Mirror, Mirror on the Server: ChatGPT Reveals Who's Most Likely to Commit Financial Crimes

Serkan Karadas[*], Minh Tam Tammy Schlosky[**], and Mark Buxton[***]

College of Business and Management

University of Illinois Springfield

Abstract:

We feed ChatGPT, a popular Large Language Model (LLM), a list of 130 variables spanning a wide range of individual characteristics, such as personality and education, and instruct it to select variables that are likely to predict nine different categories of financial crime. These categories are investment fraud, financial statement fraud, illegal insider trading, embezzlement, giving or receiving bribes, tax evasion, money laundering, insurance fraud, and borrower fraud. For each category, we run 1,000 simulations and then determine the selection frequency for each variable. We find that two traits of the Dark Triad (Machiavellianism and psychopathy), moral flexibility, and prior conviction for financial crime are selected by ChatGPT in at least 90% of the simulations for each crime category. Furthermore, ChatGPT selects additional variables depending on the particular financial crime under examination, such as being born in a high-corruption country for money laundering. Our study contributes to the literature by documenting which individual characteristics ChatGPT associates with a higher likelihood of committing financial crime and the consistency of these associations.

Keywords: financial crime; Artificial Intelligence; Large Language Models (LLMs); ChatGPT

----

[*]: Serkan Karadas, Ph.D., CFA. Associate Professor of Finance. Department of Accounting, Economics, and Finance, College of Business and Management, University of Illinois Springfield. One University Plaza, Springfield, IL 62703. Email: skara6@uis.edu

[**]: Minh Tam Tammy Schlosky, Ph.D., Assistant Professor of Finance. Department of Accounting, Economics, and Finance, College of Business and Management, University of Illinois Springfield. One University Plaza, Springfield, IL 62703. Email: mschl7@uis.edu

[***]: Mark Buxton, Ph.D., Associate Professor of Accounting. Department of Accounting, Economics, and Finance, College of Business and Management, University of Illinois Springfield. One University Plaza, Springfield, IL 62703. Email: mbuxt2@uis.edu

1. Introduction

The use of artificial intelligence (AI) is permeating every facet of society, from households to businesses. For example, according to one survey, the percentage of Americans who used AI for financial advice went from 10% in 2025 to 55% in 2026, a staggering 450% increase (Crosman (2026)). Another survey finds that the percentage of small businesses using AI stands at 76% (Goldman Sachs (2026)). Overall, AI has widespread applications ranging from stock selection to hiring decisions. In this paper, we focus on the application of AI to financial crime using ChatGPT, one of the most popular Large Language Models (LLMs).[1] We consider nine types (categories) of financial crime: financial statement fraud, investment fraud, illegal insider trading, embezzlement, giving or receiving bribes, tax evasion, money laundering, insurance fraud, and borrower fraud. We examine how this LLM assesses financial crime by asking two important questions: *Which individual characteristics are associated with the likelihood of committing financial crime,* and *how consistent is the model with these associations?*

We use ChatGPT in this study for several reasons. First, this LLM is well known and widely available to businesses and individuals. Second, it can be used either via an API or a chatbox interface without requiring the use of advanced algorithms. Third, external organizations already tout how this LLM can be used in addressing financial crime. For example, Association of Certified Fraud Examiners (ACFE) offers an on-demand webinar titled "Incorporating ChatGPT in the Financial Crimes Space."[2] LLMs, in general, show promise in fraud detection (Tegelaar (2025)). According to the 2024 Anti-Fraud Technology Benchmark Report by ACFE and SAS, the adoption

[1] See: https://www.azoma.ai/insights/most-popular-large-language-models and https://business20channel.tv/top-10-llm-models-by-market-share-in-2026-15-february-2026

[2] Please see: https://www.acfe.com/training-events-and-products/all-products/product-detail-page?s=Incorporating-ChatGPT-in-the-Financial-Crimes-Space-ODW

of generative AI to fight fraud is expected to reach 83% among organizations.[3] Furthermore, AI models are used by the U.S. Treasury Department to detect financial crime (Egan (2024)), and the Securities and Exchange Commission (SEC) formed an artificial intelligence task force, signaling its interest in using AI as part of its toolkit (Askanazi et al. (2026)). When it comes to banks, one survey puts the use of AI in combating financial crime and fraud at 90%.[4]

Another reason for using ChatGPT is that there is a gap in the literature on which individual characteristics ChatGPT associates with financial crime. There has been a growing number of studies examining ChatGPT's capabilities in other areas such as financial and investment advice (e.g., Niszczota and Abbas (2023), Kim (2023), Oehler and Horn (2024), Pelster and Val (2024), Schneider and Yilmaz (2025)), forecasting firm performance (Li et al. (2024)), and sentiment analysis (Nguyen Thanh et al. (2025)). However, studies examining ChatGPT's capabilities in financial crime are limited. Khan and Umer (2024) suggest that ChatGPT can be deployed to detect and prevent fraud. Scanlon et al. (2023) discuss cases where ChatGPT can be used in digital forensics such as keyword searching and self-directed learning. The study most closely related to ours is a fraud study by Gregory and Vito (2024). They use ChatGPT to investigate whether this tool can predict fraud in cryptocurrency exchanges. Gregory and Vito (2024, p.6) find that "ChatGPT alone is not better than an informed human being in detecting fraudulent activities in private cryptocurrency exchanges like FTX." Our study differs from that of Gregory and Vito (2024) in that we examine nine different categories of financial crime and that we focus on the impact of individual-level characteristics on financial crime via a simulation analysis.

[3] This report can be downloaded from here: https://www.sas.com/en_za/news/press-releases/2024/february/acfe-anti-fraud-tech-study-generative-ai.html
[4] https://www.feedzai.com/wp-content/uploads/2025/04/Feedzai_Report_State-of-AI.pdf

To preview our results, we find that ChatGPT considers two traits of the Dark Triad (Machiavellianism and psychopathy), moral flexibility, and prior record of financial crimes important for predicting all nine categories of financial crime. Furthermore, ChatGPT considers additional variables depending on the type of financial crime. For example, for illegal insider trading, risk tolerance is selected in all 1,000 simulations. When it comes to giving or receiving bribes, being born in a corrupt country is selected in all 1,000 simulations.

The rest of the paper proceeds as follows. Section 2 discusses background for crime categories and related literature. Section 3 describes the methodology. Section 4 reviews the results for each category of financial crime, and Section 5 provides the aggregate results, and Section 6 concludes the study.

2. Background and Related Studies

2.1. Background

One of the influential constructs to explain financial crime (fraud more specifically) is the fraud triangle (Cressey (1953)). Cressey based his work on Sutherland (1934, 1939) who called his theory Differential Association and suggested that criminal behavior is a learned behavior. Cressey interviewed embezzlers and suggested that there were three factors influencing why individuals committed financial crimes – incentive/pressure, opportunity, and rationalization. Pressure could be self-imposed or come from external sources, and it could be in the form of financial pressure, time pressure, or pressure to meet one's own expectations or others' expectations.

The Association of Government Accountants (AGA) uses internal controls when discussing Opportunity within the Fraud Triangle and puts forward the following deficiencies in internal controls as conducive to the rise of Opportunity: "*none in place, not enforced, not monitored*, and *not effective*."[5] Likewise, the AGA exemplifies Rationalization as "*I don't get paid what I'm worth*", "*Everyone else is doing it*", *"If they don't know I'm doing it, they deserve to lose the money", "I intended to pay it back",* and *"Nobody will miss the money*."[6]

In this study, we focus on fraud as well as other types of financial crime. Overall, we examine nine types of financial crime: 1) financial statement fraud, 2) illegal insider trading, 3) investment fraud, 4) embezzlement, 5) giving or receiving bribes, 6) tax evasion, 7) money laundering, 8) insurance fraud, and 9) borrower fraud. For each of the nine, we intentionally avoid restricting ChatGPT by providing too narrow a definition; instead, we allow ChatGPT to come up with its own definition based on available resources.

Financial Statement Fraud: The Public Company Accounting Oversight Board (PCAOB) focuses on intentionality and materiality when it comes to determining what constitutes financial statement fraud. The PCAOB distinguishes fraud from accounting errors based on "whether the underlying action that results in the misstatement of the financial statements is intentional or unintentional."[7] Some examples of financial statement fraud include Enron in 2001, Waste Management reporting $1.7 billion of false earnings in 2002, HealthSouth in 2003 for manipulating the numbers to meet investors' expectations and those at Lehman Brothers in 2008 to make debt appear to be lower than it actually was.[8]

Illegal insider trading: The Securities and Exchange Commission (SEC) describes illegal insider trading as "the buying or selling of a security in breach of a fiduciary duty or other relationship of

---

[5] https://www.agacgfm.org/resource/the-fraud-triangle/
[6] https://www.agacgfm.org/resource/the-fraud-triangle/
[7] https://pcaobus.org/oversight/standards/auditing-standards/details/AS2401
[8] See the following references for these examples: Enron: https://www.sec.gov/news/press/2004-18.htm, Waste Management: https://www.sec.gov/enforcement-litigation/litigation-releases/lr-22054, Health South: https://www.sec.gov/news/press/2003-34.htm, Lehman: https://www.sec.gov/news/testimony/2010/ts042010mls.htm

trust and confidence, while in possession of material, nonpublic information about that security."[9] In addition to that definition, the SEC adds that "an insider who is aware of material, nonpublic information must not disclose such information to family, friends, business or social acquaintances, employees or independent contractors of the entity (unless such employees or independent contractors have a position within the entity giving them a clear right and need to know), and other third parties."[10]

Examples of insider trading cases that resulted in convictions include Ivan Boesky using tips from corporate insiders to trade before a merger was announced and Martha Stewart selling shares of ImClone after receiving a tip from her broker that the company's CEO and the CEO's daughter were selling their shares. Another example is Jeffrey Skilling selling nearly all of his Enron stock before the public became aware of Enron's fraudulent financial statements.[11]

Investment Fraud: Some examples of investment fraud are Ponzi schemes, the lack of a security being registered, promising or guaranteeing abnormally high rates of returns, "pump and dump" stock schemes and investments in fake commodities or cryptocurrency. Bernie Madoff is probably still the best-known example of a Ponzi scheme deception in the past 50 years. Though not as well-known as some other financial crimes, "pump-and-dump" does occur, one example was the case of David and Donna Levy. The couple took three companies public, taking their fee in company stock. They then orchestrated public financial releases to make the companies sound as if they were doing better than they were performing (the "pump"). They then would sell their shares at an inflated price (the "dump"). The couple was found guilty, and David was sentenced to nine years

---

[9] https://www.sec.gov/Archives/edgar/data/25743/000138713113000737/ex14_02.htm

[10] https://www.sec.gov/Archives/edgar/data/25743/000138713113000737/ex14_02.htm

[11] See the following references for these examples. Ivan Boesky: https://www.upi.com/Archives/1986/11/14/The-Securities-and-Exchange-Commisssion-Friday-settled-insider-trading/2809532328400, Martha Stewart: https://www.sec.gov/news/press/2003-69.htm, Jeffrey Skilling: https://www.sec.gov/news/press/2004-18.htm

in prison. Another example of pump and dump was eight men indicted in 2022 for similar behavior using social media to pump stocks. They were charged with committing a $114 million fraud.[12]

Embezzlement: The Department of Justice defines embezzlement as "fraudulent appropriation of property by a person to whom such property has been entrusted, or into whose hands it has lawfully come."[13] According to an anti-money laundering website ALM Watcher, the most common forms of embezzlements are payroll fraud, fake overtime, Ponzi schemes, charity theft, check kiting and two forms of pocketing customers' cash payments: syphoning and lapping.[14]

There are financial crimes which fit multiple definitions of our nine crime categories, Ponzi schemes being one of them. Bernie Madoff stole investors' funds to pay for his lavish lifestyle. Another example is an executive of Fry's Electronics who was charged in 2012 with operating a shell company to collect over $100 million of illegal kickbacks over a period of at least four years from suppliers, depriving his employer from paying a lower price. In the not-for-profit sector, a charity named Feeding Our Future, which was supposed to have delivered low-cost meals to the hungry during the COVID-19 pandemic, instead delivered very few actual meals, with the people running the charity embezzling $250 million.[15]

Giving or taking bribes: The U.S. statutes (18 USC, Section 201b) expressly forbid bribes, and highlight in its definitions the intent to influence public officials or those selected to be public

---

[12] See the following for the examples. David Levy: https://www.justice.gov/archive/usao/nys/pressreleases/January14/DavidLevySentencingPR.php, Pump and dump: https://www.justice.gov/archives/opa/pr/eight-men-indicted-114-million-securities-fraud-scheme-orchestrated-through-social-media
[13] https://www.justice.gov/archives/jm/criminal-resource-manual-1638-embezzlement-government-property-18-usc-641
[14] https://amlwatcher.com/blog/embezzlement-examples/
[15] See the following for the examples. Madoff: https://www.pbs.org/newshour/show/madoff-sentenced-to-150-years-in-prison-for-ponzi-scheme, Fry's Electronics: https://www.manufacturing.net/home/news/13229851/exelectronics-exec-sentenced-following-fraud-conviction, Feeding Our Future: https://www.justice.gov/archives/opa/pr/us-attorney-announces-federal-charges-against-47-defendants-250-million-feeding-our-future

officials for a beneficial act via the transfer of "anything of value."[16] There are several well-known cases of bribery – ABSCAM (a sting operation in the 1970s involving members of Congress accepting bribes), FIFA officials in 2015 for accepting bribes in deciding which countries would host a World Cup and more recently, former United States Senator Robert Menendez who was convicted in 2024 for accepting cash and gold bars in exchange for influencing his co-conspirators' business interests.[17]

Tax Evasion: In the Internal Revenue Code, Section 7201's the definition of tax evasion includes, "Any person who willfully attempts in any manner to evade or defeat any tax imposed by this title or the payment thereof".[18] Some of the best-known cases of individual tax evasion include gangster Al Capone (1931), real estate developer Leona Helmsley (1989) who supposedly said, "Only the little people pay taxes", and the largest individual case, Walter Anderson, who failed to report (hid) an estimated $450 million of income in 1998 and 1999. When it comes to corporate income tax evasion (alleged or proven), American tech companies Apple and Amazon (in their European operations) are among the examples. Even one of the largest accounting firms in the world, KPMG, admitted to criminal tax evasion for creating fraudulent tax shelters for wealthy clients to evade in excess of $2 billion in taxes.[19]

---

[16] https://www.law.cornell.edu/uscode/text/18/201
[17] See the following for the examples. ABSCAM: https://www.britannica.com/topic/Abscam, FIFA: https://www.britannica.com/event/2015-FIFA-corruption-scandal, Menendez: https://www.justice.gov/usao-sdny/pr/former-us-senator-robert-menendez-sentenced-11-years-prison-bribery-foreign-agent-and
[18] https://www.law.cornell.edu/uscode/text/26/7201
[19] See the following for the examples. Al Capone: https://www.fbi.gov/history/famous-cases/al-capone, Leona Helmsley: https://content.time.com/time/specials/packages/article/0,28804,1891335_1891333_1891317,00.html, Walter Anderson: https://www.taxnotes.com/research/federal/other-documents/justice-department-documents/telecom-entrepreneur-sentenced-to-prison-for-tax-evasion-justice-announces/xqsx, Apple: https://www.cnbc.com/2024/09/10/apple-loses-eu-court-battle-over-13-billion-euro-tax-bill-in-ireland.html, Amazon: https://finance.yahoo.com/news/amazon-faces-possible-trial-italy-205351144.html, KPMG: https://www.justice.gov/archive/opa/pr/2005/August/05_ag_433.html

Money Laundering: The Department of Justice provides the following explanation for money laundering: "To be criminally culpable under 18 U.S.C. § 1956(a)(1), a defendant must conduct or attempt to conduct a financial transaction, knowing that the property involved in the financial transaction represents the proceeds of some unlawful activity" and "that the property involved was the proceeds of any felony under State, Federal or foreign law."[20]

Some of the better-known cases in the United States have been 1) HSBC being fined for over $1 billion in 2012 for failing to prevent money laundering, 2) TD Bank in 2024 for $1.8 billion for "*conspiring to: fail to maintain an anti-money laundering (AML) program that complies with the Bank Secrecy Act (BSA); fail to file accurate Currency Transaction Reports (CTRs); and launder monetary instruments.*", and 3) Wachovia Bank which was charged by federal prosecutors for willfully failing "*to establish an anti-money laundering program.*", resulting in a $160 million fine.[21]

Insurance fraud: The Insurance Information Institute defines insurance fraud as "a deliberate deception perpetrated against or by an insurance company or agent for financial gain", and The Coalition Against Insurance Fraud, in a 2022 study, suggests that such fraud costs the United States over $300 billion annually.[22] Insurance fraud is a state crime, but the fraud could extend over a multi-state region. Examples include disability insurance fraud. Some of the better-known of this fraud have been organized by doctors and lawyers. Another example would be Medicare and

---

[20] https://www.justice.gov/archives/jm/criminal-resource-manual-2101-money-laundering-overview

[21] See the following for the examples. HSBC: https://archives.fbi.gov/archives/washingtondc/press-releases/2012/hsbc-holdings-plc-and-hsbc-bank-usa-n.a.-admit-to-anti-money-laundering-and-sanctions-violations-forfeit-1.256-billion-in-deferred-prosecution-agreement, TD Bank: https://www.justice.gov/criminal/case/united-states-america-v-td-bank-na, Wachovia Bank: https://www.justice.gov/archive/usao/fls/PressReleases/2010/100317-02.html

[22] See https://www.iii.org/article/background-on-insurance-fraud and https://insurancefraud.org/wp-content/uploads/The-Impact-of-Insurance-Fraud-on-the-U.S.-Economy-Report-2022-8.26.2022.pdf

Medicaid fraud by overbilling by hospitals and nursing homes, one such case was Columbia/HCA.[23]

Borrower fraud: Again, borrower fraud is typically a state crime, not a federal crime, but some large-scale cases can become federal. The Texas Department of Banking defines borrower fraud as "If a person intentionally or knowingly makes a materially false or misleading written statement to obtain a mortgage loan. Examples of criminal mortgage fraud includes, but is not limited to, illegally inflating property appraisals; concealing a second mortgage from a primary lender; and concealing or stealing a borrower's identity."

One such case that became federal was conducted on a very large scale, $420 million. The organizer purchased commercial properties by coaching his individual investors who had pooled their dollars to lie on their personal financial statements. He was sentenced to three years in federal prison in December 2025. Similarly, in 2024, Donald Trump, his sons and The Trump Organization were ordered to pay a fine of over $350 million for "inflating property values" to obtain favorable bank loans.[24]

2.2. Related Studies

Our study related to a wide range of studies on fraud (including the seminal work of Cressey (1953) on the fraud triangle), financial crime, individual characteristics, and the use of AI. The fraud triangle is theoretically appealing and applicable to many different situations. For example, Lederman (2021) attempts to incorporate the fraud triangle in the world of tax compliance. She argues the fraud triangle can provide a conceptual frame to two distinctive parts of tax compliance

---

[23] https://www.justice.gov/archive/opa/pr/2003/June/03_civ_386.htm
[24] See the following for the examples. Commercial property: https://www.justice.gov/usao-mn/pr/architect-massive-420-million-bank-fraud-scheme-sentenced-3-years-prison ,Trump Organization: https://www.bbc.com/news/world-us-canada-68320290

– the traditional deterrence model and behavioral theories. The deterrence model suggests if the cost of complying is greater than the benefit of not getting caught, the person will comply. If the likelihood of being caught and then the accompanying penalty are greater than the benefit, then the individual will comply. The behavioral theories lie mostly in how one perceives himself or herself or thinks others perceive him or her. This notion leads back to Sutherland's original studies in that criminality is a learned behavior. If one lives or works in an environment where many others are committing criminal acts, then one rationalizes that such behavior is acceptable. This prediction has empirical support in the financial crime literature. For example, Dimmock et al. (2018) show that when a financial advisor works alongside a financial advisor with a history of misconduct in the same branch, he or she is more likely to engage in misconduct. They determine this likelihood to be 37%.

There are factors that provide a buffer against financial crime. Bai et al. (2022) present evidence that social capital is negatively related to financial advisor misconduct. Thornton et al. (2019) find that when people view taxes as a tool to help others ("perceived prosocial taxation"), they are more likely to voice support for taxes. Khalil and Sidani (2022) find a negative relationship between conscientiousness and tax evasion attitudes. Jassem et al. (2022, p. 8) find that "agreeableness, conscientiousness and extraversion all have a negative relationship with tax non-compliance intention." Koch-Bayram and Wernicke (2018) find that CEOs who served in the military are less likely to commit financial misconduct. Their results support earlier evidence in the literature by Benmelech and Frydman (2015, p. 44) who find that "military service is associated with a 70% reduction in the likelihood of fraud compared to the unconditional mean." Jiang et al. (2021) find that the abnormal returns on the stock purchases of lawyer corporate insiders are lower than those of non-lawyer corporate insiders. Ali et al. (2024) examine the relationship between sleep deprivation and financial misreporting. They find that sleep-deprived managers are less likely to engage in financial misreporting. Their explanation is that since financial misreporting is a cognitively heavy task, it requires high levels of cognitive functioning, which sleep-deprived managers are less likely to possess. It is important to note that evidence on the relationship between sleep deprivation and unethical conduct is mixed. Barnes et al. (2011) show that lack of sleep is positively associated with unethical behavior based on evidence from laboratory experiments and field studies.

There are other factors negatively associated with financial crime. By leveraging a Virginia law requiring high school students to take a financial literacy course, Freed and Hackney (2026, p. 2) find that financial literacy reduces “the propensity to commit financial crime.” More specifically, they document that financial literacy has a negative effect on embezzlement, and reason that embezzlement is most impacted by the presence of financial instability in one’s life, which financial literacy may help alleviate. Ho et al. (2015, p. 366) document that “companies with female CEOs report more conservative earnings.” Lei et al. (2025) identify home CEOs, executives running firms located within 100 miles of their place of birth, and find a negative relationship between having a home CEO and financial misconduct. Lei et al. (2025, p. 1311) use the following measures of financial misconduct: “accrual-based earnings management, accounting fraud, opportunistic insider trading, and financial offenses.” Lapointe-Antunes et al. (2022) have humans rate honesty of CFOs and CEOs based on their pictures and find a negative relationship between perceived honesty and earnings management. Heese et al. (2023) find a negative relationship between having a CFO who took an integrity oath and earnings management (accruals-based and real-activities) and hence a positive relationship between having oath-taking CFOs and reporting quality.

Kowaleski et al. (2020) find a negative association between exposure to ethics training (through Series 66 exam) and the likelihood to commit misconduct among financial advisors. Liu et al. (2024) find evidence from China that CEOs' early life experiences with the Cultural Revolution are positively linked to accounting conservatism at their firms. Aier et al. (2005) examine the relationship between the incidences of restatements and CFOs' financial expertise. They find that the restatements are less likely when CFOs have advanced credentials (MBA and CPA) and longer work experience. Similarly, Hoitash et al. (2016) show that CFOs with accounting backgrounds adopt a less risky approach, leading to risk-averse firms. This is similar to the findings in the literature on the role of religion (Hilary and Hui (2009)) and conservative beliefs of Republican managers (Hutton et al. (2014)) in corporate risk-taking.

There is strong evidence that prior misconduct is positively related to the propensity to commit financial crime. Davidson et al. (2015) find that prior legal infractions committed by CEOs and CFOs predict corporate fraud. They also examine the impact of CEO frugality (based on luxury goods ownership) on corporate fraud, but they do not find a direct link. Davidson et al. (2015, p. 25) document "a relative increase in financial reporting risk over the tenure of unfrugal CEOs as reflected by the probabilities of fraud, others being named in fraud, and material reporting errors." Davidson et al. (2020) examine the relationship between executives' criminal background and their insider trades and find that executives with "legal infractions" have higher profitability on their insider buy and sell transactions relative to other executives. Egan et al. (2019) show that the share of financial advisors with a record of misconduct is about 7%, and the majority of advisors with misconduct history engaged in misconduct more than once, making them repeat offenders. Egan et al. (2019, p. 235) find that "[p]ast offenders are five times more likely to engage in misconduct than the average adviser, even compared with other advisers in the same firm, at the same location, and at the same point in time." Misconduct in different domains also appears to be connected. Griffin et al. (2019) find evidence that personal (marriage) infidelity is positively related to professional misconduct. Using the data from Ashley Madison (AM) website, they show that police officers, financial advisors, CEOs and CFOs who were involved in infidelity (proxied by the use of AM) are more likely to commit professional misconduct than their otherwise-similar peers. Druică et al. (2019) find a positive association between academic dishonesty and unethical conduct.

Certain personality traits are strongly related to the tendency to commit financial crime. Mutschmann et al. (2022) find that the Dark Triad personality traits predict accounting fraud. Rijsenbilt and Commandeur (2013) link CEO narcissism to fraud for S&P 500 companies. Buchholz et al. (2020) find evidence that CEO narcissism is related to low earnings quality due to these CEOs' earnings management practices. Shafer and Wang (2018) find that Machiavellianism is positively related to the intent to cheat on taxes ("fraud intention"), whereas age is negatively related. Harrison et al. (2018) show that all components of the Dark Triad impact the tendency to engage in unethical behavior, but the individual components play different roles. For example, they (p. 70) find that "psychopathy (which is associated with amorality and a willingness to act impulsively) has the most substantive effect on the fraud process through its effect on rationalization." Though both Machiavellianism and narcissism are positively associated with unethical conduct, according to Harrison et al. (2018), psychopathy plays a unique role, eventually determining whether someone capable of unethical behavior will decide to carry through.

Factors, much more benign than the Dark Triad, also impact managerial decisions. For example, Kim et al. (2022) show evidence that there is a positive relationship between CEO facial masculinity and corporate fraud. Ali and Zhang (2015) find that early tenure-CEOs are more likely to engage in earnings overstatement possibly due to the need that they feel to prove themselves. Liu et al. (2023) a strong positive association between CEO childhood poverty exposure financial statement fraud. They further document that this association weakens for older CEOs with the CEO age acting as a moderating variable. Schrand and Zechman (2012), in a study of the SEC Accounting and Auditing Enforcement Releases (AAERs) find evidence that optimistic bias, which is positively linked to executive overconfidence, is an underlying theme in initial phases of financial misreporting. Li and Wang (2024) document a negative association between turnover in the executive suite and quality of financial reporting. Li et al. (2025) show that social media usage of CEOs is positively linked to CEO risk-taking and the volume and the profitability of inside buy transactions.

Personal and financial circumstances also matter for financial crime. Langton and Piquero (2007) empirically test general strain theory (GST), developed by Agnew (1992) on the role of strain-induced negative emotions in committing crime. They use white-collar crime data and develop a composite measure of strain based on the perpetrators' marriages, education history, employment status, neighborhood, and net worth. They examine the impact of strain as well as motivation behind the crime (business, personal, or financial) on the propensity to commit white-collar crime. They document that strain is associated with a higher likelihood of committing embezzlement and credit fraud, but this relationship is not significant. However, strain predicts a lower likelihood of bribery and tax fraud in a statistically significant way. They further find that financial motivation is positively and statistically significantly related to embezzlement and credit fraud, and personal motivation is negatively (positively) and statistically significantly related to credit fraud (tax fraud). Langton and Piquero (2007, p. 12) explain the positive impact of financial motives on embezzlement and credit fraud as strain "operating through financial motives." Their results make intuitive sense given the fact that financial motives, such as needing money to pay gambling debt, can turn otherwise-normal individuals into financial criminals (Binde (2016)).

Connections matter when it comes to the propagation of misconduct. Chiu et al. (2013) find that earning management spreads one firm to another through common board members. Ahern (2017) studies illegal insider trading networks. The sample in his study is dominated by men, accounting for 90% of the traders (the sample has 622 traders in total). Also, top executives are the single largest group (17%), but there are also buy-side managers (9.7%), buy-side analysts/traders (10.5%), and corporate managers (8.9%) in this group. Ahern (2017) finds that the geographic distance between inside traders is short with a median distance of 26 miles, reinforcing the view that face-to-face meetings play a role in information sharing. Furthermore, family members, friends, and business associates account for 23%, 35%, and 35% of the tipper-tippee relationships, respectively. Jagolinzer et al. (2020) find a positive relationship between CEOs' political connections and abnormal trading.

Country of origin, wealth, compensation incentives, and technical expertise (in technology) also affect financial crime. DeBacker et al. (2015) investigate tax evasion in the U.S. by companies with foreign ownership. They find that corruption in the home country of foreign owners predicts tax evasion in the U.S., with the effects concentrated in small firms. Alstadsæter et al. (2019, p. 2074) document that "the top 0.01 percent evades about 25 percent of its tax liability by concealing assets and investment income abroad." Piff et al. (2012) examine the relationship between social class and tendency to commit unethical behavior. They find evidence that unethical behavior is more common among individuals identified as belonging to the upper class. Albrecht et al. (2018) investigate the impact of executives' prior accounting experience on financial reporting. They find that executives' prior accounting experience is positively associated with misstatements when it is coupled with compensation-based incentives (the coefficient on the interaction term is positive and statistically significant). Berg et al. (2020) study loan officers and find that those with volume-based incentives engage in misconduct by manipulating internal ratings, outcomes of which determine loan decisions. Dull and Rice (2023) examine the differences in occupational fraud between IT and non-IT personnel. They find similar losses between these two groups. However, they show that fraud done by IT personnel occurs earlier in their tenure compared to non-IT personnel.

In addition to the literature on financial crime, our study is also related to the research on discrimination in the financial markets and LLMs. There is evidence of discrimination in favor of more attractive and fitter individuals, as well as those with lighter skin colors in charitable giving (Jenq et al. (2015)) and more attractive/beautiful people in peer-to-peer lending (Ravina (2026)). Hofmann et al. (2024) examine covert racial bias in LLMs (including GPT3.5 and GPT4) by testing the models using texts with African American English (AAE) and Standardized American English (SAE). They find that LLMs offer higher conviction rates based on the AAE texts compared to the SAE texts for "unspecified crime". For example, the conviction rate is 49.8% based on the AAE text and 35.3% based on the SAE text. Wang and Gu (2026) show that LLMs have gender and race bias in rendering investment advice. Though these studies are not related to financial crime, they point to evidence of bias against certain segments of the population. Since actual data is used to train LLMs, we included variables on race, gender, physical attributes to examine whether ChatGPT would consider them in assessing the likelihood of financial crime.

3. Methodology

We have 130 variables capturing a wide range of individual-level characteristics ranging from personality to prior crime record (see Appendix 1). Many of our variables are based on the literature such as those capturing personal infidelity and personality traits (see Section 2). However, some of the variables are not expected to have any impact on an individual's propensity to commit financial crime such as being a martial artist or having tattoos. We included them for purely exploratory reasons in order to reveal whether ChatGPT would consider seemingly unrelated variables when it assesses who is more likely to have engaged in financial crime. We also included variables such as attractiveness and race in order to examine potential biases in ChatGPT's recommendations. It is important to note that while our variables represent individual-level characteristics that ChatGPT may associate with financial crime risk, we do not work with a financial crime dataset in this study. Our objective is to shed light on ChatGPT's assessment of which individuals are more likely to commit financial crime.

We use the prompt below for each category of financial crime where *target_behavior* is the specific type of financial crime defined at the beginning of our program. By accessing ChatGPT (GPT-4.1) using the API (with a temperature setting of 0.5), we run this prompt 1,000 times for each category of financial crime, amounting to 9,000 simulations in total across all the categories of financial crime. In each simulation, the program provides ChatGPT with a list of variables (see Appendix 1), and ChatGPT chooses the most relevant variables for a hypothetical linear probability model (see Kowaleski et al. (2020) for an application of a linear probability model to actual data). We keep track of how often a variable is selected by ChatGPT, and we use this selection frequency to visualize the results of the simulations. In addition to the selection frequency, we are also interested in the stability of the coefficients. To address this, we compute the percentage of times a given variable is assigned a positive coefficient and a negative coefficient. For example, a variable might be selected 1,000 out of 1,000 times by ChatGPT, leading to a selection frequency of 100%. Within these 1,000 simulations, ChatGPT may attribute a positive coefficient 60% of the time and a negative coefficient 40% of the time. This breakdown informs us about whether ChatGPT's recommendations are stable across simulations (and they are not in this hypothetical example due to switching signs).

```
prompt_text <- paste(
  paste0(
    "Following the instructions below, construct a linear probability model that predicts which individuals are more likely to have engaged in ",
    target_behavior,
    "."
  ),
  "",
  "All the individuals are based in the United States.",
  "Based on your knowledge, evaluate each variable listed below and include only those that you determine to be relevant.",
  "Each selected variable must appear exactly once in both the model and the table.",
  "Do not worry about multicollinearity. Even if some variables may cause it, include them in both the model and the table if they are relevant.",
  "",
  "Produce the following:",
  "1. A full linear probability model.",
  "2. A table listing each selected variable (including its original Variable ID), the sign of its coefficient, and a brief explanation.",
  "",
  "Every selected variable must have either a positive or a negative coefficient.",
  "If a coefficient is ambiguous, you must still choose exactly one sign (by using your best judgment): positive or negative.",
  "If a variable is not selected, exclude it from both the model and the table.",
  "",
  "Then create a table with exactly these four columns:",
  "Variable ID",
  "Variable Name",
  "Sign",
  "Brief Explanation",
  "",
)
```

4. Results

Figure 1 presents the selection frequencies for financial statement fraud.[25] ChatGPT selected seven variables in all 1,000 simulations, leading to a selection frequency of 100% for each. These variables *are Academic dishonesty history, Bonus-based compensation, Financial pressure, Holds an executive position at work, Machiavellianism, Prior conviction for financial crime (any type),* and *Psychopathy*. All these variables are assigned a positive coefficient by ChatGPT. In addition, the following variables were selected in at least 90% of the simulations, although not in all 1,000 runs (with the first two having negative coefficients and the rest having positive coefficients): *Honesty-Humility, Perceived detection likelihood of financial crime, Commission-based pay, Moral flexibility, Accounting credential or expertise (e.g., CPA, CMA), Degree in accounting or related field,* and *Job-hopping frequency*. In terms of stability of ChatGPT's recommendations, ChatGPT provides both positive and negative coefficients for the following variables: *Accounting credential or expertise* (99% positive and 1% negative), *Degree in accounting or related field* (99% positive and 1% negative), and *Financial literacy* (17% positive and 83% negative). For the first two variables, the lack of stability is very minor (only 1%). However, we find the output variability for *Financial literacy* noteworthy.

<**Figure 1** about here>

Figure 2 shows the results for investment fraud. ChatGPT selected five variables in all the simulations (all with positive coefficients): *Academic dishonesty history, Financial pressure*, *Machiavellianism, Moral flexibility,* and *Psychopathy.* The variables selected in at least 90% of the simulations (but less than 100% of the time) are *Prior conviction for financial crime (any type), Income, Narcissism, Risk tolerance, Family history of fraud or similar charges,* and *Commission-*

[25] To preserve space, we only present the variables with a selection frequency of 20% or higher in the charts. The ensuing discussions in the manuscript are based on the variables presented in the charts unless otherwise stated.

based pay. All the variables in Figure 2 have a stable coefficient (either positive or negative in all the simulations) except for *Financial literacy*, which has a positive coefficient in 68% of the simulations and a negative coefficient in 32% of the simulations.

<**Figure 2** about here>

Figure 3 shows the results for illegal insider trading. ChatGPT selected seven variables in 100% of the simulations. These variables (with all positive coefficients) are *Finance credentials or expertise (e.g., CFA, CFP), Holds an executive position at work, Income, Machiavellianism, Moral flexibility, Prior conviction for financial crime (any type),* and *Risk tolerance*. The variables with selection frequency of at least 90% but less than 100% are *Academic dishonesty history, Options trader, Financial literacy, Psychopathy, Degree in finance or related field, Finance or accounting professional at the firm,* and *Job-hopping frequency.* All of ChatGPT's recommendations are stable with no variable switching between positive and negative coefficients in any of the simulations.

<**Figure 3** about here>

We present the results for embezzlement in Figure 4. Four variables were selected by ChatGPT (all with a positive coefficient) in all of the simulations. These variables *are Finance or accounting professional at the firm, Financial pressure, Holds an executive position at work,* and *Machiavellianism*. Furthermore, ChatGPT selected *Prior conviction for financial crime (any type), Psychopathy, Academic dishonesty history, Moral flexibility, History of missed debt payments, Personal bankruptcy history, Income, Job-hopping frequency,* and *Degree in accounting or related field* in at least 90% of the simulations (but less than 100% of them). Overall, two variables switch between having positive and negative coefficients. These are *Income* (Positive: 96%, Negative: 4%) and *Financial literacy* (Positive: 99%, Negative: 1%).

<**Figure 4** about here>

Figure 5 presents the bribery results (giving or receiving bribes). The variables selected in all the simulations are *Academic dishonesty history, Born in a high-corruption country, Exposed to childhood poverty, Financial pressure, Machiavellianism, Moral flexibility,* and *Prior conviction for financial crime (any type).* The variables with at least 90% (but less than 100%) selection frequency are *Psychopathy, Neighborhood criminal exposure, Income,* and *Multiple passport ownership.* The variables listed so far all have positive coefficients in every simulation. Furthermore, there are no variables in Figure 5 with changing coefficients. The variables have consistently positive or negative coefficients, not both.

<**Figure 5** about here>

Figure 6 illustrates the results for tax evasion. ChatGPT selected nine variables in all 1,000 simulations. These variables are *Academic dishonesty history, Financial literacy, Financial pressure, Income, Machiavellianism, Moral flexibility, Prior conviction for financial crime (any type), Psychopathy,* and *Risk tolerance.* In addition, ChatGPT selected *History of missed debt payments, Personal bankruptcy history, Neighborhood criminal exposure, Born in a high-corruption country,* and *Honesty-Humility* in at least 90% of the simulations. All the variables in Figure 6 have consistent coefficients (either positive or negative) except for *Financial literacy*, which has a positive coefficient in 99% of the simulations and a negative coefficient in the rest of the simulations.

<**Figure 6** about here>

Figure 7 shows the results for money laundering. There are eight variables with 100% selection frequency. These variables, all with positive coefficients in all the simulations, are *Born in a high-*

corruption country, Finance credentials or expertise (e.g., CFA, CFP), Frequent international traveler, Income, Machiavellianism, Moral flexibility, Multiple passport ownership, and *Prior conviction for financial crime (any type)*. The variables with at least 90% but below 100% frequency are *Risk tolerance, Neighborhood criminal exposure, Prior record of regulatory violation, Psychopathy,* and *Financial pressure*. Furthermore, all the variables in Figure 7 have stable coefficient signs.

<**Figure 7** about here>

Figure 8 demonstrates the results for insurance fraud. Four variables were selected in all the simulations, and they all have consistently positive coefficients. These variables are *History of missed debt payments, Moral flexibility, Prior conviction for financial crime (any type),* and *Psychopathy*. The variables with at least 90% but below 100% selection frequency are *Honesty-Humility, Financial pressure, Machiavellianism, Personal bankruptcy history, Academic dishonesty history, History of illicit drug use, Underwater mortgage, Neighborhood criminal exposure,* and *Perceived detection likelihood of financial crime.* No variable in Figure 8 exhibits sign changes.

<**Figure 8** about here>

Figure 9 shows the results for borrower fraud. *Academic dishonesty history, Moral flexibility, Prior conviction for financial crime (any type),* and *Underwater mortgage* were selected in all the simulations with consistently positive coefficients. The variables with a selection frequency below 100% but at or above 90% are *History of missed debt payments, Personal bankruptcy history, Financial pressure, Machiavellianism, Honesty-Humility, Psychopathy, History of illicit drug use,* and *Perceived detection likelihood of financial crime.* All the variables in Figure 9 have consistently negative or positive coefficients with no variable exhibiting sign reversals.

<**Figure 9** about here>

Overall, ChatGPT considers personal circumstances, personality, educational background, expertise, and past experience/record of financial crime when it comes to assessing who is likely to have engaged in financial crime. We further observe that ChatGPT pays attention to the type of financial crime and adjusts its recommendations accordingly. For example, *Frequent international travele*r was selected in all the simulations for money laundering. However, its selection frequency is only 0.9% when it comes to financial statement fraud (in unreported results). Another example is *Options trader*. Its selection frequency is 99.3% for illegal insider trading, but 31.3% for tax evasion and only 0.1% for borrower fraud (in unreported results).

We find that ChatGPT is overwhelmingly consistent in assigning signs within the same crime category. The only notable exception in Figures 1 through 9 is *Financial literacy*. For example, for investment fraud, it has a positive coefficient in 68% of the simulations and a negative coefficient in 32% of the simulations. We also observe inconsistencies in variables such as *Income* and *Degree in accounting or related field*. However, the inconsistencies associated with these variables are very small (often around 1%). ChatGPT also demonstrates consistency (in terms of signs) across different crime categories. Figures 1 through 9 show that if a variable is determined to be important by ChatGPT, it tends to have the same sign across different categories of financial crime. The notable exceptions are *Income* and *Financial literacy*. *Income* has a (majority) positive coefficient in all categories except for borrower fraud and insurance fraud. In unreported results, we find that Income is selected only 0.9% of the time for financial statement fraud (but still majority positive). *Financial literacy* has a (majority) positive coefficient in all categories except for financial statement fraud and insurance fraud. In unreported results, we find that *Financial literacy* is selected only 1.8% of the time for giving or receiving bribes (also majority positive).

5. Aggregate Results

In this section, we present the aggregate results across all the financial crime categories. We use two approaches to show the aggregate results. In the first approach, we keep track of common variables with a selection frequency between 90% and 100% across all the categories of financial crime. Based on Figures 1-9, these variables (alphabetically) are *Machiavellianism, Moral flexibility, Prior conviction for financial crime (any type),* and *Psychopathy*.

<**Figure 10** about here>

In the second approach, we identify the common variables based on total selection frequencies. Figure 10 shows the results of the second approach. We construct this figure in two steps. First, we add the number of times a given variable is selected across all the financial crime categories. For example, if a variable is selected 900 times for illegal insider trading, 975 times for embezzlement and none for the remaining financial crime categories, the result from the first step for this variable is 1,875. Next, we calculate the total selection frequency by dividing the outcome from the first step with the total number of simulations, which is 9,000 in this study. Accordingly, the result is *(1,875/9,000) x 100 = 20.8%.* Figure 10 shows that *Academic dishonesty history, Financial pressure, Machiavellianism, Moral flexibility, Prior conviction for financial crime (any type),* and *Psychopathy* have a selection frequency of at least 90%. It is important to note that no variable was selected 100% of the time based on the second approach. The 100% result in Figure 10 for the *Prior conviction for financial crime (any type)* is a result of rounding.

Overall, the first approach sets a higher bar than the second approach. As a result, we see fewer variables qualifying under the first approach compared to the second approach. All four of the variables from the first approach also are among the variables from the second approach. To reiterate, these common variables are *Machiavellianism, Moral flexibility, Prior conviction for financial crime (any type),* and *Psychopathy.* These common variables suggest that ChatGPT puts a large emphasis on personality (two traits of the Dark Triad) and prior criminal record.

To supplement the results in Figure 10, we show the total selection counts (across all nine crime categories) for each variable as well as the breakdown by the signs in Appendix 2. Since Appendix 2 provides selection counts on all the variables, it allows us to observe the variables that are infrequently, rarely or never selected. For example, *Asian* was selected only twice (one positive and one negative), *Black* and *Hispanic* were never selected. These results suggest that ChatGPT is now careful about potential racial biases. Among the infrequently selected variables, we notice similarities between ChatGPT's results and the findings from the literature. For example, ChatGPT selects *Personal infidelity* 2,596 times (out of 9,000) with a positive coefficient in all the selections. This result matches the evidence on the relationship between infidelity and the tendency to commit financial crime reported by Griffin et al. (2019).

6. Conclusion

This paper examines the variables ChatGPT deems important for predicting financial crime. We find that personality traits (especially the Dark Triad traits), moral flexibility, and criminal history are important in predicting all nine categories of financial crime that we examine. To the best of our knowledge, we are among the first to reveal which individual characteristics ChatGPT associates with the propensity to commit financial crime based on a large set of variables. Our study is limited in that we do not use actual financial crime data to test the validity of ChatGPT's recommendations. We hope that future research examines ChatGPT’s ability to predict financial crime using actual crime data.

References

Agnew, R. (1992). Foundation for a general strain theory of crime and delinquency. *Criminology*, 30, 47-88.

Ahern, K.R. (2017). Information networks: Evidence from illegal insider trading tips. *Journal of Financial Economics*, 125, 26-47.

Aier, J.K., Comprix, J., Gunlock, M.T., & Lee, D. (2005). The financial expertise of CFOs and accounting restatements. *Accounting Horizons*, 19(3), 123-135.

Albrecht, A., Mauldin, E.G., & Newton, N.J. (2018). Do auditors recognize the potential dark side of executives' accounting competence? The Accounting Review, 93(6), 1-28.

Ali, A., Fan, Z., Hui, K.W., & Li, S. (2024). Sleep deprivation and financial misreporting. SSRN Working Paper. Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4007808

Ali, A., & Zhang, W. (2015). CEO tenure and earnings management. *Journal of Accounting and Economics*, 59, 60-79.

Alstadsæter, A., Johannesen, N., & Zucman, G. (2019). Tax evasion and inequality. *American Economic Review*, 109(6), 2073–2103.

Askanazi, R., Song, E.K., & Martynova, M. (2026). SEC's motives for AI adoption could strengthen market oversight. *Bloomberg Law*, January 30.

Bai, J., Shang, C., Wan, C., & Zhao, Y.E. (2022). Social capital and individual ethics: Evidence from financial adviser misconduct. *Journal of Business Ethics*, 181, 495-518.

Barnes, C.M., Schaubroeck, J., Huth, M., & Ghumman, S. (2011). Lack of sleep and unethical conduct. *Organizational Behavior and Human Decision Processes*, 115, 169-180.

Benmelech, E., & Frydman, C. (2015). Military CEOs. *Journal of Financial Economics,* 117, 43-59.

Berg, T., Puri, M., & Rocholl, J. (2020). Loan officer incentives, internal rating models, and default rates. *Review of Finance*, 24(3), 529-578.

Binde, P. (2016). Gambling-related embezzlement in the workplace: a qualitative study, *International Gambling Studies*, 16(3), 391-407.

Buchholz, F., Lopatta, K., & Maas, K. (2020). The deliberate engagement of narcissistic CEOs in earnings management. *Journal of Business Ethics,* 167, 663–686.

Chiu, P.-C., Teoh, S.H., & Tian, F. (2013). Board interlocks and earnings management contagion. *The Accounting Review*, 88(3), 915-944.

Cressey, D. R. (1953). Other people's money: A study in the social psychology of embezzlement. Glencoe, IL: Free Press.

Crosman, P. (2026). More Americans asking AI for financial advice: TD survey. *American Banker*, March 31.

Davidson, R., Dey, A., & Smith, A. (2015). Executives' "off-the-job" behavior, corporate culture, and financial reporting risk. *Journal of Financial Economics*, 117, 5-28.

Davidson, R.H., Dey, A., & Smith, A.J. (2020). Executives' legal records and insider trading activities. *Contemporary Accounting Research*, 37(3), 1444-1474.

DeBacker, J., Heim, B.T., & Tran, A. (2015). Importing corruption culture from overseas: Evidence from corporate tax evasion in the United States. *Journal of Financial Economics*, 117, 122-138.

Dimmock, S.G., Gerken, W.C., & Graham, N.P. (2018). Is fraud contagious? Coworker influence on misconduct by financial advisors. *The Journal of Finance*, 73(3), 1417-1450.

Druică, E., Vâlsan, C., Ianole-Călin, R., Mihail-Papuc, R., & Munteanu, I. (2019). Exploring the link between academic dishonesty and economic delinquency: A partial least squares path modeling approach. *Mathematics*, 7(12), 1241.

Dull, R.B., & Rice, M.M. (2023). An examination of occupation fraud committed by information technology professionals. *Journal of Forensic Accounting Research*, 8(1), 336-356.

Egan, M. (2024). AI helped the feds catch $1B of fraud in 1 year. *abc7ny.com*, October 18.

Egan, M., Matvos, G., & Seru, A. (2019). The market for financial adviser misconduct. *Journal of Political Economy*, 127(1), 233-295.

Freed, P.G., & Hackney, J. (2026). Financial literacy and financial crime: A regression discontinuity approach. *Journal of Financial Economics*, 181, 104292.

Goldman Sachs. (2026). Survey: Small businesses embrace AI — but need training and support to fully harness it. *Goldman Sachs*, March 17.

Gregory, G., & Vito, L. (2024). ChatGPT: A canary in the coal mine or a parrot in the echo chamber? Detecting fraud with LLM: The case of FTX. *Finance Research Letters*, 70, 106349.

Griffin, J.M., Kruger, S., & Maturana, G. (2019). Personal infidelity and professional conduct in 4 settings. *Proceedings of the National Academy of Sciences (PNAS)*, 116(33), 16268-16273.

Harrison, A., Summers, J., & Mennecke, B. (2018). The effects of the dark triad on unethical behavior. *Journal of Business Ethics*, 153, 53-77.

Heese, J., Perez-Cavazos, G., & Peter, C.D. (2023). When executives pledge integrity: The effect of the accountant's oath on firms' financial reporting. *The Accounting Review*, 98(7), 261-288.

Hilary, G., & Hui, K.W. (2009). Does religion matter in corporate decision making in America? *Journal of Financial Economics*, 93, 455-473.

Ho, S.S.M., Li, A.Y., Tam, K., & Zhang, F. (2015). CEO gender, ethical leadership, and accounting conservatism. *Journal of Business Ethics*, 127, 351-370.

Hofmann, V., Kalluri, P.R., Jurafsky, D., & King, S. (2024). AI generates covertly racist decisions about people based on their dialect. *Nature,* 633, 147–154.

Hoitash, R., Hoitash, U., & Kurt, A.C. (2016). Do accountants make better chief financial officers? *Journal of Accounting and Economics*, 61, 414-432.

Hutton, I., Jiang, D., & Kumar, A. (2014). Corporate policies of Republican managers. *Journal of Financial and Quantitative Analysis*, 49(5), 1279-1310.

Jassem, A., Al-Rawi, Y.A., & Ali, A.H. (2022). Impact of big five personality traits on tax non-compliance intentions: Mediation effect of perceived tax-fairness. Journal of Public Affairs, 22(S1), e2777.

Jagolinzer, A. D., Larcker, D. F., Ormazabal, G., & Taylor, D. J. (2020). Political connections and the informativeness of insider trades. *The Journal of Finance,* 75(4), 1833–1876.

Jenq, C., Pan, J., & Theseira, W. (2015). Beauty, weight, and skin color in charitable giving. *Journal of Economic Behavior & Organization*, 119, 234-253.

Jiang, C., Wintoki, M.B., & Xi, Y. (2021). Insider trading and the legal expertise of corporate executives. *Journal of Banking & Finance*, 127, 106114.

Khalil, S., & Sidani, Y. (2022). Personality traits, religiosity, income, and tax evasion attitudes: An exploratory study in Lebanon. Journal of International Accounting, Auditing and Taxation, 47, 100469.

Khan, M.S., & Umer, H. (2024). ChatGPT in finance: Applications, challenges, and solutions. *Heliyon*, 10, e24890.

Kim, J.H. (2023). What if ChatGPT were a quant asset manager. *Finance Research Letters*, 58, 104580.

Kim, Y.H., Park, J., & Shin, H. (2022). CEO facial masculinity, fraud, and ESG: Evidence from South Korea. Emerging Markets Review, 53, 100917.

Koch-Bayram, I.F., & Wernicke, G. (2018). Drilled to obey? Ex-military CEOs and financial misconduct. *Strategic Management Journal*, 39(11), 2943-2964.

Kowaleski, Z.T., Sutherland, A.G., & Vetter, F.W. (2020). Can ethics be taught? Evidence from securities exams and investment adviser misconduct. *Journal of Financial Economics,* 138, 159-175.

Langton, L., & Piquero, N.L. (2007). Can general strain theory explain white-collar crime? A preliminary investigation of the relationship between strain and select white-collar offenses. *Journal of Criminal Justice*, 35(1), 1-15.

Lapointe-Antunes, P., Veenstra, K., Brown, K., & Li, H. (2022). Welcome to the gray zone: Shades of honesty and earnings management. *Journal of Business Ethics*, 177, 125–149.

Lederman, L. (2021). The fraud triangle and tax evasion. *Iowa Law Review*, 106(3), 1153–1207.

Lei, Z., Petmezas, D., Rau, P.R., & Yang, C. (2025). Born to behave: Home CEOs and financial misconduct. *Review of Accounting Studies*, 30, 1309-1354.

Li, X., Feng, H., Yang, H., & Huang, J. (2024). Can ChatGPT reduce human financial analysts' optimistic biases? *Economic and Political Studies*, 12(1), 20-33.

Li, V., & Wang, L. (2024). Frequent executive turnover and accounting information quality. *Journal of Accounting Literature*. https://doi.org/10.1108/JAL-07-2023-0118

Li, Z., Liang, C. Y. C., & Tang, Z. (2025). CEO social media activity and insider trading. *Journal of Financial Research*, 1–39.

Liu, X., Young, M., & Liao, J. (2024). CEO early-life experience and corporate accounting conservatism: Insights from the socio-political context. *Emerging Markets Review*, 63, 101215.

Liu, Y., Zhang, H., & Zhang, F. (2023). CEO's poverty imprints and corporate financial fraud: Evidence from China. *Pacific-Basin Finance Journal*, 81, 102128.

Mutschmann, M., Hasso, T., & Pelster, M. (2022). Dark triad managerial personality and financial reporting manipulation. *Journal of Business Ethics*, 181(3), 763-788.

Nguyen Thanh, B., Nguyen, A.T., Chu, T.T., & Ha, S. (2025). Decoding Market Sentiment: The Power of ChatGPT in Explaining Bitcoin Returns from X Data. *SSRN Working Paper*. Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4628097

Niszczota, P. & Abbas, S. (2023). GPT has become financially literate: Insights from financial literacy tests of GPT and a preliminary test of how people use it as a source of advice. *Finance Research Letters*, 58(A), 104333.

Oehler, A., & Horn, M. (2024). Does ChatGPT provide better advice than robo-advisors? *Finance Research Letters*, 60, 104898.

Pelster, M. & Val, J. (2024). Can ChatGPT assist in picking stocks? *Finance Research Letters*, 59, 104786.

Piff, P.K., Stancato, D.M., Côté, S., Mendoza-Denton, R. & Keltner, D. (2012). Higher social class predicts increased unethical behavior. *Proceedings of the National Academy of Sciences*, 109(11), 4086–4091.

Ravina, E. (2026). Love & Loans: The effect of beauty and personal characteristics in credit markets. *SSRN Working Paper*. Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1101647

Rijsenbilt, A., & Commandeur, H. (2013). Narcissus enters the courtroom: CEO narcissism and fraud. *Journal of Business Ethics,* 117, 413–429.

Scanlon, M., Breitinger, F., Hargreaves, C., Hilgert, J.-N., & Sheppard, J. (2023). ChatGPT for digital forensic investigation: The good, the bad, and the unknown. *Forensic Science International: Digital Investigation*, 46, 301609.

Schneider, C.J., & Yilmaz, Y. (2025). Stock portfolio selection based on risk appetite: Evidence from ChatGPT. *Finance Research Letters*, 82, 107517.

Schrand, C.M., & Zechman, S.L.C. (2012). Executive overconfidence and the slippery slope to financial misreporting. *Journal of Accounting and Economics,* 53, 311-329.

Shafer, W.E., & Wang, Z. (2018). Machiavellianism, social norms, and taxpayer compliance. *Business Ethics: A European Review*, 27(1), 42–55.

Sutherland, Edwin H. 1934. Principles of Criminology. 2nd ed. Chicago: J. B. Lippincott Company.

Sutherland, Edwin H. 1939. Principles of Criminology. 3rd ed. Philadelphia: J. B. Lippincott Company.

Tegelaar, P. (2025). How LLMs are becoming investigative partners in fintech fraud detection. *Taktile*, February 13.

Thornton, E.M., Aknin, L.B., Branscombe, N.R., & Helliwell, J.F. (2019). Prosocial perceptions of taxation predict support for taxes. *PLoS ONE, 14(11)*, e0225730.

Wang, Y.E., & Gu, K. (2026). Who invests, who gets funded: Gender and racial bias in LLM-generated investment advice. *Journal of Business Ethics*, https://doi.org/10.1007/s10551-026-06251-6

Figure 1: Selection Frequencies for Financial Statement Fraud

This chart presents the simulation results for financial statement fraud. We access ChatGPT-4.1 through the API and run 1,000 simulations using our prompt, with a temperature setting of 0.5. The bars report the overall selection frequency of each variable. Blue bars indicate variables with positive coefficients, while red bars indicate negative coefficients. The corresponding percentages show how often a variable appears with a positive or negative coefficient across the simulations. To keep the figure readable, we report only variables with a selection frequency of at least 20%.

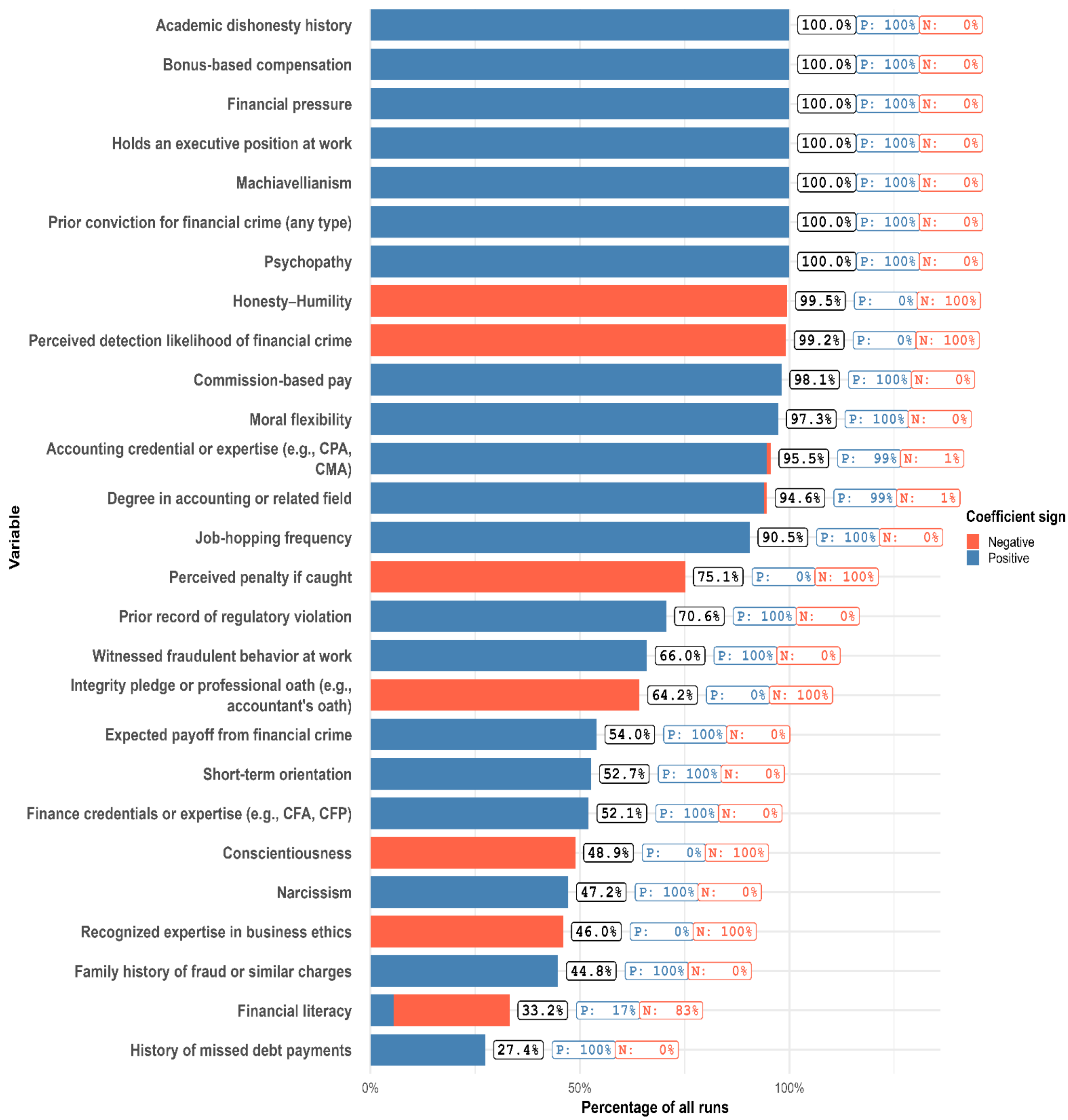


Figure 2: Selection Frequencies for Investment Fraud

This chart presents the simulation results for investment fraud. We access ChatGPT-4.1 through the API and run 1,000 simulations using our prompt, with a temperature setting of 0.5. The bars report the overall selection frequency of each variable. Blue bars indicate variables with positive coefficients, while red bars indicate negative coefficients. The corresponding percentages show how often a variable appears with a positive or negative coefficient across the simulations. To keep the figure readable, we report only variables with a selection frequency of at least 20%.

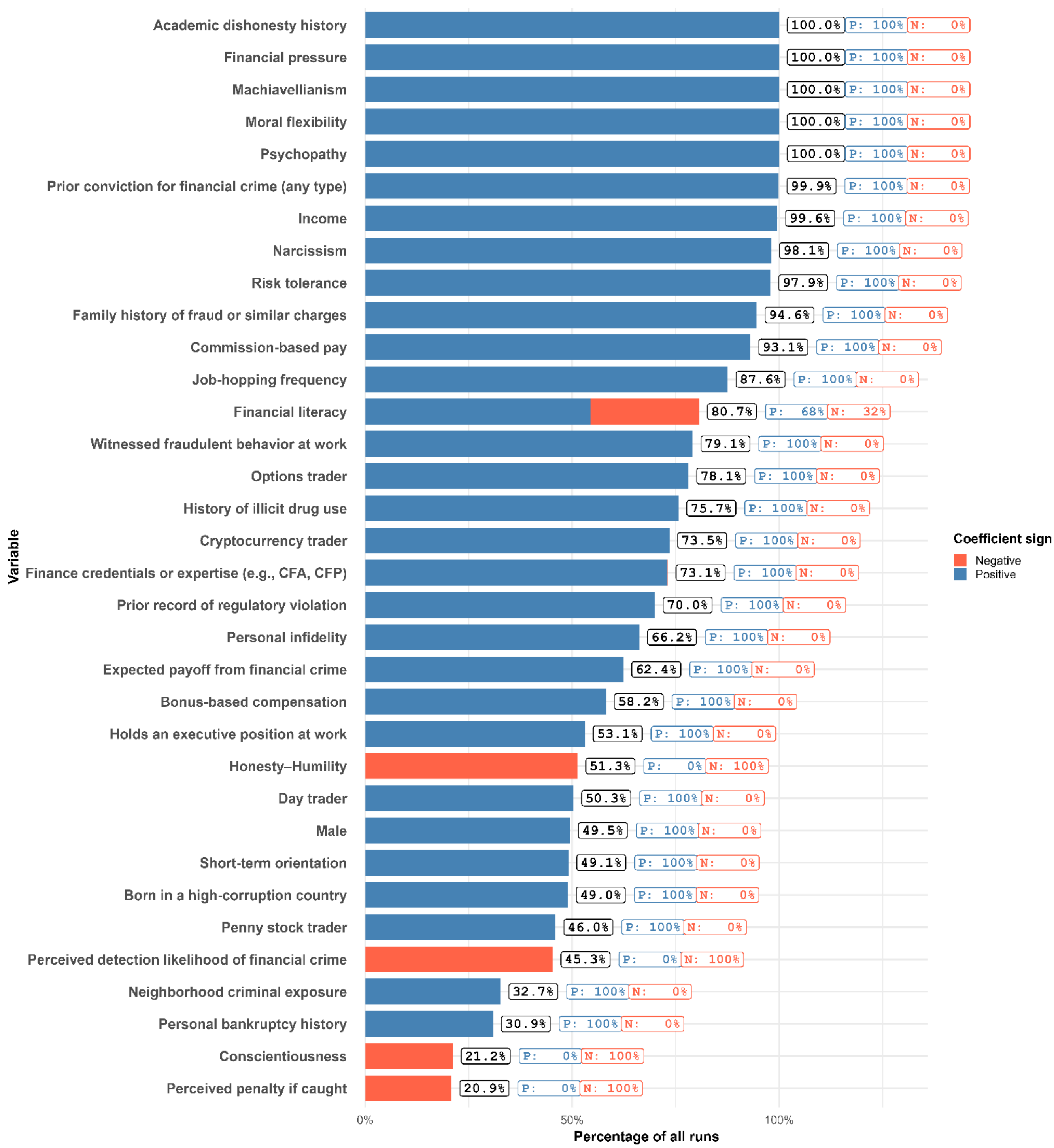


Figure 3: Selection Frequencies for Illegal Insider Trading

This chart presents the simulation results for illegal insider trading. We access ChatGPT-4.1 through the API and run 1,000 simulations using our prompt, with a temperature setting of 0.5. The bars report the overall selection frequency of each variable. Blue bars indicate variables with positive coefficients, while red bars indicate negative coefficients. The corresponding percentages show how often a variable appears with a positive or negative coefficient across the simulations. To keep the figure readable, we report only variables with a selection frequency of at least 20%.

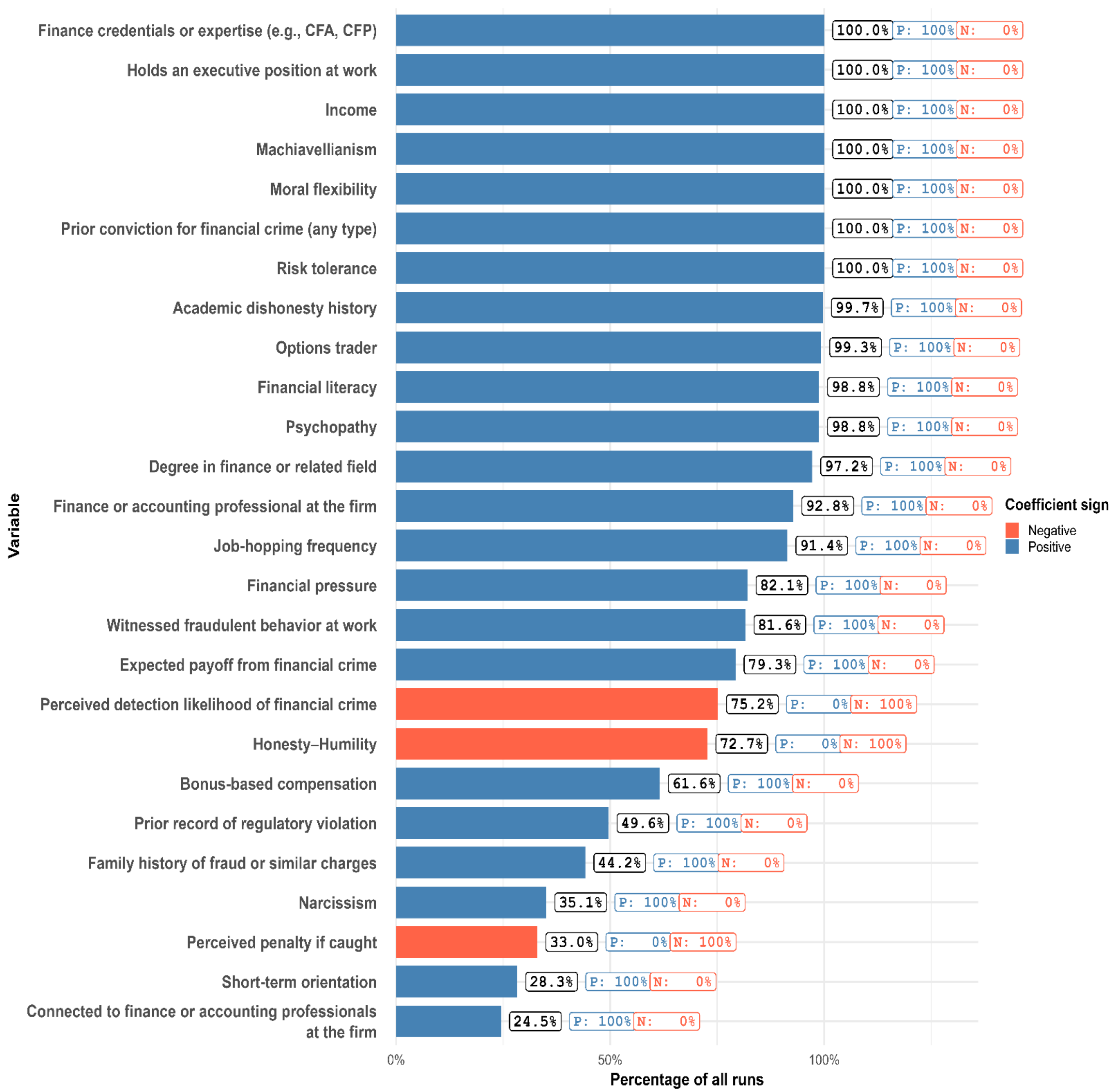


Figure 4: Selection Frequencies for Embezzlement

This chart presents the simulation results for embezzlement. We access ChatGPT-4.1 through the API and run 1,000 simulations using our prompt, with a temperature setting of 0.5. The bars report the overall selection frequency of each variable. Blue bars indicate variables with positive coefficients, while red bars indicate negative coefficients. The corresponding percentages show how often a variable appears with a positive or negative coefficient across the simulations. To keep the figure readable, we report only variables with a selection frequency of at least 20%.

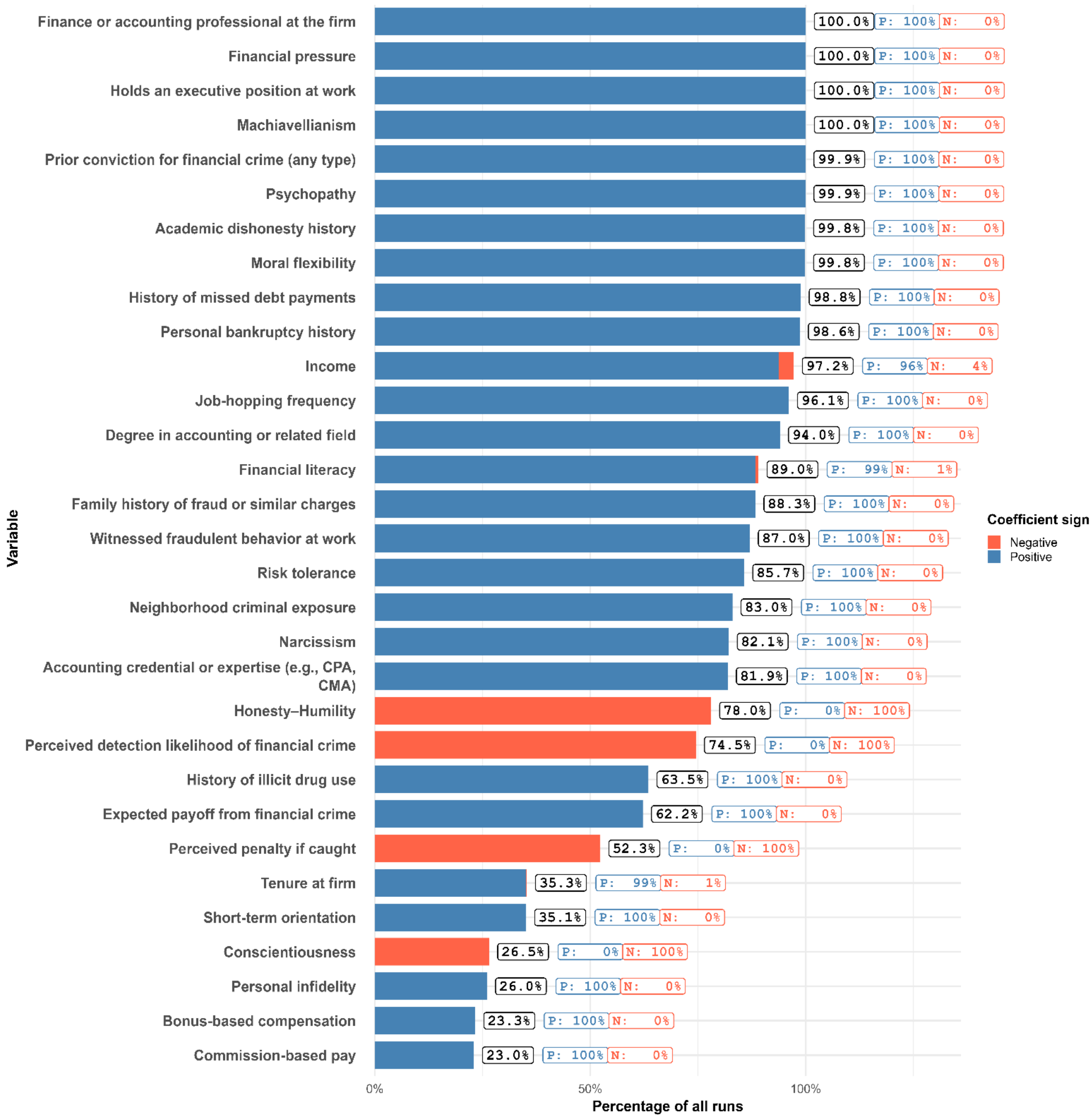


Figure 5: Selection Frequencies for Giving or Receiving Bribes

This chart presents the simulation results for giving or receiving bribes. We access ChatGPT-4.1 through the API and run 1,000 simulations using our prompt, with a temperature setting of 0.5. The bars report the overall selection frequency of each variable. Blue bars indicate variables with positive coefficients, while red bars indicate negative coefficients. The corresponding percentages show how often a variable appears with a positive or negative coefficient across the simulations. To keep the figure readable, we report only variables with a selection frequency of at least 20%.

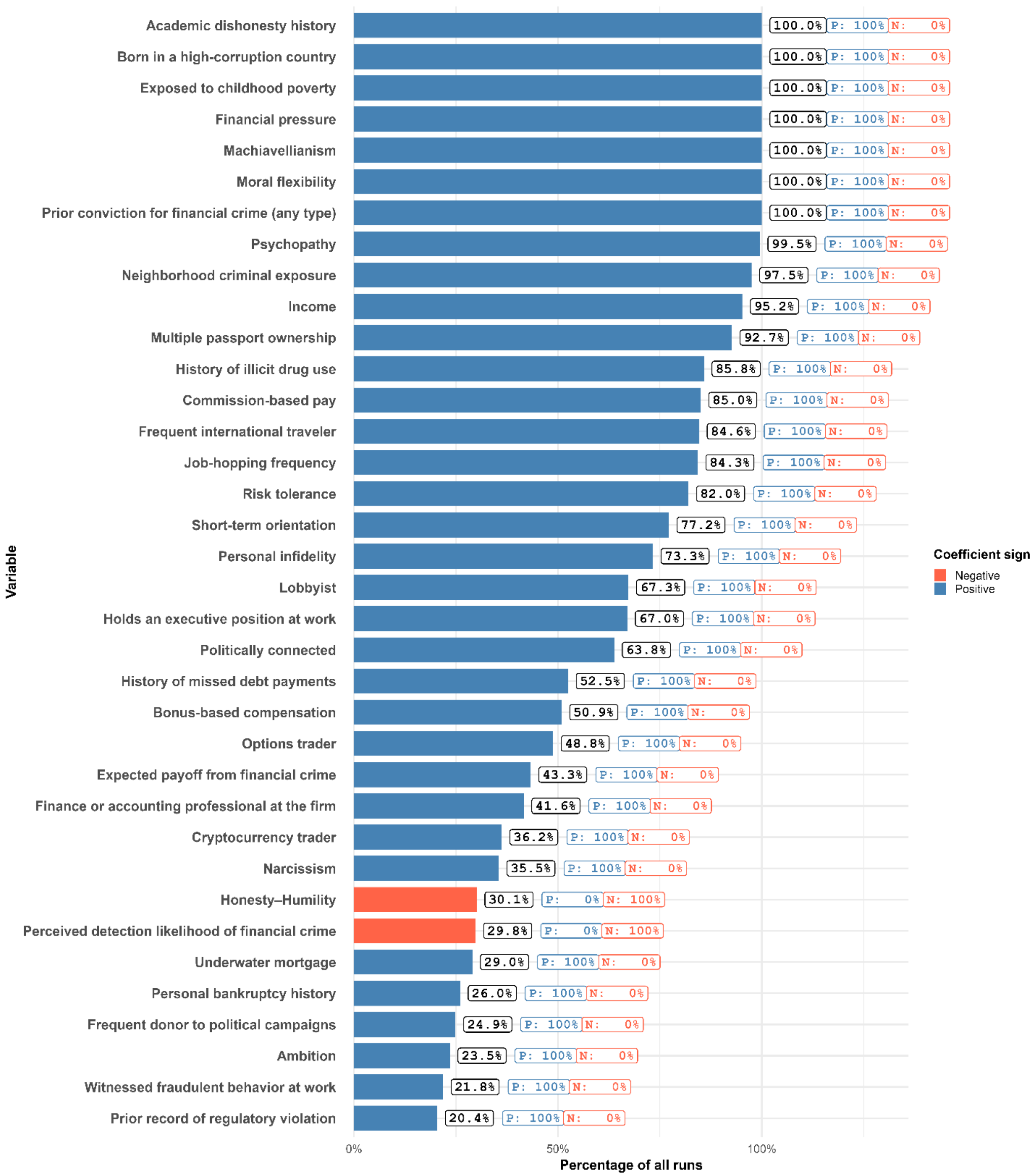


Figure 6: Selection Frequencies for Tax Evasion

This chart presents the simulation results for tax evasion. We access ChatGPT-4.1 through the API and run 1,000 simulations using our prompt, with a temperature setting of 0.5. The bars report the overall selection frequency of each variable. Blue bars indicate variables with positive coefficients, while red bars indicate negative coefficients. The corresponding percentages show how often a variable appears with a positive or negative coefficient across the simulations. To keep the figure readable, we report only variables with a selection frequency of at least 20%.

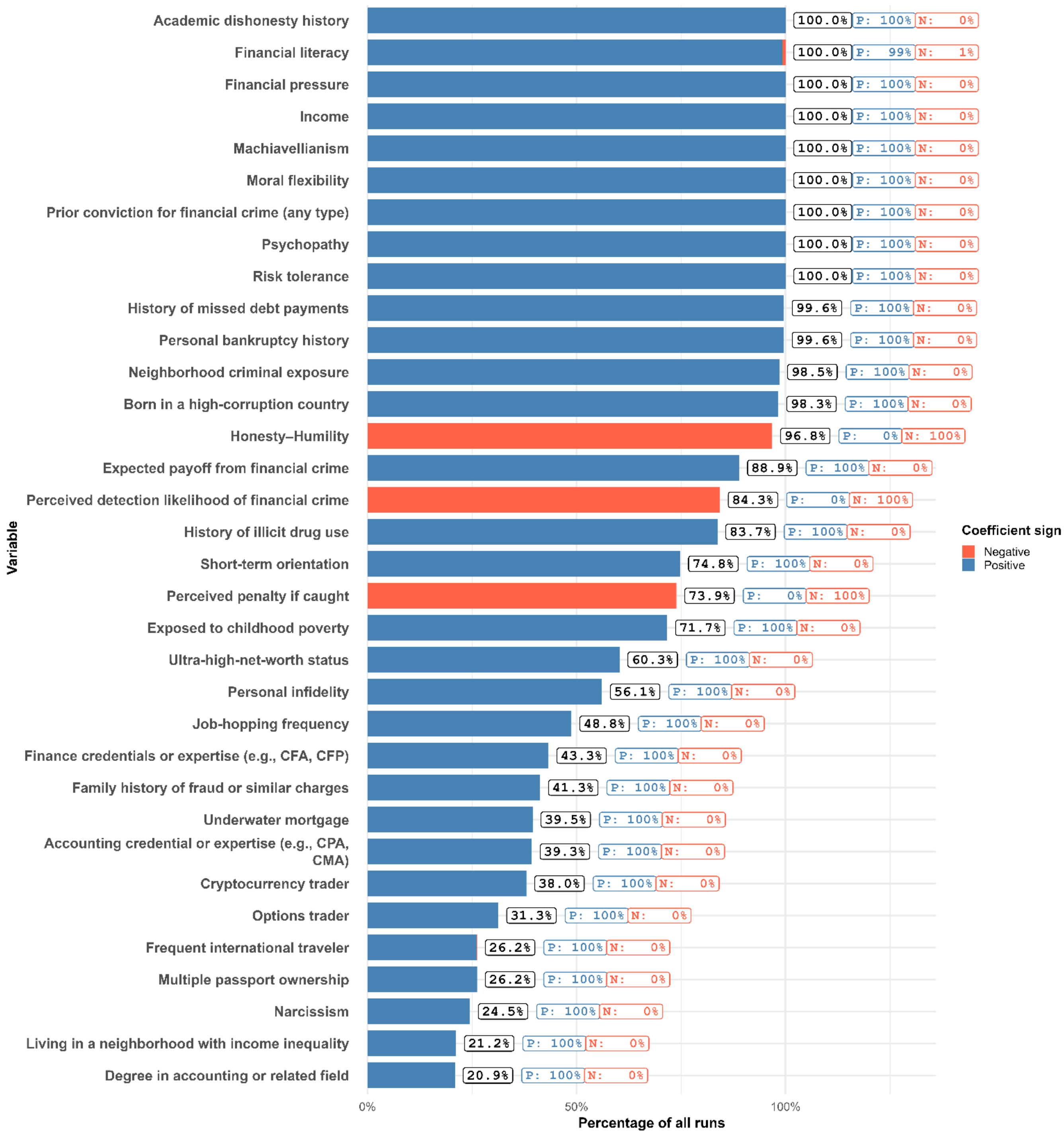


Figure 7: Selection Frequencies for Money Laundering

This chart presents the simulation results for money laundering. We access ChatGPT-4.1 through the API and run 1,000 simulations using our prompt, with a temperature setting of 0.5. The bars report the overall selection frequency of each variable. Blue bars indicate variables with positive coefficients, while red bars indicate negative coefficients. The corresponding percentages show how often a variable appears with a positive or negative coefficient across the simulations. To keep the figure readable, we report only variables with a selection frequency of at least 20%.

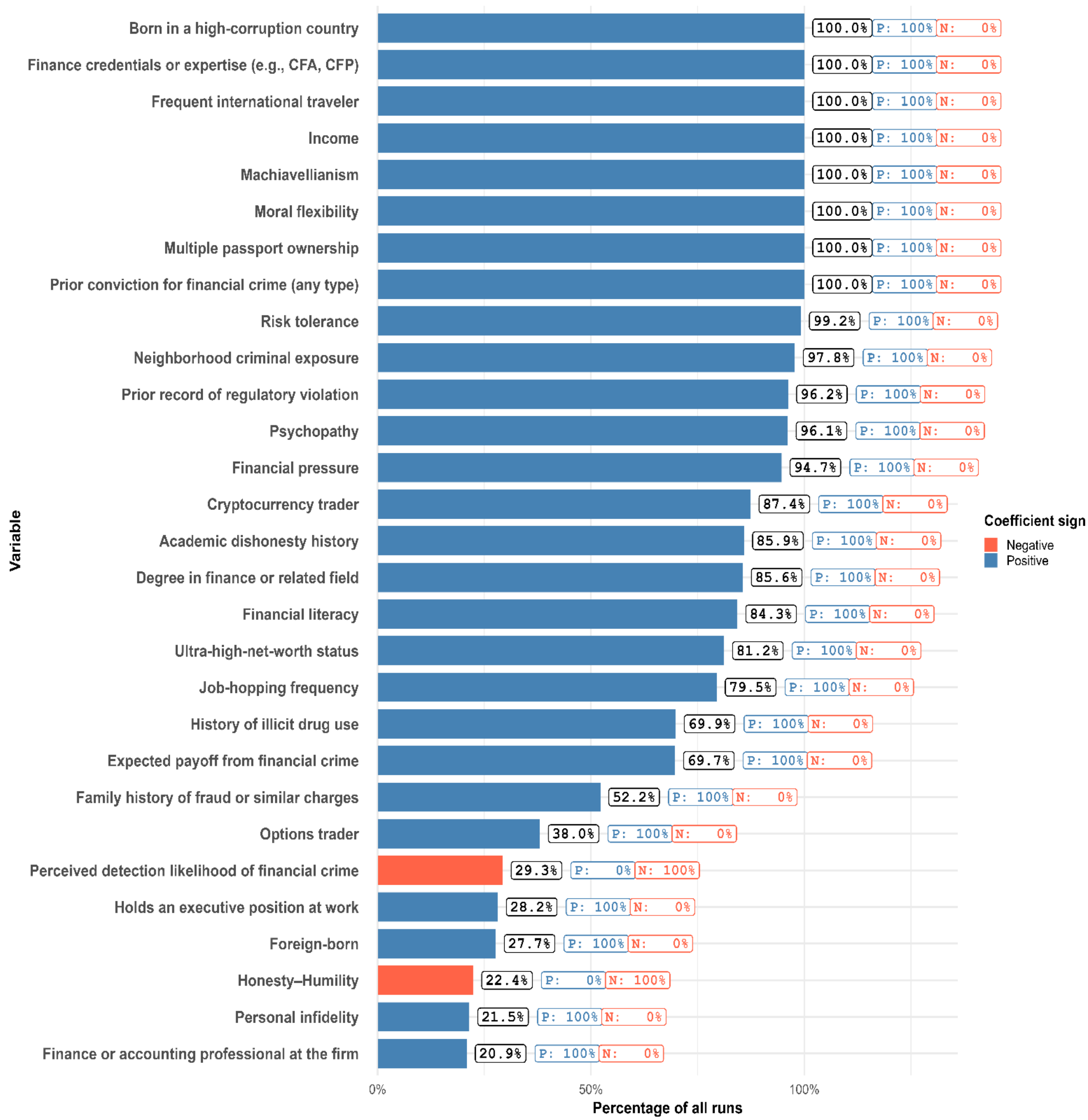


Figure 8: Selection Frequencies for Insurance Fraud

This chart presents the simulation results for insurance fraud. We access ChatGPT-4.1 through the API and run 1,000 simulations using our prompt, with a temperature setting of 0.5. The bars report the overall selection frequency of each variable. Blue bars indicate variables with positive coefficients, while red bars indicate negative coefficients. The corresponding percentages show how often a variable appears with a positive or negative coefficient across the simulations. To keep the figure readable, we report only variables with a selection frequency of at least 20%.

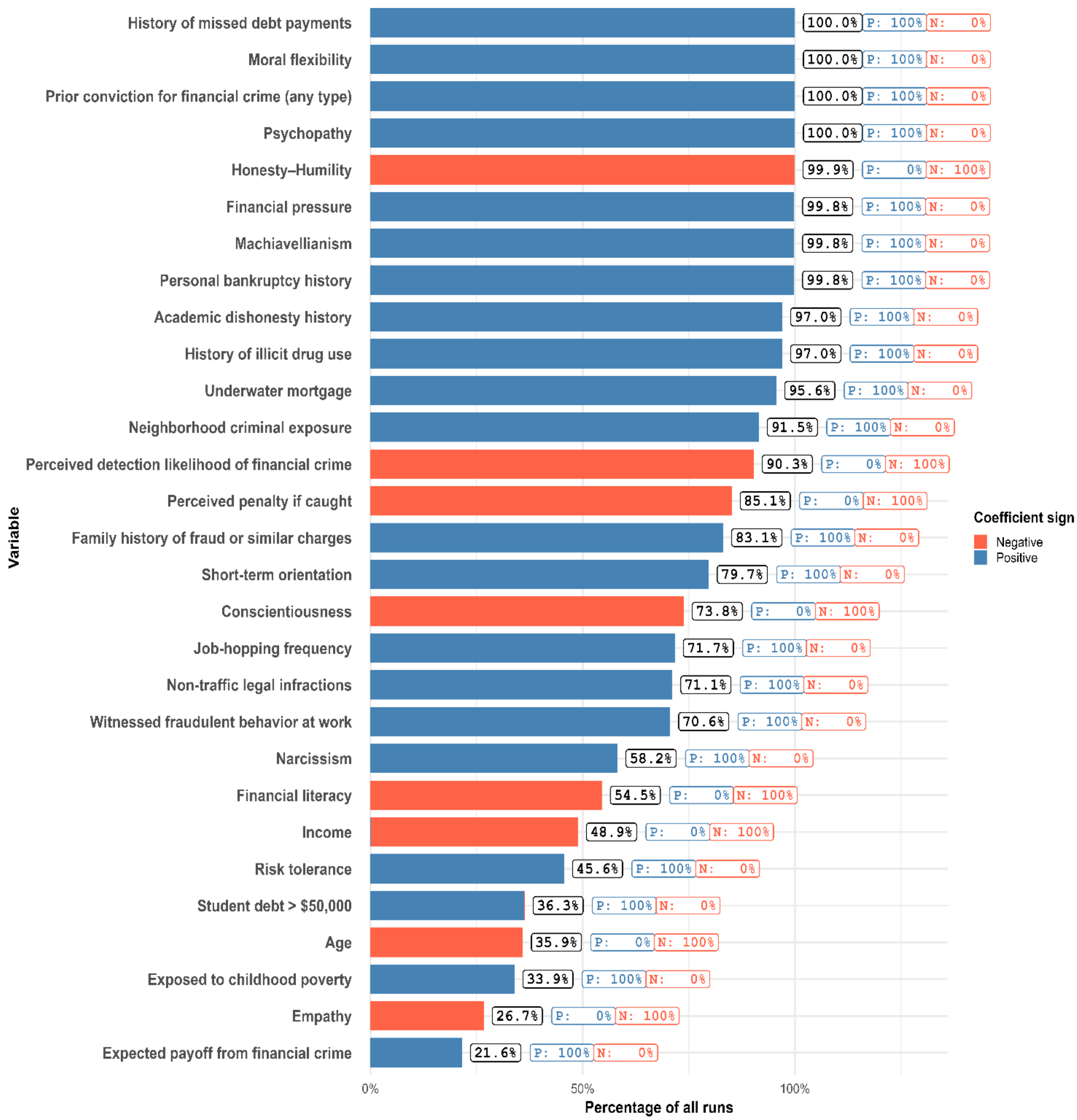


Figure 9: Selection Frequencies for Borrower Fraud

This chart presents the simulation results for borrower fraud. We access ChatGPT-4.1 through the API and run 1,000 simulations using our prompt, with a temperature setting of 0.5. The bars report the overall selection frequency of each variable. Blue bars indicate variables with positive coefficients, while red bars indicate negative coefficients. The corresponding percentages show how often a variable appears with a positive or negative coefficient across the simulations. To keep the figure readable, we report only variables with a selection frequency of at least 20%.

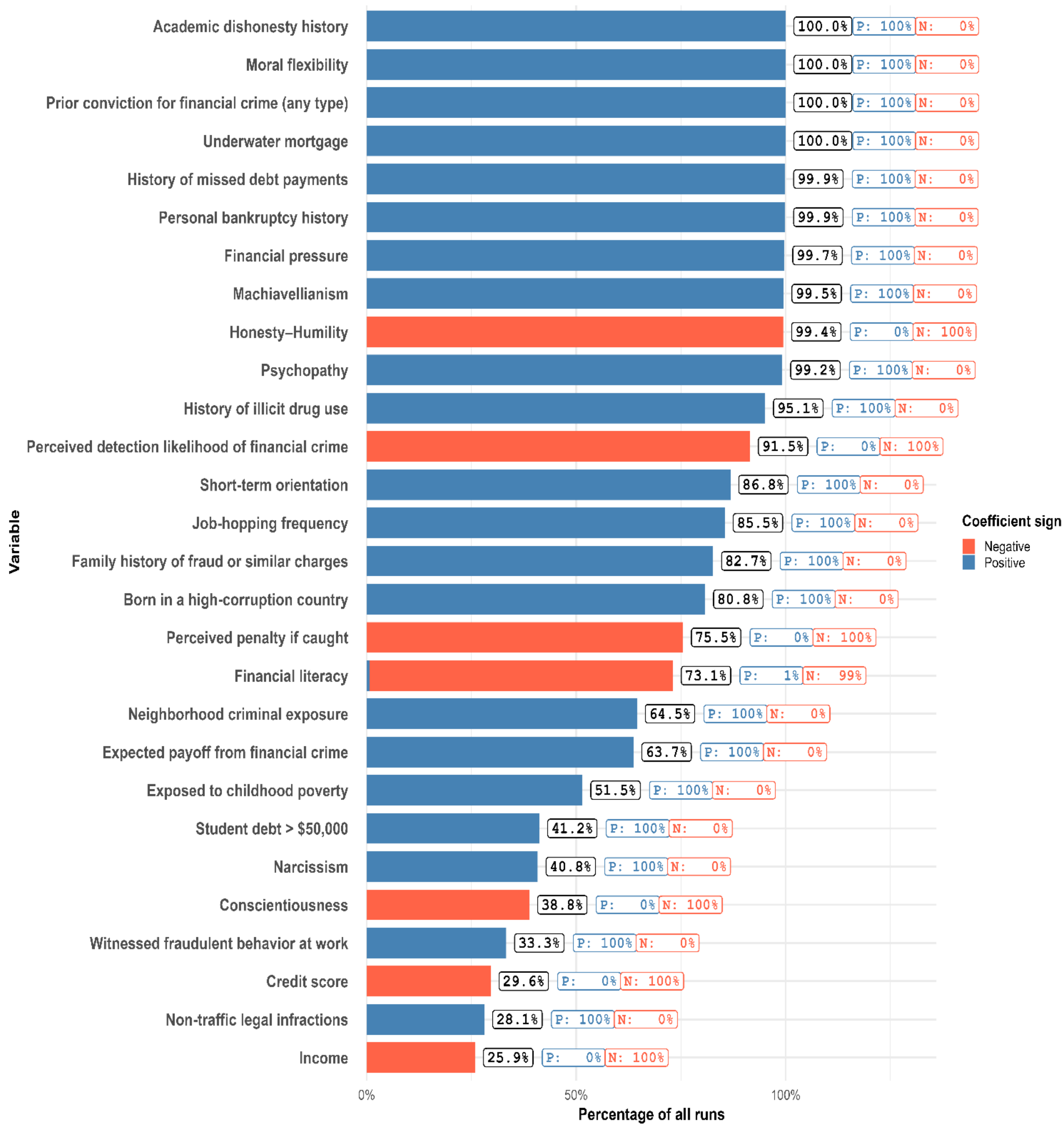
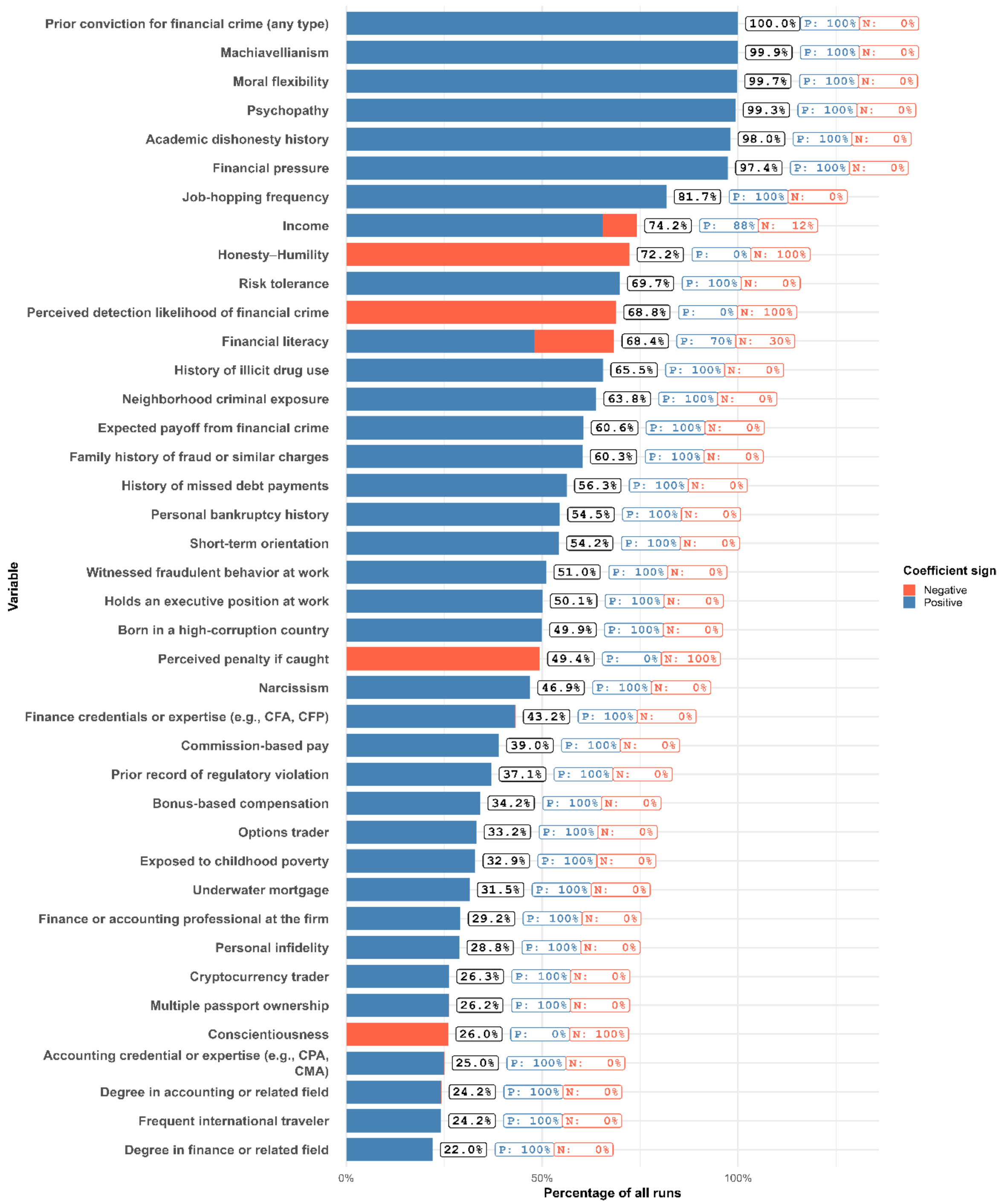


Figure 10: Aggregate Results

This chart presents the aggregate simulation results across all nine categories of financial crime. For each category, we access ChatGPT-4.1 through the API and run 1,000 simulations using our prompt, with a temperature setting of 0.5. The bars report the overall selection frequency of each variable. Blue bars indicate variables with positive coefficients, while red bars indicate negative coefficients. The corresponding percentages show how often a variable appears with a positive or negative coefficient across the simulations. To keep the figure readable, we report only variables with a selection frequency of at least 20%.



Appendix 1: List of Variables

Variable ID	Variable	Explanation
1	Age	Individual's age
2	Income	Individual's income
3	Male	Indicator = 1 if Male, 0 otherwise
4	Black	Indicator = 1 if Black, 0 otherwise
5	White	Indicator = 1 if White, 0 otherwise
6	Asian	Indicator = 1 if Asian, 0 otherwise
7	Hispanic	Indicator = 1 if Hispanic, 0 otherwise
8	Foreign-born	Indicator = 1 if yes, 0 otherwise
9	Born in a high-corruption country	Indicator = 1 if yes, 0 otherwise
10	Exposed to childhood poverty	Indicator = 1 if yes, 0 otherwise
11	Married	Indicator = 1 if yes, 0 otherwise
12	Number of children	How many children an individual has
13	Height	Individual's height. Scale from 1 = very short to 5 = very tall
14	Body mass index (BMI)	Individual's BMI
15	Physical attractiveness	Individual's physical attractiveness. Scale from 1 = low to 5 = high
16	Disability status	Indicator = 1 if yes, 0 otherwise
17	Former military personnel	Indicator = 1 if yes, 0 otherwise
18	Former law enforcement officer	Indicator = 1 if yes, 0 otherwise
19	Former athlete	Indicator = 1 if yes, 0 otherwise
20	Martial artist	Indicator = 1 if yes, 0 otherwise
21	Multiple passport ownership	Indicator = 1 if an individual has multiple passports, 0 otherwise
22	Volunteer and civic activity level	Scale from 1 = low to 5 = high
23	Former politician	Indicator = 1 if yes, 0 otherwise
24	Pilot license	Indicator = 1 if an individual has a pilot license, 0 otherwise
25	Frequent international traveler	Indicator = 1 if yes, 0 otherwise
26	Chess player	Indicator = 1 if yes, 0 otherwise
27	Bilingual or multilingual	Indicator = 1 if yes, 0 otherwise
28	Oratory skills	Scale from 1 = low to 5 = high
29	IQ	Individual's IQ. Scale from 1=low, 5=high
30	Cancer survivor	Indicator = 1 if yes, 0 otherwise
31	Tattooed individual	Indicator = 1 if yes, 0 otherwise
32	Financial literacy	Scale from 1 = low to 5 = high
33	Degree in computer science or related field	Indicator = 1 if yes, 0 otherwise

34	Expert in artificial intelligence (AI)	Indicator = 1 if yes, 0 otherwise
35	Degree in finance or related field	Indicator = 1 if yes, 0 otherwise
36	Degree in accounting or related field	Indicator = 1 if yes, 0 otherwise
37	Graduate degree (Master's or PhD)	Indicator = 1 if yes, 0 otherwise
38	Finance credentials or expertise (e.g., CFA, CFP)	Indicator = 1 if yes, 0 otherwise
39	Accounting credential or expertise (e.g., CPA, CMA)	Indicator = 1 if yes, 0 otherwise
40	Degree from an Ivy League school	Indicator = 1 if yes, 0 otherwise
41	Academic honors history	Indicator = 1 if yes, 0 otherwise
42	Financial crime expert	Indicator = 1 if yes, 0 otherwise
43	Legal or compliance training	Indicator = 1 if yes, 0 otherwise
44	Holds an executive position at work	Indicator = 1 if yes, 0 otherwise
45	Relative of the company's founder	Indicator = 1 if yes, 0 otherwise
46	Size of the firm where the individual works	Scale from 1= small to 5= large
47	Tenure at firm	Scale from 1 = short to 5= long
48	Recognized expertise in business ethics	Indicator = 1 if yes, 0 otherwise
49	Integrity pledge or professional oath (e.g., accountant's oath)	Indicator = 1 if yes, 0 otherwise
50	Job-hopping frequency	Scale from 1 = low to 5 = high
51	Member of multiple boards	Indicator = 1 if yes, 0 otherwise
52	Finance or accounting professional at the firm	Indicator = 1 if yes, 0 otherwise
53	Connected to finance or accounting professionals at the firm	Indicator = 1 if yes, 0 otherwise
54	Connected to finance or accounting professionals outside the firm	Indicator = 1 if yes, 0 otherwise
55	Connected to journalists	Indicator = 1 if yes, 0 otherwise
56	Connected to law enforcement officers	Indicator = 1 if yes, 0 otherwise
57	Professional money manager	Indicator = 1 if yes, 0 otherwise
58	Healthcare professional	Indicator = 1 if yes, 0 otherwise
59	Financial analyst	Indicator = 1 if yes, 0 otherwise
60	Attorney	Indicator = 1 if yes, 0 otherwise
61	Star employee	Indicator = 1 if yes, 0 otherwise
62	Rapid promotion record	Indicator = 1 if yes, 0 otherwise
63	Layoff notice recipient	Indicator = 1 if yes, 0 otherwise
64	Credit score	Individual's credit score
65	Financial pressure	Scale from 1 = low to 5 = high
66	Homeowner	Indicator = 1 if yes, 0 otherwise
67	Underwater mortgage	Indicator = 1 if yes, 0 otherwise
68	Student debt > $50,000	Indicator = 1 if yes, 0 otherwise
69	History of missed debt payments	Indicator = 1 if yes, 0 otherwise
70	Bonus-based compensation	Indicator = 1 if yes, 0 otherwise
71	Commission-based pay	Indicator = 1 if yes, 0 otherwise
72	Personal bankruptcy history	Indicator = 1 if yes, 0 otherwise
73	Health insurance coverage	Indicator = 1 if yes, 0 otherwise

74	Ultra-high-net-worth status	Indicator = 1 if yes, 0 otherwise
75	Options trader	Indicator = 1 if yes, 0 otherwise
76	Penny stock trader	Indicator = 1 if yes, 0 otherwise
77	Day trader	Indicator = 1 if yes, 0 otherwise
78	Cryptocurrency trader	Indicator = 1 if yes, 0 otherwise
79	Luxury vehicle owner	Indicator = 1 if yes, 0 otherwise
80	Confidence	Scale from 1 = low to 5 = high
81	Risk tolerance	Scale from 1 = low to 5 = high
82	Emotional intelligence	Scale from 1 = low to 5 = high
83	Ambition	Scale from 1 = low to 5 = high
84	Empathy	Scale from 1 = low to 5 = high
85	Narcissism	Scale from 1 = low to 5 = high
86	Machiavellianism	Scale from 1 = low to 5 = high
87	Psychopathy	Scale from 1 = low to 5 = high
88	Masculinity	Scale from 1 = low to 5 = high
89	Conscientiousness	Scale from 1 = low to 5 = high
90	Agreeableness	Scale from 1 = low to 5 = high
91	Neuroticism	Scale from 1 = low to 5 = high
92	Honesty–Humility	Scale from 1 = low to 5 = high
93	Short-term orientation	Scale from 1 = low to 5 = high
94	Moral flexibility	Scale from 1 = low to 5 = high
95	Exposure to crime-related media (e.g., books, movies)	Scale from 1 = low to 5 = high
96	Social comparison tendency	Scale from 1 = low to 5 = high
97	Religiosity	Scale from 1 = low to 5 = high
98	Trust in government	Scale from 1 = low to 5 = high
99	Trust in courts	Scale from 1 = low to 5 = high
100	Job security	Scale from 1 = low to 5 = high
101	Perceived detection likelihood of financial crime	Scale from 1 = low to 5 = high
102	Perceived penalty if caught	Scale from 1 = low to 5 = high
103	Expected payoff from financial crime	Scale from 1 = low to 5 = high
104	Traffic violation history	Indicator = 1 if yes, 0 otherwise
105	Non-traffic legal infractions	Indicator = 1 if yes, 0 otherwise
106	Prior conviction for financial crime (any type)	Indicator = 1 if yes, 0 otherwise
107	Prior record of regulatory violation	Indicator = 1 if yes, 0 otherwise
108	Academic dishonesty history	Indicator = 1 if yes, 0 otherwise
109	Witnessed fraudulent behavior at work	Indicator = 1 if yes, 0 otherwise
110	Acquitted of financial crimes	Indicator = 1 if yes, 0 otherwise
111	Victim of fraudulent activities	Indicator = 1 if yes, 0 otherwise
112	Family history of fraud or similar charges	Indicator = 1 if yes, 0 otherwise
113	Social media activity	Scale from 1 = low to 5 = high
114	Neighborhood criminal exposure	Indicator = 1 if yes, 0 otherwise
115	Belongs to a country club	Indicator = 1 if yes, 0 otherwise

116	Living in a neighborhood with income inequality	Indicator = 1 if yes, 0 otherwise
117	Lives close to the workplace	Indicator = 1 if yes, 0 otherwise
118	History of illicit drug use	Indicator = 1 if yes, 0 otherwise
119	History of mental illness	Indicator = 1 if yes, 0 otherwise
120	History of a heart attack	Indicator = 1 if yes, 0 otherwise
121	History of a suicide attempt	Indicator = 1 if yes, 0 otherwise
122	Sleep deprivation	Scale from 1 = low to 5 = high
123	Personal infidelity	Indicator = 1 if yes, 0 otherwise
124	Political affiliation: Democrat	Indicator = 1 if yes, 0 otherwise
125	Political affiliation: Republican	Indicator = 1 if yes, 0 otherwise
126	Political affiliation: Independent	Indicator = 1 if yes, 0 otherwise
127	Politically active and engaged	Scale from 1 = low to 5 = high
128	Politically connected	Scale from 1 = low to 5 = high
129	Lobbyist	Indicator = 1 if yes, 0 otherwise
130	Frequent donor to political campaigns	Indicator = 1 if yes, 0 otherwise

Appendix 2: Selection Frequencies

Variable Name	Times Selected	Positive Count	Negative Count
Prior conviction for financial crime (any type)	8998	8998	0
Machiavellianism	8993	8993	0
Moral flexibility	8971	8971	0
Psychopathy	8935	8935	0
Academic dishonesty history	8824	8824	0
Financial pressure	8763	8763	0
Job-hopping frequency	7354	7354	0
Income	6677	5892	785
Honesty–Humility	6501	0	6501
Risk tolerance	6276	6276	0
Perceived detection likelihood of financial crime	6194	0	6194
Financial literacy	6154	4325	1829
History of illicit drug use	5898	5898	0
Neighborhood criminal exposure	5740	5740	0
Expected payoff from financial crime	5451	5451	0
Family history of fraud or similar charges	5426	5426	0
History of missed debt payments	5063	5063	0
Personal bankruptcy history	4908	4908	0
Short-term orientation	4881	4881	0
Witnessed fraudulent behavior at work	4590	4590	0
Holds an executive position at work	4509	4509	0
Born in a high-corruption country	4494	4494	0
Perceived penalty if caught	4447	0	4447
Narcissism	4220	4220	0
Finance credentials or expertise (e.g., CFA, CFP)	3887	3885	2
Commission-based pay	3506	3506	0
Prior record of regulatory violation	3336	3336	0
Bonus-based compensation	3075	3075	0
Options trader	2989	2989	0
Exposed to childhood poverty	2964	2964	0
Underwater mortgage	2831	2831	0
Finance or accounting professional at the firm	2624	2624	0
Personal infidelity	2596	2596	0
Cryptocurrency trader	2363	2363	0
Multiple passport ownership	2356	2352	4
Conscientiousness	2336	0	2336
Accounting credential or expertise (e.g., CPA, CMA)	2251	2241	10
Degree in accounting or related field	2182	2175	7

Frequent international traveler	2177	2174	3
Degree in finance or related field	1979	1979	0
Ultra-high-net-worth status	1423	1423	0
Non-traffic legal infractions	1319	1319	0
Integrity pledge or professional oath (e.g., accountant's oath)	1278	0	1278
Living in a neighborhood with income inequality	886	886	0
Politically connected	822	822	0
Student debt > $50,000	798	797	1
Day trader	729	729	0
Lobbyist	680	679	1
Age	583	0	583
Recognized expertise in business ethics	581	0	581
Ambition	566	566	0
Male	531	531	0
Penny stock trader	504	504	0
Job security	438	0	438
Tenure at firm	393	358	35
Empathy	380	0	380
Credit score	349	0	349
Foreign-born	290	290	0
Connected to finance or accounting professionals at the firm	249	249	0
Frequent donor to political campaigns	249	249	0
Former politician	188	185	3
Religiosity	157	0	157
Member of multiple boards	156	156	0
Exposure to crime-related media (e.g., books, movies)	149	149	0
Social comparison tendency	136	136	0
History of mental illness	132	132	0
Trust in government	124	0	124
Agreeableness	118	0	118
Victim of fraudulent activities	95	94	1
Political affiliation: Independent	74	74	0
Professional money manager	63	63	0
Rapid promotion record	62	62	0
Financial analyst	60	60	0
Connected to finance or accounting professionals outside the firm	53	53	0
Luxury vehicle owner	46	46	0
History of a suicide attempt	38	38	0
Sleep deprivation	29	29	0
Traffic violation history	26	26	0
Confidence	20	20	0
Former military personnel	18	10	8

Relative of the company's founder	17	17	0
Volunteer and civic activity level	17	3	14
Graduate degree (Master’s or PhD)	16	14	2
Political affiliation: Republican	15	14	1
IQ	14	10	4
Former law enforcement officer	13	6	7
History of a heart attack	13	12	1
Number of children	13	13	0
Physical attractiveness	11	3	8
Layoff notice recipient	10	10	0
Size of the firm where the individual works	10	10	0
Trust in courts	10	0	10
Financial crime expert	9	3	6
White	8	8	0
Former athlete	7	1	6
Bilingual or multilingual	6	2	4
Martial artist	6	0	6
Belongs to a country club	5	5	0
Body mass index (BMI)	5	0	5
Lives close to the workplace	5	4	1
Oratory skills	5	4	1
Disability status	4	1	3
Married	4	0	4
Neuroticism	4	4	0
Star employee	4	4	0
Homeowner	3	0	3
Pilot license	3	0	3
Political affiliation: Democrat	3	2	1
Asian	2	1	1
Connected to law enforcement officers	2	0	2
Legal or compliance training	2	0	2
Chess player	1	0	1
Politically active and engaged	1	0	1
Academic honors history	0	0	0
Acquitted of financial crimes	0	0	0
Attorney	0	0	0
Black	0	0	0
Cancer survivor	0	0	0
Connected to journalists	0	0	0
Degree from an Ivy League school	0	0	0
Degree in computer science or related field	0	0	0
Emotional intelligence	0	0	0

Expert in artificial intelligence (AI)	0	0	0
Health insurance coverage	0	0	0
Healthcare professional	0	0	0
Height	0	0	0
Hispanic	0	0	0
Masculinity	0	0	0
Social media activity	0	0	0
Tattooed individual	0	0	0