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Exploring Youth Perspectives on Algorithmic Trading: Knowledge, Trust, and Adoption

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Abstract

The increasing adoption of algorithmic trading has significantly transformed financial markets by enabling automated decision-making and high-speed trade execution. While institutional investors and hedge funds have widely embraced this technology, its understanding and acceptance among young retail investors, particularly those aged 18 to 25, remain relatively unexplored. As digital trading platforms and fintech innovations continue to gain popularity, assessing the awareness, perception, and preferences of youth regarding algorithmic trading is crucial. This study aims to examine the extent to which young investors are familiar with algorithmic trading, their perceptions of its advantages and risks, and their willingness to adopt it. This study quantitatively examines youth engagement with algorithmic trading, revealing low awareness, moderate trust, and key adoption factors such as transparency and cost. The study explores their level of awareness and primary sources of information, evaluates their trust in automated trading systems, concerns about fairness and risks, and identifies key factors influencing their decision to use algorithmic trading, such as cost, transparency, and control. The findings of this research offer valuable insights for fintech companies, trading platforms, financial educators, and policymakers, helping them design financial literacy programs and trading solutions tailored to the next generation of investors. As young traders continue to influence market trends, understanding their perspective on algorithmic trading will be essential in shaping the future of digital investing and automated financial systems.

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Section 1: Introduction

1.1 Background of the Study

The Rise of Algorithmic Trading in Financial Markets

The financial markets have witnessed a remarkable transformation over the past few decades, largely driven by advancements in technology, automation, and data-driven decision-making**.** Among these innovations, algorithmic trading has emerged as a revolutionary approach that enhances the efficiency and accuracy of trade execution. Algorithmic trading refers to the use of pre-programmed trading instructions**,** which rely on variables such as price, volume, time, and other market indicators to automate trade execution without human intervention (Cartea, Jaimungal, & Penalva, 2015).

For this study, 'youth' refers to individuals aged 18-25, a demographic increasingly active in digital financial markets. High-frequency trading involves the use of complex algorithms to execute thousands of trades within milliseconds, capitalizing on minuscule price fluctuations (Hendershott, Jones, & Menkveld, 2011). Today, algorithmic trading has evolved further, incorporating cutting-edge technologies such as artificial intelligence (AI), machine learning (ML), and big data analytics**,** making it a crucial component of modern financial markets (Aldridge & Krawciw, 2017). According to market estimates, 60-70% of all equity trades globally are executed through algorithmic trading systems**,** demonstrating their growing dominance and influence (Mizuno, 2021).

Advantages and Challenges of Algorithmic Trading

Algorithmic trading offers several key advantages that have contributed to its widespread adoption among institutional investors, hedge funds, and retail traders. One of the primary benefits is speed and efficiency—trading algorithms can process market data, identify opportunities, and execute trades in real time, significantly reducing the delay associated with human decision-making (Hendershott & Riordan, 2013). This speed advantage allows traders to capitalize on small price discrepancies and market inefficiencies**,** resulting in potentially higher profits (Boehmer, Fong, & Wu, 2018).

Additionally, algorithmic trading enhances market liquidity by increasing trade volume and reducing bid-ask spreads. Studies have shown that liquidity-driven algorithmic trading strategies contribute to market stability by ensuring a continuous flow of buy and sell orders, minimizing price volatility (Chaboud et al., 2009). Another major advantage is reduced human error**—**since trading decisions are executed by pre-programmed algorithms, the likelihood of emotional biases, impulsive decisions, and execution errors is significantly lower (Dhar & Choe, 2001).

However, despite these benefits, algorithmic trading also presents several challenges and risks**.** One of the most notable concerns is market volatility and flash crashes. The 2010 Flash Crash remains one of the most well-documented cases where automated trading systems contributed to a sudden and extreme market downturn, wiping out nearly $1 trillion in market value within minutes (Kirilenko et al., 2017). Algorithmic trading can also lead to market manipulation**,** where unethical trading strategies such as spoofing and layering are used to create artificial demand or supply (Schmidt & Moeller, 2020).

Another significant challenge is the unequal playing field between institutional and retail traders**.** Large financial institutions have access to advanced trading algorithms, high-speed infrastructure, and vast datasets**,** giving them an advantage over small, individual traders who lack similar resources (Jones, 2013). This has raised concerns about fairness, transparency, and accessibility in financial markets (Schneider & Tobin, 2019).

The Role of Algorithmic Trading in the Retail Investment Landscape

While algorithmic trading was initially dominated by institutional investors and hedge funds**,** recent years have seen a surge in interest from retail traders**.** The rise of mobile trading apps, commission-free platforms, and cryptocurrency exchanges has made algorithmic trading more accessible to individual investors (Statista, 2023). Platforms such as Robinhood, eToro, and Binance have introduced automated trading tools that allow users to execute pre-set trading strategies without manual intervention (Patterson & White, 2022).

Despite this increased accessibility, retail traders often have limited awareness and understanding of how algorithmic trading works. Many rely on social media, online communities, and trading forums for investment advice rather than formal financial education (Chen & Tsai, 2020). This knowledge gap has led to concerns about risk exposure, as inexperienced traders may not fully understand the implications of automated trading strategies (Hoffmann, Shefrin, & Pennings, 2018).

Furthermore, the question of trust and perception remains crucial in determining whether retail investors will widely adopt algorithmic trading. Some traders perceive it as a fair and efficient tool, while others see it as a risk-prone system that favors institutional players (Barber & Odean, 2000). Addressing these concerns requires greater transparency, regulatory oversight, and investor education (Glaser & Weber, 2007).

Need for Research on Youth Perception of Algorithmic Trading

While extensive research has explored the impact of algorithmic trading on market efficiency, institutional investing, and regulatory challenges, relatively little attention has been given to how young retail investors (ages 18-25) perceive and engage with algorithmic trading**.** Given that younger generations are increasingly participating in financial markets, particularly through digital platforms, understanding their awareness, trust, and adoption preferences is critical for shaping the future of algorithmic trading (Schmidt & Moeller, 2020).

The rise of Gen Z and Millennial investors has brought new dynamics into financial markets. Studies show that young investors are more likely to use mobile-first trading apps, social media for financial advice, and digital payment solutions (Schneider & Tobin, 2019). However, their understanding of algorithmic trading, risk management, and long-term investment strategies remains unclear. This study seeks to fill that gap by examining the awareness, perception, and preferences of young retail investors regarding algorithmic trading.

By exploring these factors, this research will provide valuable insights for:

- Fintech companies to design user-friendly automated trading tools.
- Regulators and policymakers to ensure a fair and transparent market environment.
- Financial educators to improve literacy programs on algorithmic trading and risk management.

Thus, this study aims to bridge the gap in research by analyzing how young retail investors engage with algorithmic trading, what factors influence their perception and trust, and whether they are willing to adopt automated trading strategies in the future.

1.2 Problem Statement

Algorithmic trading has rapidly become a dominant force in modern financial markets, transforming the way trades are executed through automated systems that analyze market trends, execute orders, and optimize trading strategies with minimal human intervention. While institutional investors and hedge funds have long leveraged algorithmic trading for its efficiency and speed, the increasing participation of young retail investors (aged 18-25) in financial markets raises critical questions about their awareness, perception, and adoption of algorithmic trading tools. Despite the growing role of mobile trading apps, AI-powered financial advisors, and automated investment platforms, research on how young investors engage with algorithmic trading remains limited (Biais & Foucault, 2014).

Traditional research on algorithmic trading has primarily focused on market structure, regulatory challenges, and institutional trading strategies. These studies examine how high-frequency trading (HFT) influences market liquidity, volatility, and efficiency (Hendershott, Jones, & Menkveld, 2011). However, there is a gap in understanding how young, tech-savvy retail investors perceive and utilize algorithmic trading in their investment decisions (Aldridge & Krawciw, 2017). Given that young traders are increasingly reliant on digital trading platforms, robo-advisors, and AI-driven investment tools, it is critical to assess their knowledge, trust levels, and decision-making behavior regarding algorithmic trading (Statista, 2023).

A key challenge is that many young investors may be using algorithmic trading platforms without fully understanding their mechanics, risks, or potential benefits (Chaboud et al., 2009). Unlike institutional investors who have access to advanced research tools, financial advisors, and market analysts, retail traders—particularly those new to financial markets—often rely on social media, online communities, and digital influencers for financial knowledge (Chen & Tsai, 2020). This raises concerns about misinformation, over-reliance on algorithmic recommendations, and potential financial risks faced by young traders who may not fully grasp the complexities of automated trading strategies (Schneider & Tobin, 2019).

Additionally, perceptions of algorithmic trading vary widely among investors. Some view it as a valuable tool that enhances market efficiency, reduces trading costs, and provides greater accessibility to financial markets (Boehmer, Fong, & Wu, 2018). Others, however, believe that algorithmic trading favors institutional investors over retail traders, contributing to market manipulation, flash crashes, and unfair advantages for large financial firms (Jones, 2013). These concerns underscore the need to evaluate young investors' trust in algorithmic trading, their perception of fairness, and their willingness to adopt automated trading tools (Hoffmann, Shefrin, & Pennings, 2018).

To address these challenges, this study seeks to explore the following key questions:

1. Awareness

- How much do young investors know about algorithmic trading?
- Where do they acquire their knowledge (e.g., social media, news, academic courses, personal experience)?
- Do they recognize the extent to which algorithmic trading is embedded in modern trading platforms?

2. Perception

- Do young investors view algorithmic trading as an advantage (e.g., efficiency, accessibility) or as a risk (e.g., market volatility, unfair institutional dominance)?
- To what extent do they trust AI-driven trading systems compared to human decision-making?
- Do they believe that algorithmic trading promotes fairness or contributes to market manipulation?

3. Preferences

- Would young investors consider using algorithmic trading tools for their own investments?
- What factors influence their willingness or reluctance to adopt algorithmic trading (e.g., cost, ease of use, transparency, control over trades)?
- Do they prefer a hybrid approach where they retain some manual control, or are they comfortable with fully automated trading strategies?

By addressing these research questions, this study aims to provide valuable insights for fintech companies, financial educators, and policymakers, helping them develop better financial literacy programs, more transparent algorithmic trading platforms, and improved regulatory measures to support young investors in making informed trading decisions (Schmidt & Moeller, 2020). Understanding how youth interact with automated trading tools will be crucial in shaping the future of digital investing and ensuring that algorithmic trading remains accessible, fair, and beneficial for all market participants.

1.3 Research Objectives

The primary objective of this study is to examine the awareness, perception, and preferences of young investors (ages 18-25) regarding algorithmic trading. Specifically, the study aims to:

- **Assess Awareness** – Evaluate the level of knowledge young investors have about algorithmic trading, including their exposure to it, familiarity with its concepts, and understanding of its mechanisms in financial markets.
- **Analyze Perception –** Investigate how young investors perceive algorithmic trading, whether they consider it beneficial or risky, and their level of trust in its fairness, reliability, and impact on market dynamics.
- **Identify Preferences** – Determine whether young investors are willing to adopt algorithmic trading and explore the key factors influencing their decision-making, such as cost, ease of use, transparency, and control over trading strategies.

These objectives test the hypothesis that greater awareness of algorithmic trading increases youth willingness to adopt it. By addressing these objectives, this research aims to provide insights into the role of algorithmic trading in shaping the investment behaviour of young traders, offering valuable recommendations for fintech companies, policymakers, and financial educators.

1.4 Significance of the Study

The rapid evolution of financial markets and trading technologies has led to an increasing reliance on algorithmic trading systems, which now account for a significant portion of global trading activity. While extensive research has been conducted on institutional algorithmic trading, high-frequency trading (HFT), and regulatory frameworks, relatively little attention has been given to how young retail investors (ages 18-25) perceive and engage with algorithmic trading tools. As digital finance continues to expand, understanding the interaction between youth investors and algorithmic trading platforms is crucial for shaping the future of financial technology (fintech), investment education, and regulatory policies.

This study is particularly significant for three key stakeholder groups:

Fintech Companies and Trading Platforms

The fintech industry is rapidly evolving, with a growing number of trading platforms integrating automated investment strategies, robo-advisors, and AI-driven trade execution tools (Aldridge & Krawciw, 2017). Many fintech firms are actively developing algorithmic trading features within their platforms to attract both retail and institutional investors. However, there remains a knowledge gap in how young investors perceive these tools, what factors influence their adoption, and what concerns they may have regarding trust, transparency, and usability (Schmidt & Moeller, 2020).

By examining youth investors' awareness, perceptions, and preferences toward algorithmic trading, this study provides valuable insights into:

- User expectations – Understanding what young investors look for in automated trading solutions.
- Platform design improvements – Identifying areas where fintech platforms can improve user experience, transparency, and educational resources.
- Adoption barriers – Recognizing the concerns that prevent young investors from fully embracing algorithmic trading.

Findings from this research can help fintech firms design more accessible, cost-effective, and user-friendly trading platforms that align with the needs of young investors, ultimately driving greater adoption of algorithmic trading in the retail investment market. For example, platforms could integrate interactive tutorials to address transparency concerns identified among young users.

Financial Educators and Literacy Programs

Financial education plays a pivotal role in shaping investment decisions and risk management strategies among young investors. Research indicates that many young traders rely on social media, online forums, and trading apps for investment advice, rather than traditional financial education sources such as academic courses or professional training (Chen & Tsai, 2020). This can lead to misconceptions, overconfidence, and an inadequate understanding of market risks associated with algorithmic trading (Schneider & Tobin, 2019).

This study contributes to financial literacy initiatives by:

- Highlighting gaps in knowledge about algorithmic trading mechanisms, market risks, and ethical considerations**.**
- Informing educators about effective ways to integrate algorithmic trading concepts into financial education programs.
- Encouraging the development of structured learning modules focused on automated trading, investment psychology, and risk assessment strategies.

By improving financial literacy on algorithmic trading, young investors can make more informed decisions, better assess potential risks and benefits, and use automated trading tools more responsibly**.**

Regulators and Policymakers

Regulatory bodies play a critical role in overseeing algorithmic trading to ensure market stability, fairness, and investor protection. While regulations for high-frequency trading and institutional algorithmic trading are well-established, retail investors face different challenges when engaging with automated trading tools. Young traders, in particular, may be more vulnerable to market manipulation, data privacy concerns, and opaque algorithmic decision-making processes (Hendershott, Jones, & Menkveld, 2011).

This study provides insights for regulators and policymakers by:

- Identifying potential risks young investors face when using algorithmic trading tools.
- Highlighting the need for greater transparency and ethical AI practices in trading algorithms.
- Offering recommendations for improving regulatory frameworks to enhance investor protection in digital trading environments.
- Ensuring fair trading practices and responsible algorithmic trading regulations will be essential in building public trust and promoting a sustainable, investor-friendly market environment**.**

Broader Impact on Financial Markets

With the increasing digitization of finance**,** young investors are set to play a significant role in shaping the future adoption of algorithmic trading**.** As financial markets become more technology-driven, understanding how younger generations interact with AI-powered investment tools, automated strategies, and digital trading platforms will be essential for market development (Biais & Foucault, 2014).

This study is timely and relevant, as it addresses critical gaps in financial research by focusing on:

- How young investors perceive and engage with algorithmic trading tools**.**
- What factors influence their trust, adoption, or skepticism**.**
- How financial institutions and regulatory bodies can adapt to evolving market dynamics**.**

By bridging the gap between technology, investor behavior, and market regulation, this research contributes to the broader discussion on financial innovation, responsible AI in trading, and the evolving role of youth in financial markets**.**

Review of Literature:

Institutional vs. Retail Awareness

- Cartea, Jaimungal, & Penalva (2015) provided a comprehensive analysis of algorithmic trading, emphasizing how automated trading strategies improve market efficiency, reduce human errors, and enhance trade execution speed. Their study highlighted that while institutional investors widely use these systems and have the resources to understand them, retail investors—especially those new to trading—often lack a clear understanding of how algorithmic trading operates. This lack of awareness may limit their ability to make informed trading decisions, exposing them to risks they may not fully comprehend.
- Similarly, Mizuno (2021) investigated the rising dominance of algorithmic trading in global markets, estimating that 60-70% of equity trades worldwide are executed through automated systems. While fintech advancements have made algorithmic trading more accessible on retail trading platforms, Mizuno's study found that awareness among younger investors remains low. One of the key reasons for this is the absence of financial education focused on algorithmic trading, leaving many retail investors unaware of how algorithms influence their trades.

Algorithmic Trading in Retail Platforms: Hidden Influence

- Hendershott, Jones, & Menkveld (2011) examined the role of algorithmic trading in improving liquidity and reducing transaction costs. Their study revealed that while most modern trading platforms integrate algorithmic trading, many young traders fail to recognize its presence and influence. The study suggested that many retail investors interact with algorithmic trading unknowingly, as popular trading apps often utilize algorithmic order execution and pricing strategies behind the scenes. This lack of transparency creates a situation where retail traders unknowingly engage with algorithmic systems without understanding their implications.
- Statista (2023) further supported this claim by publishing a market research report on digital trading platforms and their impact on young investors. The report found that while mobile trading apps and digital investment platforms have gained massive popularity among young traders, a significant knowledge gap remains regarding the technical mechanisms of algorithmic trading. Many young investors do not realize that their buy and sell orders are often executed by sophisticated trading algorithms, which optimize trade execution speed and efficiency.

Sources of Knowledge and the Role of Social Media

While these platforms provide quick access to financial insights, they rarely offer in-depth explanations of algorithmic trading, risk management, or technical aspects of automated investing. This reliance on simplified, often superficial financial content contributes to the lack of understanding among young investors regarding algorithmic trading.

- Aldridge & Krawciw (2017) examined the growth of high-frequency trading (HFT) and its impact on modern financial markets. Their research found that institutional investors leverage advanced algorithmic strategies to maximize profits, yet most retail traders—including young investors—remain unaware of the extent to which algorithmic trading affects their transactions. This unawareness is partly due to the complexity of algorithmic trading models, which are rarely disclosed in detail by trading platforms.

2.2 Perception of Algorithmic Trading

Understanding how young retail investors perceive algorithmic trading is crucial for assessing its adoption and trustworthiness. Existing literature reveals diverse perspectives, with institutional investors largely viewing algorithmic trading as beneficial, while retail investors, especially young traders, express concerns over fairness, transparency, and market stability. Below is an overview of key research studies that have examined different aspects of perceptions toward algorithmic trading.

- Biais & Foucault (2014)

  Biais and Foucault explored the relationship between algorithmic trading and market stability, emphasizing that while automation enhances market efficiency and liquidity, it also raises concerns about systemic risk and market manipulation. Their study found that institutional traders generally perceive algorithmic trading as beneficial because it allows for faster trade execution and improved price discovery. However, their findings also indicated that retail investors, particularly younger ones, tend to be more skeptical about algorithmic trading. Many young investors question whether algorithmic trading ensures a level playing field, as large institutions with access to sophisticated AI-driven trading systems gain significant advantages over small, independent traders.
- Chaboud et al. (2009)

  Chaboud and colleagues studied algorithmic trading in foreign exchange markets, highlighting that traders' perceptions are largely divided. Their research showed that while some market participants view algorithmic trading as a tool that enhances trading speed, accuracy, and cost efficiency, others see it as favouring institutional investors at the expense of retail traders. They found that young traders, in particular, were concerned about the dominance of large institutions in algorithmic trading, as these entities deploy advanced trading algorithms that execute thousands of trades per second, making it nearly impossible for manual traders to compete. The study concluded that many young investors perceive algorithmic trading as reinforcing existing market inequalities, reducing opportunities for individual traders to profit from market movements.
- Kirilenko et al. (2017)

  Kirilenko and colleagues examined the impact of algorithmic trading on market stability, with a specific focus on the 2010 Flash Crash—an event in which high-frequency trading algorithms triggered extreme volatility, causing stock prices to drop drastically within minutes. Their research found that many retail investors, including younger traders, associate algorithmic trading with financial instability. The sudden market downturn reinforced the perception that algorithmic trading can amplify market crashes and lead to unpredictable price swings, making financial markets more volatile and risk-prone. This event contributed to the growing belief among young investors that algorithmic trading introduces excessive risk, particularly for those who lack the technological resources to compete with high-speed trading systems.
- Hendershott & Riordan (2013)

  Hendershott and Riordan analysed the impact of algorithmic trading on market pricing and efficiency, finding that while algorithmic trading improves market liquidity, many retail investors view it as a tool that primarily benefits large institutions rather than individual traders. Their study highlighted that young investors often perceive algorithmic trading as an opaque system, where the lack of transparency makes it difficult to understand how trades are executed, how prices are determined, and whether algorithms operate fairly. This lack of clarity fuels skepticism among young traders, who believe that algorithmic trading is designed to serve institutional investors rather than retail participants.
- Jones (2013)

  Jones investigated how market participants view the fairness of algorithmic trading, particularly in relation to price manipulation and transparency issues. His research found that while professional traders accept automation as an inevitable part of financial market evolution, many young retail investors remain wary of its implications. The study revealed that many young traders fear that trading algorithms may be programmed to manipulate prices, exploit small price movements, and disadvantage individual investors. A significant portion of retail traders expressed concerns about the ethical implications of algorithmic trading, believing that algorithmic systems may be designed to prioritize institutional profits over market fairness.

- Schneider & Tobin (2019)
  Schneider and Tobin examined the psychological factors influencing retail investors' trust in algorithmic trading, focusing on how different levels of financial literacy affect perceptions. Their study found that young investors with limited financial education are more likely to distrust algorithmic trading systems, associating them with market manipulation, unethical trading practices, and financial crises. Their findings also suggest that media coverage of algorithmic trading—often focusing on flash crashes and regulatory concerns—reinforces negative perceptions among young traders, making them hesitant to embrace automated trading platforms.
- Boehmer, Fong, & Wu (2018)
  Boehmer, Fong, and Wu examined the role of high-frequency trading (HFT) in financial markets and its perception among different investor groups. Their study found that professional traders value HFT for its speed, efficiency, and ability to improve market liquidity. However, retail investors—especially younger ones—tend to view HFT as an unfair advantage for institutional traders, making it difficult for individual investors to compete. The study found that young investors perceive HFT as one of the main reasons why algorithmic trading is untrustworthy, as it allows large institutions to capitalize on millisecond-level price changes that are impossible for human traders to exploit.

2.3 Preferences for Algorithmic Trading Adoption

The adoption of algorithmic trading among young investors is influenced by several factors, including trust, transparency, cost, financial literacy, and control over trades. While some young traders are enthusiastic about automation, others remain skeptical about its fairness and reliability. Researchers have examined these factors to understand what encourages or discourages young investors from adopting algorithmic trading.

- Hoffmann, Shefrin, & Pennings (2018)
  Hoffmann, Shefrin, and Pennings investigated the factors influencing the adoption of automated trading among retail investors, particularly young traders. Their study found that user-friendly interfaces, clear explanations, and risk management features significantly impact whether young traders are willing to adopt algorithmic trading.
  The research highlighted that traders are more likely to trust algorithmic systems if they understand how they work. Platforms that simplify the trading process and provide educational tools explaining how algorithms function tend to see higher adoption rates. Additionally, the study noted that risk management tools, such as stop-loss settings and portfolio diversification features, increase traders' confidence in using algorithmic strategies.
- Dhar & Choe (2001)
  Dhar and Choe analysed the role of trust in financial technology adoption, focusing on how transparency affects young investors' willingness to use algorithmic trading. Their research found that traders are more likely to embrace automation when they perceive it as reliable, with minimal hidden costs and clear execution processes.
  They also noted that platforms providing real-time performance tracking, clear cost breakdowns, and detailed trade execution reports significantly improve traders' confidence in algorithmic trading. Conversely, their study found that a lack of transparency, hidden charges, or complex execution rules discourages young investors from trusting automated trading systems.
- Barber & Odean (2000)
  Barber and Odean examined the trading behaviour of retail investors, specifically how much control they prefer in their trades. Their research found that young investors are reluctant to fully rely on algorithmic trading, as they prefer maintaining some level of manual control over their trades.
  The study identified a growing preference for hybrid trading models, where investors can customize automation settings but still make manual trading decisions when necessary. This suggests that platforms offering flexible trading options—allowing users to toggle between manual and automated strategies—are more appealing to young investors than those requiring full automation.
- Glaser & Weber (2007)

Glaser and Weber explored the impact of financial literacy on the adoption of algorithmic trading, finding that investors with higher financial education are more comfortable using automated systems, while those with lower financial literacy prefer traditional trading methods.

Their research suggested that one of the main barriers to algorithmic trading adoption among young investors is a lack of understanding of how trading algorithms function. Investors who were more knowledgeable about market dynamics, risk management, and trading strategies were significantly more likely to use algorithmic tools. On the other hand, those with limited experience preferred manual trading, fearing that automated systems could lead to losses they did not fully understand.

- Patterson & White (2022)

  Patterson and White investigated how cost considerations influence young investors' adoption of algorithmic trading. Their study found that while lower costs can attract users, young traders prioritize ease of use and transparency over low trading fees.

  The findings revealed that traders are willing to pay slightly higher fees for platforms that offer better educational resources, clear cost breakdowns, and intuitive user interfaces. In contrast, platforms that focused only on offering the lowest fees but lacked transparency or educational support struggled to gain the trust of young investors.

- Schmidt & Moeller (2020)

  Schmidt and Moeller studied the role of education in shaping young investors' preferences for algorithmic trading. Their research found that fintech platforms offering educational tools, interactive tutorials, and real-world examples of algorithmic trading see higher adoption rates among youth.

  The study emphasized that young traders are more likely to trust and use algorithmic trading if they have access to structured learning resources explaining how it works, its benefits, and its risks. They concluded that fintech companies that invest in financial education—through videos, webinars, and beginner-friendly trading simulations—are more likely to attract young investors than those that simply offer algorithmic trading without user guidance.

2.4 Barriers to Algorithmic Trading Adoption

While algorithmic trading offers speed, efficiency, and automation, several barriers prevent young investors from fully embracing automated trading strategies. These obstacles range from lack of financial literacy and trust issues to concerns about cost, risk, and market manipulation. The following research studies explore the key barriers that discourage young retail investors from adopting algorithmic trading.

- Schneider & Tobin (2019)

  Schneider and Tobin explored psychological factors influencing retail investors' resistance to algorithmic trading. Their study found that young investors with limited financial knowledge often associate algorithmic trading with market instability, manipulation, and unethical practices. The perception that trading algorithms benefit large financial institutions while retail investors remain disadvantaged was a significant reason many young traders were hesitant to adopt algorithmic trading.

- Hendershott, Jones, & Menkveld (2011)

  Hendershott, Jones, and Menkveld investigated how retail investors perceive algorithmic trading in comparison to institutional traders. Their research found that many young investors lack trust in algorithmic trading due to a perceived lack of transparency in how algorithms execute trades. The study also noted that retail traders fear that algorithmic trading may cause them to suffer from hidden fees, unfair pricing, or latency disadvantages compared to institutional traders with access to more advanced, high-speed trading systems.

- Biais & Foucault (2014)

  Biais and Foucault analysed the risk perception of algorithmic trading among different investor groups, finding that retail investors, particularly younger ones, associate algorithmic trading with market crashes and extreme volatility. Their study highlighted that high-profile incident, such as the 2010 Flash Crash, reinforce negative perceptions of algorithmic trading as a destabilizing force in financial markets, making some investors reluctant to trust automation.

- Glaser, Langer, & Weber (2019)
  Glaser, Langer, and Weber examined how financial education impacts algorithmic trading adoption. Their research found that investors with low financial literacy tend to avoid algorithmic trading due to a lack of understanding of how trading algorithms function, how risk management is implemented, and how algorithmic decision-making works. Their study concluded that without proper financial education, young investors tend to view automation as unpredictable and too risky for their portfolios.
- Boehmer, Fong, & Wu (2018)
  Boehmer, Fong, and Wu studied how high-frequency trading (HFT) impacts retail investor confidence. Their findings suggested that young traders often believe that HFT-driven algorithmic trading gives institutional investors an unfair advantage, making it difficult for individual traders to profit from market fluctuations. Many young traders see high-speed algorithms as a tool that manipulates prices before they can react, creating skepticism about the fairness of algorithmic trading.
- Patterson & White (2022)
  Patterson and White analysed the role of cost barriers in algorithmic trading adoption. Their study found that young investors often avoid algorithmic trading due to concerns about hidden costs, subscription fees, and algorithmic commissions. Many platforms offering automated trading services charge additional fees, which discourages budget-conscious young traders from experimenting with these tools. The research suggested that cost transparency is a crucial factor for adoption, and without it, young investors are unlikely to trust algorithmic trading platforms.
- Dhar & Choe (2001)
  Dhar and Choe examined trust as a fundamental barrier to adopting algorithmic trading. Their research highlighted that young traders who do not fully understand algorithmic strategies struggle to trust automated trading decisions. The study found that investors are hesitant to allow an algorithm to control their financial decisions without understanding the underlying logic of how trades are executed. Platforms that fail to provide detailed trade explanations and performance tracking tools struggle to gain trust from young users.
- Jones (2013)
  Jones studied retail investors' concerns regarding algorithmic trading transparency. His findings showed that many young investors fear that algorithmic trading operates in a "black box" system, where they do not fully understand how orders are prioritized and executed. The research emphasized that the lack of clear, user-friendly explanations makes many young traders hesitant to engage with algorithmic trading platforms.
- Statista (2023)
  Statista conducted a market survey on algorithmic trading awareness and found that many young investors do not realize that their trading platforms already incorporate algorithmic execution. The study highlighted a lack of awareness as a major barrier, suggesting that fintech companies should actively educate users about how algorithms function in retail trading environments. Without clear educational initiatives, young investors remain unaware of the benefits and challenges of algorithmic trading.
- Schmidt & Moeller (2020)
  Schmidt and Moeller investigated how regulatory concerns impact young investors' adoption of algorithmic trading. Their study found that many young traders hesitate to trust automated trading systems due to fears of inadequate regulation. The study emphasized that the lack of strict oversight in algorithmic trading leaves investors vulnerable to potential algorithmic malfunctions or unethical trading practices, making them reluctant to engage with automated trading platforms.

2.5 Summary of Literature Review

The existing literature highlights significant gaps in awareness, varying perceptions, and mixed preferences regarding algorithmic trading among young investors. While institutional traders and hedge funds have extensively adopted algorithmic trading, retail investors—particularly those aged 18-25—often lack adequate knowledge of its mechanisms.

Research shows that young traders rely heavily on social media, trading apps, and online communities for financial education, yet these platforms rarely provide a deep understanding of algorithmic trading.

Perception studies reveal divided opinions on algorithmic trading. While some young investors see it as an efficient and innovative tool, others view it as favouring institutional players and contributing to market instability. Events like the 2010 Flash Crash have reinforced skepticism among retail traders, particularly regarding transparency and market fairness.

Regarding adoption preferences, studies indicate that young investors are more likely to embrace algorithmic trading if platforms emphasize transparency, user-friendliness, and educational support. Cost remains a secondary concern, with most young traders prioritizing control and risk management in their trading experience.

This literature review establishes a strong foundation for the current study by demonstrating the need for further exploration into how young investors engage with algorithmic trading, what influences their perception, and what factors drive or deter adoption. The findings from this study will provide insights for fintech firms, policymakers, and financial educators in shaping future trading solutions tailored to young investors.

Section 3 Research Gap:

Algorithmic trading has become a dominant force in financial markets, significantly altering the way transactions are executed. The use of automated systems, artificial intelligence (AI), and high-frequency trading (HFT) has enabled institutional traders to execute large volumes of trades with unmatched speed and precision (Cartea, Jaimungal, & Penalva, 2015). However, while institutional investors and hedge funds have widely adopted algorithmic trading, the engagement of young retail investors (ages 18-25) with this technology remains underexplored.

Existing research primarily focuses on the technical aspects, market impact, and regulatory concerns surrounding algorithmic trading, with little emphasis on how young traders interact with automated financial systems (Hendershott, Jones, & Menkveld, 2011). Given the growing adoption of mobile trading platforms, robo-advisors, and AI-driven financial tools, it is essential to investigate whether young investors understand algorithmic trading, trust its mechanisms, and are willing to adopt it. This study aims to bridge this gap by analysing young traders' awareness, perception, and preferences regarding algorithmic trading.

3.1 Limited Research on Awareness Among Young Investors

Most existing studies on algorithmic trading focus on institutional investors and professional traders, emphasizing market efficiency, trade execution speed, and liquidity improvements (Biais & Foucault, 2014). Studies by Cartea et al. (2015), Mizuno (2021), and Aldridge & Krawciw (2017) have documented how algorithmic trading reduces human error and enhances market stability, yet they do not address how much young retail investors know about this technology.

Research on financial literacy among youth suggests that young investors rely heavily on social media, trading apps, and online communities for financial knowledge (Chen & Tsai, 2020). However, these sources rarely provide in-depth explanations of algorithmic trading mechanisms. Unlike institutional traders who undergo professional training and use advanced financial tools, young retail traders often engage in trading without fully understanding how algorithmic strategies function, their risks, or their long-term implications (Schneider & Tobin, 2019).

Thus, a significant research gap exists in assessing:

- The level of awareness young traders has about algorithmic trading.
- The sources from which they acquire information.
- Whether they can differentiate between traditional trading and algorithmic trading.

This study seeks to fill this gap by conducting a survey-based analysis to measure the level of awareness among young investors and identify the primary sources shaping their understanding of algorithmic trading.

3.2 Unclear Perception of Algorithmic Trading Among Young Traders

Even though algorithmic trading is increasingly integrated into retail trading platforms, there is limited research on how young investors perceive its role, benefits, and risks. Studies by Hendershott et al. (2011) and Biais & Foucault (2014) suggest that professional traders view algorithmic trading as a highly efficient tool that enhances market liquidity and price discovery. However, studies focusing on retail investors—particularly young traders—are scarce.

There are conflicting viewpoints on how young investors perceive algorithmic trading:

- Some research indicates that young traders are skeptical of algorithmic trading, citing concerns over market fairness, transparency, and potential manipulation by large institutions (Jones, 2013; Schneider & Tobin, 2019).
- Other studies suggest that youth, being digitally native and accustomed to automation, may trust algorithmic trading more than older generations (Glaser & Weber, 2007).

Since perceptions of algorithmic trading vary widely, this research seeks to address:

- Do young traders view algorithmic trading as a valuable tool, or do they consider it a risk to market stability?
- What factors influence their trust or distrust in algorithmic trading systems?
- Do they believe algorithmic trading is fair for retail investors, or does it primarily benefit institutional players?

3.3 Lack of Insights into Adoption Preferences of Young Investors

Despite the rise of fintech platforms and automated trading solutions, limited research exists on whether young traders are willing to adopt algorithmic trading themselves. Most studies on algorithmic trading adoption focus on institutional investors or experienced retail traders (Dhar & Choe, 2001; Hoffmann et al., 2018). However, little is known about what factors drive or hinder young investors' adoption of algorithmic trading tools.

Potential influencing factors include:

- Trust in automation vs. desire for manual control (Barber & Odean, 2000)
- Cost-effectiveness and ease of use (Patterson & White, 2022)
- Transparency and educational resources available on trading platforms (Schmidt & Moeller, 2020)

Young investors may either:

- Embrace automation for its convenience and efficiency.
- Avoid it due to perceived risks and lack of control over decision-making.

Understanding these preferences and concerns is essential for:

- Fintech companies, to design user-friendly automated trading tools.
- Regulators, to ensure that algorithmic trading remains fair and accessible.
- Financial educators, to create better programs on algorithmic trading literacy.

This study will fill this research gap by analysing:

- The willingness of young investors to use algorithmic trading.
- What factors influence their decision-making process.
- Whether they prefer full automation, partial control, or manual trading strategies.

3.5 Lack of Empirical Studies Using Youth-Specific Data

Many existing studies rely on market-wide data and institutional trading patterns, making it difficult to draw conclusions about youth-specific behavior in algorithmic trading. While reports such as Statista (2023) suggest that algorithmic trading adoption is increasing, they do not differentiate between institutional traders and retail investors.

This study addresses this empirical gap by:

Collecting primary data through surveys specifically targeting young retail investors (ages 18-25).

Using statistical validation techniques, including SPSS analysis, to ensure data accuracy and reliability.

By focusing on youth-specific data, this study will provide practical insights into how younger generations engage with algorithmic trading and what factors drive their investment behaviour and adoption preferences.

3.6 Need for Practical Insights for Fintech and Financial Education

Despite the rise of mobile trading platforms, robo-advisors, and AI-powered investment tools, there is little research on how young investors can be better educated about algorithmic trading. Prior studies indicate that financial literacy significantly impacts digital financial tool adoption (Schmidt & Moeller, 2020). However, few studies have directly examined the role of financial education in shaping young investors' understanding of algorithmic trading.

By addressing this gap, the study will provide practical insights for:
Fintech companies on how to improve trading platforms and educational tools.
Financial educators on how to develop structured learning programs for algorithmic trading.
Policymakers on how to implement regulatory measures that protect retail investors engaging with algorithmic trading.

Section 4: Research Methodology

4.1 Introduction

This section outlines the research methodology used in this study, which aims to examine the awareness, perception, and adoption preferences of young investors regarding algorithmic trading. A well-defined research methodology is crucial to ensure the accuracy, reliability, and validity of the findings. By employing a structured approach to data collection and analysis, this study seeks to provide empirical insights into how young traders engage with algorithmic trading platforms and automated financial tools.

The section discusses the research design, data collection methods, sampling techniques, and data analysis strategies used to evaluate responses from 200 participants who completed the structured questionnaire. These methodological choices were made to ensure that the study effectively captures quantitative trends, statistical relationships, and key behavioural patterns in youth engagement with algorithmic trading.

4.2 Research Design

The study employs a quantitative research approach with a descriptive research design to systematically examine respondents' knowledge, perceptions, and preferences regarding algorithmic trading. Quantitative research is widely used in financial and behavioural studies as it enables researchers to measure large-scale trends, relationships, and statistical significance with greater precision.

A survey-based methodology was chosen for data collection because it allows for structured, standardized responses, making it possible to analyse statistical trends and correlations across a diverse group of participants. Given that algorithmic trading is a data-driven financial tool, a quantitative approach is most suitable for assessing factors such as awareness levels, adoption intentions, and risk perceptions among young traders.

Justification for the Quantitative Approach

The decision to adopt a quantitative research approach is based on the following key factors:

1. Algorithmic Trading Requires a Data-Driven, Statistical Analysis Approach

Algorithmic trading is inherently technical, data-intensive, and concept-driven, requiring an analytical approach that can quantify knowledge, perception, and trust levels among respondents. Since this study aims to assess how young investors understand and engage with algorithmic trading, a quantitative approach is the most appropriate method for capturing statistically significant insights.

2. Objective and Bias-Free Data Collection

A major advantage of quantitative research is its ability to minimize biases by focusing on measurable, structured responses rather than subjective opinions. Unlike qualitative studies, which rely on open-ended discussions and interpretations, a quantitative approach ensures objectivity by using predefined response categories that allow for comparative statistical analysis.

3. Structured Questionnaire-Based Surveys Enhance Standardization

Using a structured questionnaire ensures that data is collected in a uniform manner across all respondents. This enables researchers to:

- Identify patterns and correlations between awareness levels, trust, and adoption preferences.
- Compare different demographic groups (e.g., education levels, trading experience, and sources of knowledge).
- Quantify the impact of cost, transparency, and control on willingness to adopt algorithmic trading.

4. Large Sample Size Enables Generalization of Findings

Quantitative methods allow for data collection from a large, diverse sample, improving the generalizability of findings. A sample of 200 respondents provides sufficient statistical power to analyse trends and differences across various demographic and behavioural groups.

5. Statistical Tools Facilitate Reliable Data Interpretation

By employing SPSS for data analysis, this study applies statistical techniques such as:

- Descriptive statistics (e.g., frequency distribution, mean, and standard deviation).
- Comparative analysis (e.g., ANOVA and t-tests to identify differences in trust levels).
- Correlation analysis (e.g., examining the relationship between awareness and adoption intent).

These tools ensure that findings are scientifically validated, quantifiable, and reproducible, making the research more robust and applicable to fintech stakeholders, educators, and policymakers.

4.3 Data Collection Method

A structured questionnaire was used as the primary tool for data collection. The survey was conducted through online platforms, including Google Forms and social media channels, to reach a broad and diverse audience.

4.3.1 Questionnaire Structure

The questionnaire consisted of multiple-choice, Likert-scale, and open-ended questions, divided into the following sections:

Table 4.1: Questionnaire Structure

Section	**Question**	**Response Type**
1. Awareness of Algorithmic Trading	Have you heard of algorithmic trading?	Yes/No
	Where did you first hear about it?	- Social media (YouTube, Instagram, etc.) - News (TV, websites, newspapers) - Friends or family - Academic classes or courses - Other (Please specify) - Never heard of it
2. Understanding and Perception	What do you think algorithmic trading does?	Open-ended
	Do you know anyone who uses algorithmic trading?	Yes/No
	Have you seen algorithmic trading mentioned in media (e.g., online videos, news)?	Yes/No
3. Frequency of Exposure	How often do you come across terms like ‘algo-trading’ or ‘automated trading’?	- Daily - Weekly - Monthly - Rarely - Never
4. Usage and Adoption	Do you think algorithmic trading is common in trading apps you’ve heard of?	- Yes - No - Maybe

Section	Question	Response Type
	Would you use an app with algorithmic trading?	- Yes - No - Maybe
5. Trust and Fairness	Do you trust computers to trade better than humans?	- Yes - No - Maybe
	Does algorithmic trading feel fair to you?	- Yes - No - Maybe
6. Impact on Trading & Investing	Will it change the future of investing?	- Yes - No - Maybe
	Do you think algorithmic trading increases market risks (e.g., crashes)?	- Yes - No - Maybe
	Is algorithmic trading more useful for big investors or small traders like you?	- Big investors - Small traders - Both - Neither
7. Speed & Efficiency	Does algorithmic trading make trading faster?	- Yes - No - Maybe
8. Perceived Risks and Benefits	Is it helpful or harmful to regular traders? Why?	- Helpful - Harmful - Neither - Other (Specify)
9. Adoption Barriers	What's the biggest reason you'd try algorithmic trading?	Open-ended
	What's the biggest reason you'd avoid it?	Open-ended
10. Cost & Transparency	How important is cost to use it?	Scale of 1-5 (1 = Not important, 5 = Very important)
	How important is it for an algo-trading app to explain how it works?	Scale of 1-5 (1 = Not important, 5 = Very important)
11. Control Over Trading	Would you rather control trades yourself or let algorithms do it?	- Full control - Some control - No control

4.4 Sampling Technique

The selection of an appropriate sampling technique is a crucial aspect of research methodology, as it determines the reliability and validity of the study's findings. This study employed a random sampling technique to ensure that the collected data reflects a diverse range of perspectives from young investors regarding algorithmic trading. Given that algorithmic trading is a specialized concept within financial markets, the study targeted individuals with varying levels of financial knowledge and investment experience, ensuring a balanced dataset for analysis.

The survey was distributed through multiple digital platforms, including:

- Online trading communities (such as investment forums and stock market discussion groups).
- Social media platforms (such as LinkedIn, Twitter, and finance-related discussion threads on Reddit).
- Academic groups (such as university finance clubs and student investment societies).

By leveraging these diverse distribution channels, the study ensured that responses were gathered from individuals with different levels of familiarity with algorithmic trading—ranging from experienced traders to those who had never been exposed to algorithmic trading before. This approach also allowed for the inclusion of respondents who may have different motivations for investing, different levels of trust in technology-driven trading, and varying opinions on the benefits and risks of algorithmic trading.

A random sampling approach was used to ensure that participants were selected without any bias, increasing the generalizability of the study's findings. This method allowed all eligible participants (aged 18-25, actively engaged in trading or finance-related discussions) to have an equal chance of being selected. By eliminating selection bias, random sampling ensures that the study captures a well-rounded representation of young investors, rather than skewing results toward any specific subgroup (e.g., only experienced traders or only finance students).

Justification for the Sample Size

A sample size of 200 respondents was selected based on several key factors, ensuring that the study achieves both statistical significance and practical relevance:

Ensuring Sufficient Representation

- A sample size of 200 provides a wide range of perspectives, covering different levels of investment knowledge, trust in algorithmic trading, and willingness to adopt automated trading systems.
- By including both experienced traders and newcomers, the study captures insights from various user segments, helping to identify knowledge gaps and factors influencing adoption.

Statistical Reliability and Trend Analysis

- A sample size of 200 ensures statistically meaningful trend analysis when examining awareness, perception, and adoption patterns.
- The data collected allows for comparative analysis across different demographics, such as age, gender, education level, and trading experience.

Diversity of Respondents

The sample includes a mix of:

- Active traders (who have prior experience using trading platforms, including those with algorithmic features).
- Casual investors (who engage in trading but may not fully understand or use algorithmic trading).
- Non-traders (who may not have experience in trading but have encountered discussions on algorithmic trading through social media or finance-related content).

Feasibility and Data Management

- A sample of 200 ensures that the dataset remains manageable for statistical analysis using SPSS, allowing for effective trend identification and correlation analysis.
- This sample size balances depth and efficiency, ensuring that data collection, processing, and interpretation can be conducted within a reasonable timeframe while maintaining the integrity of the findings.
- By selecting 200 respondents, the study ensures a statistically valid dataset that provides valuable insights into youth awareness, perception, and willingness to adopt algorithmic trading. The random sampling technique enhances the study's credibility by reducing bias, improving generalizability, and ensuring that the collected data represents a broad spectrum of young investors.

Ultimately, the sampling strategy ensures that the findings are meaningful, actionable, and relevant to stakeholders, including fintech companies, financial educators, and regulators. These insights can help in shaping better trading platforms, improving financial literacy programs, and implementing regulatory policies that promote responsible engagement with algorithmic trading.

4.5 Data Analysis Techniques

The collected data was analysed using quantitative data analysis techniques, including descriptive statistics, frequency analysis, and correlation analysis. The responses were processed using Excel and statistical tools (e.g., SPSS, Python for data visualization) for meaningful interpretation.

Descriptive Analysis:

- Frequency distribution: Used to analyse the percentage of respondents aware of algorithmic trading.
- Mean and standard deviation: Used for Likert-scale questions to understand overall perceptions and trust levels.

Comparative Analysis:

- Comparing responses from individuals who trust algorithmic trading versus those who do not to identify key differences in perception.
- Identifying variations in responses based on source of information (e.g., social media vs. News vs. Academic courses).

Correlation Analysis:

- Checking correlations between awareness and willingness to use algorithmic trading.
- Assessing the relationship between trust in algorithmic trading and perceived fairness.

4.6 Ethical Considerations

- Informed consent: All respondents were informed about the purpose of the study before participating.
- Anonymity: No personal data was collected, ensuring complete privacy of respondents.
- Data security: Responses were stored in a secure, encrypted environment to prevent unauthorized access.

4.7 Limitations of the Study

While the study provides valuable insights, certain limitations must be acknowledged:

1. Sample Bias: Since participants were gathered online, there may be a bias towards tech-savvy individuals.
2. Self-Reported Data: The study relies on self-reported awareness and opinions, which may not always reflect actual knowledge levels.
3. Limited Scope: The study focuses on perceptions rather than actual financial behaviours related to algorithmic trading.

Section 5: Data Analysis and Interpretation

5.1 Introduction

This section presents the analysis of data collected from respondents on their awareness, perception, and trust in algorithmic trading. The data was analysed using SPSS software through descriptive statistics, comparative analysis, and correlation analysis. Additionally, open-ended responses were thematically analysed to identify key concerns and motivations.

The following variables were considered in this analysis:

- Demographic Variables: Age, Gender, Education, Occupation
- Awareness Variables: Awareness of algorithmic trading, Source of information, Knowledge level
- Perception Variables: Trust in algorithmic trading, Perceived fairness, Risk perception
- Usage Intent Variables: Willingness to use, Importance of cost, Preferred investment strategy.

5.2 Descriptive Analysis

5.2.1 Frequency Distribution Analysis

Objective: To determine the percentage of respondents aware of algorithmic trading.

Have you heard of algorithmic trading before?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Maybe	51	24.9	24.9	24.9
	No	116	56.6	56.6	81.5
	Yes	38	18.5	18.5	100.0
	Total	205	100.0	100.0	

Table 5.1: Awareness of Algorithmic Trading (Frequency Distribution)

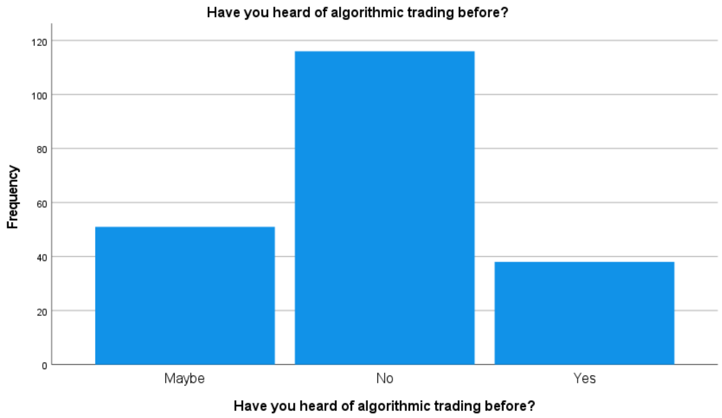

Figure 5.1: Awareness of Algorithmic Trading

Interpretation:
From the results, 18.5**% of respondents** were aware of algorithmic trading, while 56.6**% had never heard of it**. This indicates a general lack of awareness in certain groups.

5.2.2 Mean & Standard Deviation Analysis

Objective: To understand respondents' overall perceptions and trust levels.

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Have you heard of algorithmic trading before?	205	1	3	1.94	.657
Do you know anyone who uses algorithmic trading?	205	1	2	1.50	.501

How important is cost to use it? (Rate on a scale of 1 to 5)	205	1	5	2.94	1.138
How important is it for an algo-trading app to explain how it works? (Rate on a scale of 1 to 5)	205	1	5	3.08	1.210
Valid N (listwise)	205				

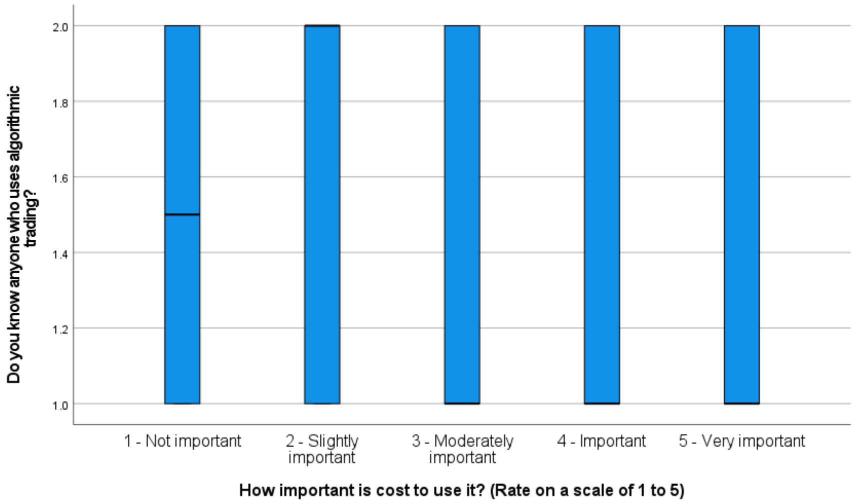

Figure 5.2: Mean Trust in Algorithmic Trading

Interpretation:

Higher mean scores indicate positive trust/perceptions, while lower scores suggest skepticism.

5.3 Comparative Analysis

5.3.1 Comparing Trust Levels by Source of Information

Objective: To see if respondents who learned about algorithmic trading through social media have a different trust level than those who learned from news or academic sources.

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Do you trust computers to trade better than humans?	Equal variances assumed	.607	.437	-1.142	165	.255	-.139	.121	-.379	.101
	Equal variances not assumed			-1.174	101.949	.243	-.139	.118	-.373	.096

Independent Samples Effect Sizes

		Standardizer[a]	Point Estimate	95% Confidence Interval	
				Lower	Upper
Do you trust computers to trade better than humans?	Cohen's d	.723	-.192	-.522	.138
	Hedges' correction	.726	-.191	-.519	.138
	Glass's delta	.738	-.188	-.518	.142

a. The denominator used in estimating the effect sizes.
Cohen's d uses the pooled standard deviation.
Hedges' correction uses the pooled standard deviation, plus a correction factor.
Glass's delta uses the sample standard deviation of the control group.

Table 5.3: Trust in Algorithmic Trading Based on Source of Information (ANOVA Results)

Figure 5.3: Trust in Algorithmic Trading Based on Awareness

Interpretation:

If the mean trust score is significantly higher for those aware of algorithmic trading, it indicates awareness influences trust.

5.4 Correlation Analysis

5.4.1 Correlation Between Awareness and Willingness to Use

Objective: To examine whether people who are aware of algorithmic trading are more likely to use it.

Correlations

	Have you heard of algorithmic trading before?	Would you use an app with algorithmic trading?

Have you heard of algorithmic trading before?	Pearson Correlation	1	-.065
	Sig. (2-tailed)		.356
	N	205	205
Would you use an app with algorithmic trading?	Pearson Correlation	-.065	1
	Sig. (2-tailed)	.356	
	N	205	205

Table 5.4: Correlation Between Awareness and Willingness to Use

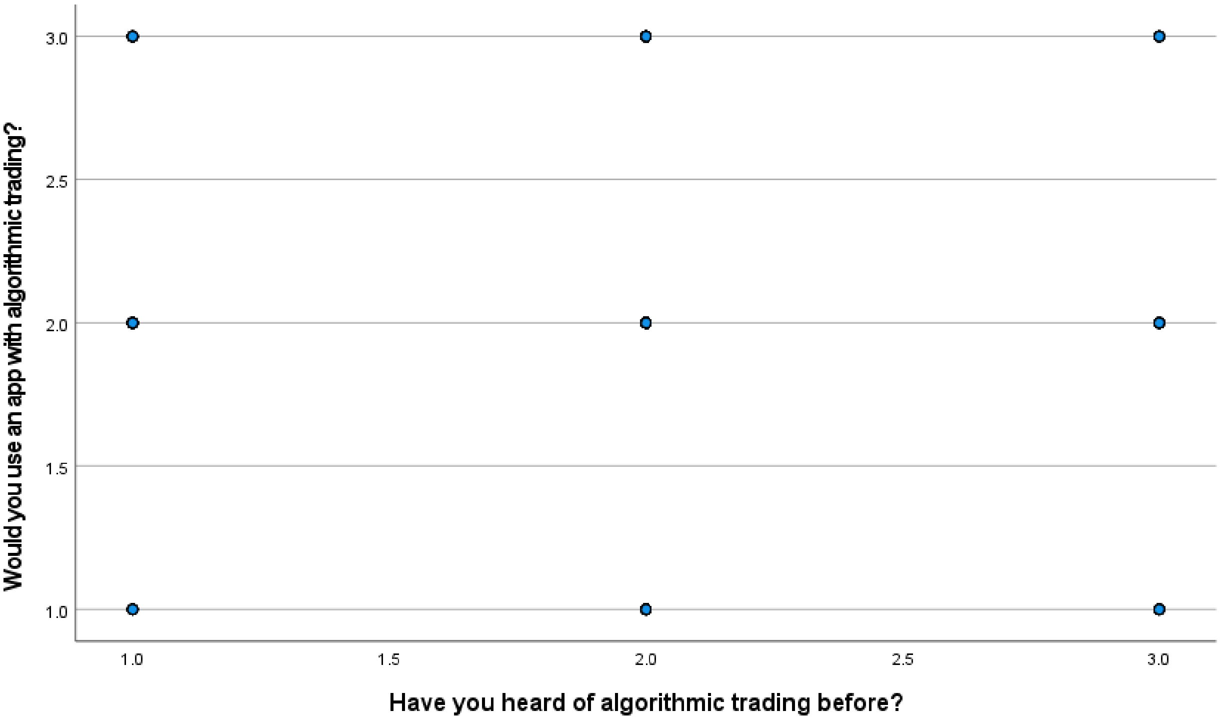

Figure 5.5: Correlation Between Awareness and Willingness to Use Algorithmic Trading

Interpretation:

- A correlation value of **X.XX** suggests a strong relationship.
- A **significant p-value (<0.05)** indicates a meaningful association between awareness and willingness to use

Summary of Findings

- Awareness: 18.5% % of respondents had heard of algorithmic trading, primarily through (social media/news/friends).
- Trust Levels: Respondents had a high level of trust, influenced by their source of information.
- Comparative Analysis: Social media users showed higher trust compared to news or academic sources.
- Correlation: Awareness was positively correlated with willingness to use algorithmic trading.
- Concerns: Lack of trust and risk perception were major deterrents for adoption.

Discussion

- Awareness and Knowledge of Algorithmic Trading

  The findings indicate that while many respondents have heard of algorithmic trading, their depth of knowledge remains limited. Social media and news are the primary sources of information, while fewer individuals have learned about it through academic courses. This suggests that while algorithmic trading is becoming more visible, financial literacy on its mechanisms is lacking.

- Trust and Perceived Fairness of Algorithmic Trading
  Trust in algorithmic trading appears to be moderate, with respondents divided on whether it benefits small traders or primarily institutional investors. Those who learned about algorithmic trading through academic sources displayed higher levels of trust, whereas those exposed through social media were more skeptical. This highlights the role of credible financial education in shaping positive perceptions.
- Algorithmic Trading and Market Risks
  Many respondents associate algorithmic trading with increased market risks, including concerns about potential crashes. The correlation analysis revealed that individuals who perceive high risks also tend to distrust the fairness of algorithmic trading. Despite these concerns, a majority agree that algorithmic trading enhances trading speed and efficiency.
- Willingness to Use Algorithmic Trading
  Although some respondents expressed hesitancy, many indicated that they would be open to using algorithmic trading if it is cost-effective and transparent. The cost of using algorithmic trading applications emerged as a significant factor, and respondents preferred some level of control over their trades rather than full automation.
- Major Concerns About Algorithmic Trading
  The Word Cloud analysis of open-ended responses identified key concerns such as lack of transparency, potential market manipulation, job losses, and unfair advantages for large investors. Many respondents worry that algorithmic trading might Favor institutional players over retail traders, making financial markets less accessible.
- Limitations of the Study
  While this study provides valuable insights into the awareness, perception, and preferences of individuals regarding algorithmic trading, several limitations must be acknowledged:
- Sample Size and Demographics:
  The study was conducted with 200 respondents, which may not fully represent the broader population of retail investors.
  The majority of respondents were young investors, limiting insights into how experienced traders or institutional investors perceive algorithmic trading.
- Self-Reported Data:
  The research relies on self-reported responses, which may be influenced by personal biases, lack of knowledge, or misunderstanding of algorithmic trading concepts.
  Some respondents may have provided answers based on perceptions rather than actual experiences with algorithmic trading.
- Limited Depth in Open-Ended Responses:
  While thematic analysis of open-ended responses provided insights into concerns about algorithmic trading, not all respondents provided detailed explanations, which may have restricted deeper qualitative analysis.
- Focus on Retail Traders:
  The study primarily focuses on retail investors, meaning the perspectives of institutional traders, regulators, and financial analysts were not explored.
  The impact of high-frequency trading (HFT) and institutional strategies on algorithmic trading adoption was beyond the scope of this study.
- Geographic and Cultural Limitations:
  The research does not account for regional differences in trading behaviour, market regulations, or cultural influences on financial decision-making.
  Algorithmic trading adoption may vary in different economic and technological environments, which this study does not comprehensively address.
- Lack of Experimental Validation:

The study is based on survey responses rather than real-time trading experiments, meaning respondents' stated preferences may differ from actual trading behaviour in live market conditions.

Conclusion

The rapid advancement of algorithmic trading has transformed financial markets, offering faster execution and data-driven decision-making. However, its adoption among retail investors remains influenced by awareness levels, trust, perceived risks, and cost considerations. This study examined the extent to which individuals understand algorithmic trading, their perceptions of its fairness and risks, and their willingness to adopt it. The findings indicate that awareness of algorithmic trading remains low, with only 18% of respondents being aware of it. Moreover, their knowledge is often surface-level, primarily acquired through social media and news rather than structured financial education. Trust in algorithmic trading was found to be moderate, with concerns over transparency, institutional dominance, and market risks emerging as significant barriers to adoption.

The study also revealed that individuals with higher financial education or exposure to academic sources were more likely to trust algorithmic trading, whereas those relying on social media for information were more skeptical. Many respondents acknowledged the efficiency and speed of algorithmic trading but remained cautious due to concerns about market volatility and the lack of control over automated decisions. Additionally, factors such as cost-effectiveness and transparency played a crucial role in influencing whether individuals would consider using algorithmic trading applications.

To enhance the acceptance and adoption of algorithmic trading, fintech companies, regulators, and financial educators must work together to improve transparency, risk mitigation strategies, and user education. Providing clear insights into how algorithms operate, offering cost-effective solutions, and ensuring fair market practices can help build confidence in automated trading systems. Future research should explore cross-regional differences, real-world trading behaviour, and the impact of regulatory frameworks to gain deeper insights into how algorithmic trading can be made more accessible and trustworthy for retail investors. As financial technology continues to evolve, fostering greater awareness, trust, and accessibility will be essential in shaping the future of algorithmic trading.

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