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A New Era in Fintech and Insurtech using AI

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Abstract-

The domain of artificial intelligence, which is frequently abbreviated as AI, is presently experiencing a profound and transformative phase characterized by its substantial capacity to modify and redefine the core practices and operational methodologies employed within both the financial and insurance industries, thereby establishing entirely new frameworks and avenues for innovation as well as enhanced efficiency. Although it is true that the individuals who engage with these sophisticated technological advancements are not simply passive observers or uninvolved participants within this rapidly evolving environment, there nevertheless persists a significant degree of reluctance and skepticism concerning the authenticity and reliability of these groundbreaking innovations, which could potentially impede their widespread acceptance and integration into everyday practices. This research investigation is designed to delve into and scrutinize the foundational beliefs, assumptions, and perceptions that surround the concepts of *insurtech, which relates specifically to the application of technology within the insurance industry, and fintech, which pertains to the utilization of technology in the realm of financial services, as these concepts are systematically modeled and explored in the context of this exhaustive study. Following the careful development of these two theoretical frameworks, a meticulous comparison and contrast of their respective characteristics will be undertaken with the objective of determining whether a comparable level of trust and confidence exists among users within each unique technological domain. By utilizing an advanced methodological approach known as multigroup structural equation modeling, the study aspires to rigorously evaluate whether the proposed model retains its applicability and validity within the specific contexts of both fintech innovations and the insurance sector. This comprehensive analysis aims not only to illuminate the similarities and variances in user perceptions but also to yield valuable insights regarding how these emergent technologies can be effectively harnessed to improve customer engagement and satisfaction across both the financial and insurance sectors. A considerable number of industries have successfully transitioned to digital platforms, which has resulted in a significant enhancement of their operational intelligence and has empowered them to anticipate and counteract potential changes in their respective markets. The financial sector has also reaped considerable benefits from this ongoing transformation, as investors and stakeholders are now endowed with the capability to accurately determine the most advantageous timing for executing their transactions, a significant development that can be credited to the advent of programmed finance. In light of the fact that the data analyzed within the domain of electronic finance pertains specifically to monetary transactions—wherein the margin for error is exceedingly small—research within this field is both dynamic and essential to prevent economic crises that could sometimes culminate in individual or corporate bankruptcy.*

Keywords— *investors, stakeholders, fintech, insurtech, bankruptcy.*

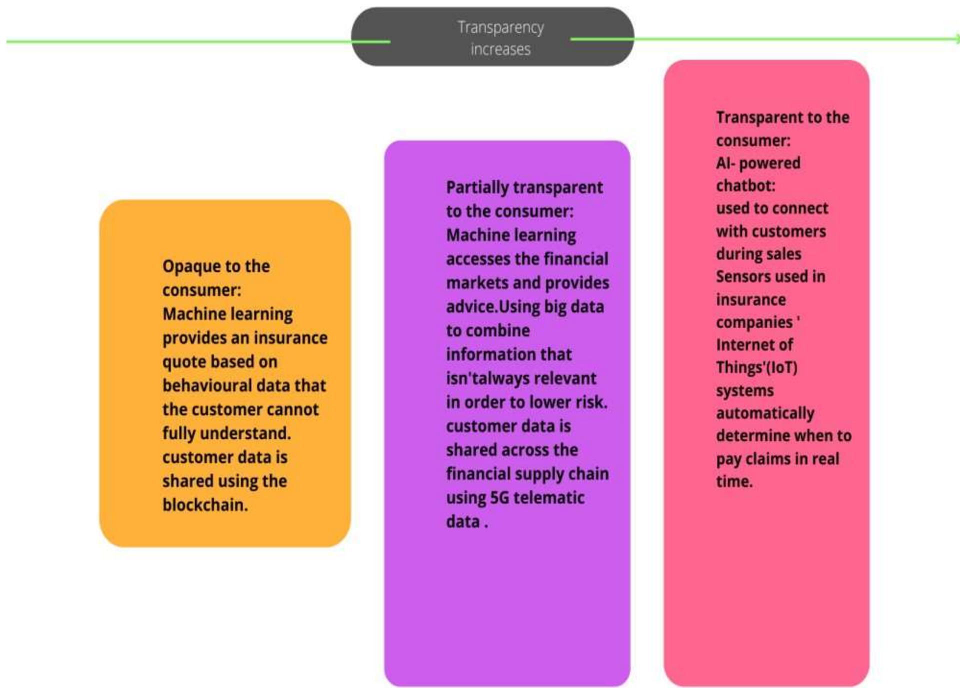
Introduction-

In today's rapidly evolving landscape, consumers are presented with a remarkable opportunity to choose from an extensive and diverse array of innovative services that are primarily centered around cutting-edge technological advancements, a phenomenon that has arisen largely due to the advent of financial technology (fintech) and insurance technology (insurtech). These groundbreaking innovations are often enthusiastically embraced by consumers, largely due to their inherently user-friendly nature and state-of-the-art functionalities, as noted by researchers Kerényi and Müller in 2019. However, despite the enthusiasm surrounding these technologies, the extent to which consumer trust plays a pivotal role in influencing the adoption and integration of these emergent technological advancements remains insufficiently understood and explored. The term fintech specifically delineates the various automation processes that have been implemented within the financial sector to enhance efficiency, whereas the term insurtech refers to similar automation practices that are applied within the insurance industry in a corresponding manner. The category of algorithms that serve to augment human cognitive abilities with the aim of enhancing intelligence or autonomy is

collectively identified as Artificial Intelligence (AI). The advancement of modern automation systems that deliver substantial insights within the economic sphere can be directly attributed to significant breakthroughs in the field of management information technology. The primary goal of these advancements is to expedite specific processes through the means of automation, thereby illustrating how AI can effectively streamline, depend upon, and facilitate the operational functions of financial entities. As a direct consequence of its versatility, its areas of application are extensive and varied, encompassing sectors such as accounting, customer service, and human resources, which are recognized as some of the most prominent fields of implementation. This innovative technology is increasingly favored by a wide array of banks and financial institutions, including large corporations, primarily due to the considerable volume of data that requires thorough analysis on a daily basis. A significant transformation is currently unfolding within the financial sector, which is marked by the extensive range of services and functionalities that can be seamlessly integrated through these technological innovations, in addition to the emergence of novel technologies that capture the attention of the finance sector. However, it is crucial to underscore that certain individuals harbor perceptions of emerging technologies as a potential threat to the existing economic landscape, which highlights the complex interplay between innovation and apprehension. The primary benefit that emerges from the incorporation of these advanced technological systems into the banking industry is intricately linked to their broad range of potential applications across various financial platforms and institutions. Looking ahead into the future, it is not only reasonable but also quite feasible to envision a fully integrated digital ecosystem, within which data can be effectively distributed and meticulously analyzed to determine the most favorable pricing strategies that are specifically designed to meet the unique needs and situations of each individual user. The provision of improved service availability, the acceleration of procedural processes, and the customization of these services for individual consumers are all significantly enhanced by the capabilities offered through artificial intelligence technology. Consequently, it becomes crucial to thoroughly understand and appreciate the perspectives and opinions of consumers regarding the new technological advancements that are relevant to the operations of financial services and insurance companies. Regrettably, this necessary understanding is made even more challenging by the inherent complexity and lack of clarity associated with these emerging technologies.

Certain technologies can be categorized into three distinct levels of transparency:

(1) Those that are highly transparent, exemplified by instances in which a chatbot interacts directly with a customer,
(2) Those that are partially transparent, where customers are able to recognize certain functions and features, and
(3) Those that remain predominantly opaque and difficult to decipher.

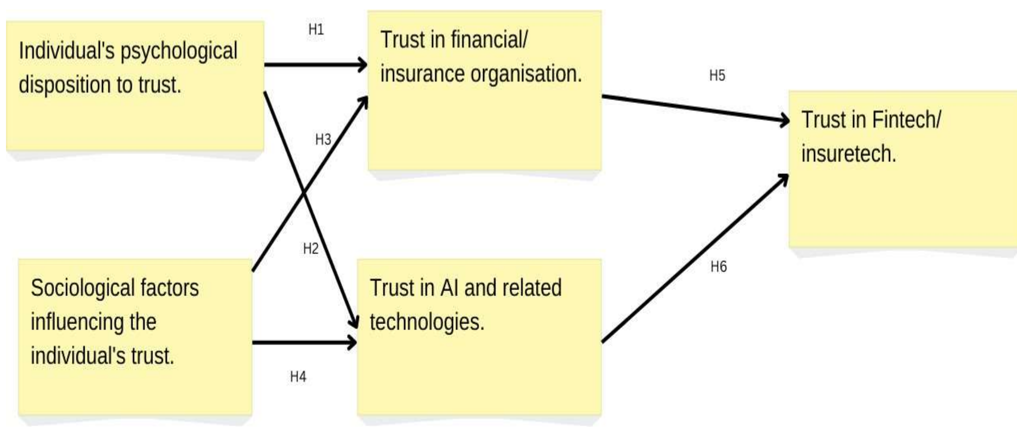


The accompanying figure serves to visually depict these three levels of transparency, which include transparent, partially transparent, and opaque categories. The various technologies that are currently being utilized in the fields of financial technology (fintech) and insurance technology (insurtech), such as the processes involved in applying for loans or handling insurance claims, represent merely a small fraction of the broader array of technologies that are both transparent and understandable to consumers at large. The analytical model that focuses on the concept of trust within the fintech and insurtech realms is increasingly coming to the forefront of discussions in these industries. While the terminology associated with this model is relatively new and has emerged in recent times, it is now being used frequently and consistently across the financial, insurance, and technological sectors. The significance of automation is rapidly growing, especially in light of the rise of automation driven by artificial intelligence, along with the incorporation of other groundbreaking innovations such as big data analytics, the Internet of Things (IoT), blockchain technology, and the implementation of 5G networks. This particular research initiative began by probing into the importance and role of trust within the realms of financial technology and insurance technology, and it seeks to determine whether this trust differs from the belief systems present in other areas. In order to effectively address this inquiry, it is imperative to break down the overarching question into its essential and fundamental components for a clearer understanding.

The foundational assumption underlying this exploration suggests that

(1) The cognitive inclinations and predispositions of individuals toward belief significantly influence their perceptions and levels of trust in the contexts of fintech and insurtech. Furthermore,
(2) The sociological aspects of trust,

(3) The trust individuals place in the financial or insurance sectors, and
(4) The trust that is extended toward artificial intelligence and its associated technologies are all critical factors that warrant consideration.



Model of Trust in Fintech and Insuretech

The figure accompanying this section offers a visual representation that illustrates the interconnectedness of these various aspects of trust within the model. The capacity of an organization to think, reason, and act independently is often described using the term agency, which encompasses a range of implications for both the organization and its technological components. Moreover,

artificial intelligence is increasingly showcasing its capabilities for self-awareness and independent agency in various contexts. Therefore, it becomes essential for consumers to place their trust not only in the organization as a whole but also in the artificial intelligence systems employed, so that they can effectively engage with both entities as they operate within their respective independent agencies. The core hypotheses of the proposed model are articulated in the following sections. The initial two hypotheses delve into how cognitive characteristics and traits impact an individual’s trust in the realms of insurance and finance, specifically:

H1: The cognitive predisposition of an individual toward belief plays a crucial role in determining their level of trust in financial institutions (H1a) and in insurance providers (H1b).

H2: The cognitive predisposition of an individual toward belief significantly affects their level of trust in artificial intelligence and other technological innovations present within the financial sector (H2a) and (H2b). An individual's perspectives and opinions are frequently molded by the influences exerted by those who are part of their immediate social circles as well as by the communities that form around specific technologies. The subsequent two hypotheses will explore how social dynamics and dimensions contribute to shaping trust in the financial and insurance sectors, respectively.

H3: The various social determinants that exert a positive influence on an individual's conviction and belief system serve to significantly bolster that individual's level of trust and confidence in both monetary institutions, as categorized under H3a, and in the providers of insurance services, as categorized under H3b.

H4: The social determinants that have the capacity to modify and alter an individual's degree of conviction have been shown to exert a favorable and beneficial effect on that individual's perception and understanding of artificial intelligence, along with similar innovations that are utilized in the sectors of insurance, as indicated by H4a, and finance, as indicated by H4b.

A thorough and comprehensive review of the existing literature leads to the conclusion that the belief in innovation is a complex phenomenon that cannot be adequately encapsulated within a singular, universal framework of action that applies across all contexts. The empirical findings that have been gathered reveal that users often harbor preexisting biases that are profoundly informed by their personal experiences and interactions with technology. The initial segment of the fifth law and theoretical framework seeks to elucidate how an individual's trust and confidence in financial institutions fundamentally shapes their overall confidence in advanced financial innovations, particularly those that fall under the umbrella of Fintech.

The subsequent articulation of the fifth law and theory posits that a comparable dynamic also holds true for the insurance sector, leading to the following conclusions:

H5a: Trust in Fintech is predominantly influenced by the confidence that individuals have in established financial organizations. **H5b**: Trust in Insurtech is predominantly influenced by the confidence that consumers place in their insurance providers. It is important to note that consumers are already quite familiar with numerous aspects related to artificial intelligence and have, to a certain extent, engaged with AI technologies in their day-to-day lives. Consequently, they possess a set of preconceived notions that encompass their understanding of the advantages, disadvantages, and potential threats that may be posed by AI technologies. The concluding law and theoretical framework asserts that the belief in AI and its associated innovations significantly informs and shapes belief, initially in the realm of Financial Technology and subsequently within the domain of Insurance Technology: H6: The belief in AI and its associated innovations exerts a positive influence on belief in Fintech, as indicated by H6a, and Insurtech, as indicated by H6b. Within this context, there exist intricate procedural frameworks that provide software developers with a foundational basis necessary for the creation and deployment of AI systems, such as the widely recognized CRISPDM model (Martinez-Plumed et al., 2021), which predominantly emphasizes the importance of the consumer relationship in its framework. Thus, this model is particularly well-suited for financial institutions and insurance companies that do not independently develop AI systems but instead utilize them with minimal modifications or customizations.

This research accentuates the pressing necessity of evaluating this model in the forthcoming segments of the study. Organizations may encounter a range of challenges in prioritizing various aspects as AI continues to infiltrate and influence multiple dimensions of personal and professional existence. At the heart of this discourse is the critical role of algorithms and AI technologies, irrespective of whether the future landscape of finance and insurance will evolve into an enhanced version of the existing model or transition into a more decentralized financial system that is powered by blockchain technology, commonly referred to as DeFi. This model primarily concentrates on four key determinants that significantly influence user belief regarding both financial technology and insurance technology. The fluctuating nature of "Belief in financial organization/insurer" is predominantly shaped and influenced by organizational factors, which take precedence over other variables that include psychological disposition, social contexts, and belief in AI systems. It is imperative for the organization to possess a comprehensive and in-depth understanding of all four parameters and to actively aim to rectify any deficiencies in those areas where it wields less influence, by concentrating its efforts on the parameters where it can exert a more substantial impact. Under varying circumstances, these four variables may be perceived and interpreted divergently by different stakeholders. Consequently, expertise in both innovation and business intelligence is requisite within the organization to enhance its relationship with AI technologies and to improve interactions with its clientele under the specified conditions. The model demonstrates a remarkable adaptability according to the unique circumstances of each firm through the strategic application of business intelligence, which leverages contextually relevant big

data and machine learning techniques (Park et al., 2020). Furthermore, the model, along with the causal relationships it delineates, could also be further explored and examined through various experimental methodologies. With regard to the presented model, it is indeed feasible to explore the potential influence that financial literacy may have on the overall dynamics at play. The streamlined processes that are offered by Fintech and Insurtech to their clientele somewhat obscure the genuine financial ramifications and implications of ongoing transactions that users may be engaged in.

Nevertheless, it stands to reason that increased confidence in utilizing Fintech and Insurtech services would likely stem from an enhancement in financial literacy among users. This study further advocates for the necessity of conducting more concentrated research focused on insurtech within the realms of business practices, statistical distributions, and economic frameworks in order to deepen the understanding of this evolving field. Subsequent investigations, which are poised to delve into the intricacies of the financial technology landscape, can more precisely articulate the numerous similarities as well as the distinct differences that exist between Financial Technology and other sectors, particularly regarding the ways in which consumer interaction occurs, the various methodologies employed in risk assessment, and the significant manner in which the ongoing digital transformation is fundamentally reshaping the organizational frameworks that underpin these industries.

Additionally, it may prove to be especially worthwhile to examine whether other influential factors, such as the nuances of legislation and regulation, serve as independent variables that could potentially impact these relationships, or whether they simply attenuate the connections that exist between these elements. The authors unequivocally affirm the complete absence of any financial or personal conflicts that could, in any way, influence the research that is presented in this comprehensive interpretation. Furthermore, the interpretation adheres strictly to the rigorous standards that have been established by the authors' affiliated institutions for conducting empirical research that meets the highest academic and ethical benchmarks. For the purpose of data collection in this study, all requisite permissions were meticulously secured to ensure compliance with institutional and ethical guidelines. The ways in which artificial intelligence is currently transforming the financial assistance sector, particularly in the realm of the financial advisory business, which incidentally spends a significant proportion of its budget on AI services compared to other industries, is indeed expanding at an exceptionally rapid pace, as evidenced by research conducted by Citi in 2018. The primary users of AI technologies within the finance sector, up until very recently, were predominantly hedge funds and high- frequency trading companies; however, there is an observable trend where banks, regulators, financial technology firms, insurance organizations, and several other entities are increasingly embracing these requisitioned AI tools. Within the financial advisory domain, artificial intelligence is exerting its profound influence across a multitude of dimensions. It assumes a pivotal role in the realm of algorithmic trading, thereby facilitating the intricate creation and management of diverse investment portfolios tailored to specific market conditions. The robo-advisors, powered by sophisticated artificial intelligence algorithms, leverage their capabilities to deliver highly personalized financial recommendations that are intricately tailored to align with individual client profiles.

The innovative virtual customer assistants significantly enhance the overall customer service experience by providing timely and relevant assistance to users. In this section, I delineate three principal methodologies through which AI is currently revolutionizing the financial services sector:

(1) Fraud Detection and Compliance,
(2) Automated Advisory Services, which include banking chatbots and robo-advisory platforms, and
(3) Algorithmic Trading, each of which plays a critical role in enhancing the efficiency and effectiveness of financial operations.

1) Fraud Detections and Compliance

In this dynamic context, artificial intelligence proves to be exceptionally advantageous, as machine learning algorithms possess the capability to scrutinize an extensive array of sample points in order to detect fraudulent transactions that typically manage to evade the scrutiny of human oversight. Machine learning techniques also serve to diminish the frequency of erroneous rejections while concurrently enhancing the overall precision of real-time approvals, thereby streamlining the fraud detection process. Presently, the practice of fraud detection extends far beyond a mere checklist of risk factors that must be monitored; instead, fraud detection systems have evolved to possess the remarkable capacity for active learning and calibration in direct response to emergent potential, or even actual, security threats, a process that is facilitated by the sophisticated methodologies inherent in machine learning. Banking systems have become adept at identifying atypical behaviors or actions that are referred to as "anomalies," and they flag these irregularities for further investigation through the utilization of advanced machine learning techniques. One of the most efficacious applications of machine learning resides in the detection of credit card fraud, where the workflow engines or monitoring systems that are employed by banks are meticulously trained on extensive historical payment data. The training algorithms, in conjunction with back-testing and validation processes, are grounded in vast datasets that comprise credit card transaction records, enabling a robust analysis.

The algorithmic classification process can be delineated into two distinct categories: "fraudulent" versus "non-fraudulent," thereby enabling the preemptive prevention of deceptive transactions, as highlighted by van Liebergen in 2017.

2) Automated Advisory Services

For an extensive duration of approximately one hundred and thirty years, the costs that are associated with the process of financial intermediation have exhibited a remarkable stability, remaining at roughly two percent, as noted in a study conducted by Philippon in the year 2015. In the aftermath of the financial crisis that occurred in the year 2008, there was a slight reduction observed in the expenses related to financial intermediation across both Europe and the United States, as reported in subsequent studies by Philippon in 2016 and Bazot in 2013. In light of the challenges presented by the landscape that followed the financial crisis, robo-advisors and chatbots have been rapidly emerging and proliferating throughout the financial services sector, providing invaluable assistance to customers in navigating the complex processes of selecting suitable investments, banking products, and insurance policies. The term "bot" is a designation used to refer to a software application that is meticulously crafted to perform specific functions by harnessing the power of artificial intelligence, as outlined in the Future Today Institute's report in 2017. A platform that is automated and that employs a systematic methodology for problem-solving or computation, which is referred to as a "robo-advisor," offers programmed financial advice or assistance designed to help individuals manage their expenditures effectively. A mere decade ago, the phrase "robo-advisor" was virtually absent from digital discussions and lacked any significant recognition, yet it has since evolved into a crucial and widely recognized term within the lexicon of the financial industry. However, it is essential to note that this term can be somewhat deceptive, as it does not have any actual connection to the field of robotics; instead, robo-advisors utilize sophisticated algorithms to adjust and optimize a user’s financial portfolio in accordance with their individual aspirations and levels of risk tolerance. The realms of natural language processing (NLP) and machine learning (ML) algorithms are increasingly being integrated into chatbots and robo-advisors, empowering these technologies to function as effective tools for delivering personalized experiences to users across a variety of different domains. Among the demographic of millennial investors, who typically do not require the presence of personal advisors to feel comfortable with the act of investing and who are generally reluctant to validate the costs associated with human advisors, chatbots and robo-advisors have witnessed a significant surge in popularity and acceptance. AI-driven chatbots possess the capacity to assist customers in a multitude of ways when it comes to managing their finances and savings, thereby contributing to the enhancement of the banking sector as a whole. For example, Plum is an innovative chatbot that can be accessed through Facebook Messenger, enabling users to effectively implement incremental financial savings strategies. Upon the user’s initial registration, Plum establishes a connection to their bank account and utilizes its powerful AI engine to meticulously analyze the user's historical earnings and spending patterns, thereby projecting their potential for savings. Subsequently, the Plum savings account is regularly credited with a series of small deposits, accompanied by consistent reporting to keep the user informed of their progress. "JP Morgan’s [AI automation] possesses the impressive capability to scrutinize an astonishing approximately twelve thousand documents within a time frame as brief as mere seconds… while a human being would require an equivalent of nearly 360,000 hours to thoroughly examine the same volume of documents," as highlighted by Brummer and Yadav in their 2019 study.

3) Algo trading

Algorithmic trading, commonly abbreviated as AT, has remarkably surfaced as an essential and transformative component within the intricate and expansive domain of international financial markets that span across geographical boundaries and involve a complex interplay of various economic factors. This innovative approach, which is frequently referred to in the industry as

―Automated Trading Systems,‖ has its historical roots that can be traced back to the progressive financial landscape of the 1970s, a decade marked by significant technological advancements and shifts in trading practices. In their insightful work, Kirilenko and Lo (2013) offer a succinct yet informative overview of the notable advancements and developments that have taken place within the rapidly evolving field of algorithmic trading. Chakravorty (2016) articulates a comprehensive definition of algorithmic trading, stating that ―Algorithmic trading encompasses the formulation of novel rules, in addition to their coding, to devise a program capable of executing trades autonomously,‖ thereby highlighting the sophisticated nature of the algorithms and the intricate processes involved in their creation and implementation. Artificial intelligence, in this context, can be comprehensively understood as a specialized subset of the broader field of machine learning, which is particularly skilled at identifying and discerning complex patterns within extensive datasets and subsequently making informed predictions regarding future events and occurrences based on those patterns. At present, the realm of algorithmic trading is significantly enhanced by the utilization of cutting-edge AI systems, which play a crucial role in facilitating a substantial proportion of equity market transactions, with notable statistics indicating that approximately 60% of futures trades and around 50% of Treasury transactions are derived from rapid and efficient trading decisions executed by sophisticated computer algorithms (Brummer and Yadav, 2019). According to Aldridge and Krawciw (2017), it is posited that the market share attributed to algorithmic trading is roughly estimated to be around 40%, underscoring its growing importance and influence within the financial landscape. The numerous advantages offered by algorithmic trading are extensive, encompassing the potential for executing trades at optimal and favorable prices, enhanced precision in trade execution, a significant reduction in the risk of errors, the capacity to evaluate an array of trading conditions simultaneously, and a notable decrease in the likelihood of human errors that may arise from cognitive biases or emotional influences. The following strategy, which is referred to as trading passion, operates under a unique methodology wherein the computer begins with no inherent knowledge of trading activities; it only gains understanding once model trade data is introduced into the algorithm, at which point it becomes familiar with the dynamics of trading and the behaviors of market participants. The primary objective of trading passion is to equip the algorithm with an appropriate and effective framework that enables it to analyze and comprehend the psychological dimensions that govern supply and demand within trading environments. Furthermore, a specific technique employed within the broader context of algorithmic trading, known as news reader, is particularly notable; this method is extensively trained to analyze and interpret news headlines, although it does not engage or react to significant political developments that may impact market conditions. Through the algorithmic trading methodology termed pattern recognition, machines have the ability to learn, adapt, and respond to emerging patterns within the data, thereby generating potential revenue opportunities. An example of this is Sentient Technologies, a hedge fund that is managed by an innovative AI startup based in the United States, which has successfully developed a highly sophisticated algorithm that meticulously scrutinizes millions of diverse data points to identify trading patterns and accurately forecast market trends. The algorithms created by Sentient leverage scenarios derived from billions of simulated trading conditions to detect, integrate, and capitalize on lucrative trading patterns while also formulating novel strategies that enhance their competitive edge. Utilizing these advanced methodologies, Sentient Technologies has the remarkable capability to condense an extensive 1,800 days of trading activity into an impressively brief and efficient timeframe, showcasing the extraordinary power of their trading algorithms.

Conclusion

The significant movement towards the integration of AI has profoundly advanced the field of e-finance; tasks that were previously performed by human traders or deduced from traditional informational models have now ascended to an unprecedented level of autonomy and predictive sophistication, marking a transformative shift in the landscape. The majority of the contributions identified from our comprehensive findings pertain to a diverse array of dimensions related to decision-making processes, assessments of insolvency, evaluations of credit ratings and creditworthiness, detection of fraudulent activities, advancements in Financial Technology, enhancements in human resources management, and the development of recommendation systems that guide investment choices. Nevertheless, it is abundantly clear that FinTech has emerged as the primary focal point of research scrutiny within the academic community, as scholars and practitioners alike delve into its myriad implications and potential. An extensive body of research on this pivotal topic has convincingly demonstrated that sophisticated predictive models such as Random Forest (RF), K-Nearest Neighbors (KNN), and Support Vector Machine (SVM) models exhibit exceptional efficacy and accuracy in executing predictive tasks, thereby establishing their significance in the field. Consequently, these impactful findings possess the remarkable potential to serve as a foundational basis for subsequent innovations that may further enhance the capabilities and applications of algorithmic trading and artificial intelligence in the financial sector.

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