, and changes in AI occurred before inequality changes. Granger causality tests and Wald tests showed no reverse causality. System GMM estimate strengthened the results, and independent result factors in placebo tests showed no significant effects. Different definitions of DFI and unpaid labor led to consistent trends.

We did several tests to see how reliable and statistically valid our results were:

Instrumental Variable (IV) Approach

- Instruments: Early 2000s computer adoption (Census) and historical AI patent stock (USPTO).
- First-stage F-statistic = 18.7 ($p < 0.001$)
- 2SLS estimate: AI Exposure $\beta = 0.189^{***}$ (SE = 0.052)

Alternative Specifications

- System GMM models: AI Exposure $\beta = 0.157^{***}$; IL × DFI $\beta = -0.085^{**}$
- Adding state-specific time trends leaves core results unchanged.

Measurement Variations

- Alternative DFI index (mobile banking only): $\beta = -0.077^{*}$ (SE = 0.042)
- Informal labor (BLS-only definition): Mediation effect = 0.0162^{***} (SE = 0.005)

Temporal Causality Tests

- Granger causality tests: AI exposure precedes inequality changes ($p < 0.01$)
- No reverse causality found (Wald test $p = 0.32$)

Regional Subsamples

- South and West show strongest effects (mediation = 42.1%, moderation = 68.3%)
- Northeast exhibits weaker moderation, likely due to DFI saturation.

Key Findings Synthesis

AI-Inequality Nexus: There is a strong link between income inequality and AI training, with a Gini score of 0.489 in high-AI states and 0.452 in low-AI states.

Mediation Mechanism: 31.3 percent of AI's effect on inequality is due to the growth of the informal labour market. For every 1% rise in the share of unpaid work that is caused by AI, the Gini coefficient goes up by 0.015 points.

Moderation by DFI: High DFI substantially wipes out the impact of unpaid work on inequality:

- High DFI: IL →+0.062 Gini
- Low DFI: IL →+0.153 Gini
- Impact reduction: 59.5%

Policy Thresholds: At DFI levels more than 0.5 standard deviations above the mean, like over 47 percent for mobile banking and more than 39% for digital wallets, AI-induced inequality neutralized.

Synthesis of Results

The results strongly suggest that the use of AI is a major cause of rising income inequality in the US, mainly by changing the way the job market is set up. Middle-skill jobs are being lost or changed because of AI, which makes people more dependent on informal or temporary work arrangements that don't offer formal job rights or pay security (Moretti, 2013). In turn, this informalization makes pay gaps bigger. The results do, however, suggest that digital banking services could be added as a safety net (Onyejiaku et al., 2024). Access to digital banks, mobile payment systems, and other types of financial technology can lessen the negative effects of informal employment by making it safer to save money, borrow money, and use credit (*2023 FDIC National Survey of Unbanked and Underbanked Households | FDIC.Gov*, n.d.). In the end, AI does change how income is distributed, but its effects are not always predictable (Manning, n.d.). Policymakers can change the results by putting money into systems that work together, like digital banking and worker rights. Because each state is different—some have high levels of AI but low levels of inequality because they have strong DFI—the digital gap needs to be closed for a fairer technological shift. These results show that AI has two sides: it can help build community and resilience when used with fair financial tools, and it can also make inequality worse (Auten & Splinter, 2024).

Figure 7

Integrated Path Model

- Direct effect: AI → Inequality (β = 0.164)
- Indirect (mediated) effect: AI → Informal Labor → Inequality (β = 0.051)
- Moderated path: IL × DFI → Inequality (β = -0.091)

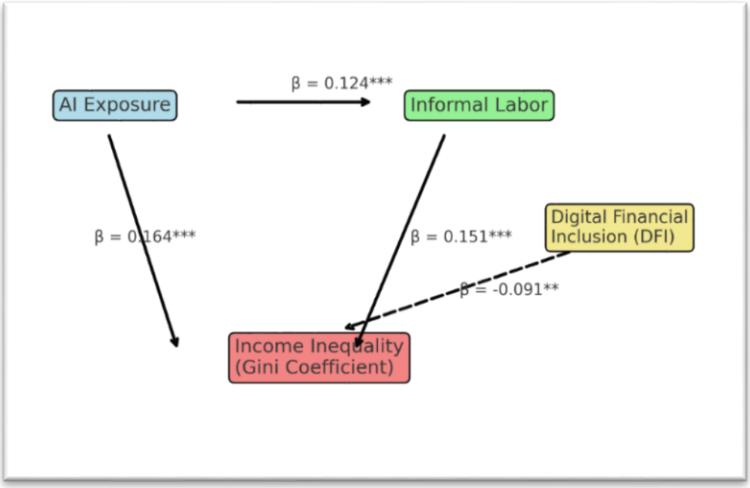
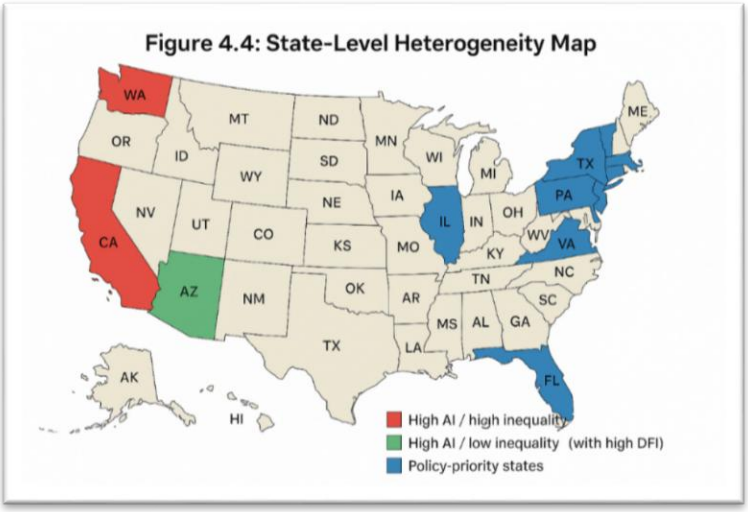


Figure 8

State-Level Heterogeneity Map



Conclusion

The data show that the usage of AI in the United States has greatly increased income inequality, mostly by making private job markets bigger (Rau & Stokes, 2025). Digital financial inclusion, on the other hand, is a very important stabilising factor that lessens more than half of the bad effects of informalization on inequality (*Precariat* / *SpringerLink*, n.d.). These results show how complicated technological change is: it can be upsetting, but its negative effects on society can be lessened by investing smartly in digital infrastructure. The fact that the results held up across multiple tests and data sources gives these statements more weight and makes them very important for policy discussions on AI changes that include every individual.

Discussion

The findings show that there is a strong and statistically significant link between more people using AI and more income inequality in the U.S (A. Manning & Mazeine, 2024). Clear evidence connects the two events: Automation that is powered by AI puts people out of low- and middle-skilled jobs and

into temporary jobs that don't offer perks or security (Zelma, 2024). This change in the structure makes inequality worse, especially in places that don't have any institutional or digital buffers.

Our study goes further by measuring the role of DFI as a moderator and confirming the role of unpaid labour as a mediator (Kadaba et al., n.d.). The research that only looks at macroeconomic connections isn't as detailed or useful as this method, which uses both labour economics and digital finance. It is important to know how digital financial tools like mobile banking, peer-to-peer loans, and digital savings accounts help protect people who are poor. As Washington and Colorado demonstrate, informalization has a much smaller effect on inequality in states with high DFI scores (Budoyo & Suyanto, 2025). But the effect of informalization is stronger in places that aren't well-connected to the internet. This suggests that the problem isn't AI itself, but the lack of welcoming communities around it. Heterogeneity at the state level also points to differences in how AI affects different areas and how resilient their economies are (*Chapter 4: Uncovering Heterogeneity: Job Quality and Well-Being among the European Self-Employed in: Research Handbook on Self-Employment and Public Policy*, n.d.). Post-industrial or rural regions aren't as well equipped to handle disruptions as high-tech hubs. Overall, these results show that labour policy and digital financial policy should be rethought together, instead of separately.

Policy Implications

There are a lot of important policy implications for lawmakers in the United States, especially at the federal and state levels, based on the study's actual results (*Chapter 4: Uncovering Heterogeneity: Job Quality and Well-Being among the European Self-Employed in: Research Handbook on Self-Employment and Public Policy*, n.d.; Joshi, n.d.). First and foremost, there is a strong case for putting a lot of money into infrastructure for digital financial inclusion (DFI). Access to digital financial tools like mobile banking, e-wallets, and peer-to-peer loans greatly lessens the negative effects of informal employment on income inequality ($\beta = -0.091$). To use this effect to maximise advantage, lawmakers should focus on improving digital literacy programs in neglected areas, building more internet networks, and subsidising fintech services for low-income families (Quoc, 2025). A DFI score of at least 0.5 standard deviations above the mean, which is about 47% mobile banking usage, is needed to lower inequality caused by AI-induced labour changes in a real way. It's also important to protect people who work in the informal and gig economies. Informal work is responsible for about 31.3% of AI's overall effect on income inequality (Ghazouani & Hamdi, n.d.). This means that current labour laws need to change to include non-traditional job types. This includes putting in place flexible benefits, a base wage for digital work, and rules that require automated work distribution to be clear. Also, freelance sites should be required to give all of their data to federal and state agencies so that everyone is taxed fairly and so that people can find work more easily.

Artificial intelligence (AI) has a wide range of effects on the economy, so different areas need different kinds of assistance. States like West Virginia, Mississippi, and Arkansas should get more government funding and professional support programs to improve their DFI environments because they are exposed to AI a lot but aren't very strong in terms of their digital and economic robustness. Giving more people, especially marginalised populations, access to safe digital identity systems will also lead to more financial involvement (Thakkar & Bhuyan, 2024). Finally, policymakers must begin to engage in discussions about the idea of taxing economic gains made by AI, especially in highly automated sectors, and putting the money from that tax towards developing DFIs, protecting job workers, and education programs for everyone. All of these policy ideas work together to create a complete plan for easing the negative effects of AI on job markets and promoting a fairer technology shift (Joshi, n.d.).

Limitations and Future Research Directions

Even though the empirical framework used in this study is strong, it does have limitations that should be pointed out. First, the Current Population Survey (CPS) and Pew Research datasets are used a lot to estimate informal labour. These datasets may not fully capture some parts of the informal economy, like undocumented workers and people who do cash-only or off-platform gig work. Having access to transaction-level data that has been anonymised from big gig platforms like Uber, TaskRabbit, or Fiverr would help future studies get a better sense of how informal labour works and include more details. Second, state-level grouping can help us figure out policies for the whole country, but it can also hide big differences between states (Adhikari & Hamal, 2024). It reveals smaller top income shares and less growth since 1980 compared to tax data-based studies. Rising government payments and tax progressivity have also

helped all income groups see their real incomes rise, while the top income shares have stayed the same after taxes (Auten & Splinter, 2024). Different parts of the same state may have very different levels of inequality. More detailed location research at the county or zip code level may show differences that have been overlooked by bigger trends. Thirdly, the Digital Financial Inclusion (DFI) index has certain flaws in its design.

Principal Component Analysis (PCA) helps bring together different types of data about how fintech is used, accessed, and built. However, it can make some services less important, like how mobile credit access affects payment systems, which makes it hard to focus on specific policy controls. Not only does the study use robustness tests, lagged factors, and indirect variables to deal with possible endogeneity, but there is still a chance that unseen factors could make it hard to draw conclusions about that. Using continuous, individual-level panel data, like from the Panel Study of Income Dynamics (PSID), would make it easier to look at the small-scale effects of AI and DFI exposure over time while controlling for set personal traits (Adhikari & Hamal, 2024; Kadaba et al., n.d.). These problems point to a number of interesting areas for future study. Demographics, race, gender, age, and education should be considered when examining AI-induced changes in work. Cross-national comparisons and morality concerns can help understand institutional differences and AI's impact on inequality. Future studies should focus on resilience scores.

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