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FinTech as a Game Changer: Overview of Research Frontiers

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Abstract. Technologies have spawned finance innovations since the early days of computer applications in businesses, most recently reaching the stage of disruptive innovations, such as mobile payments, cryptocurrencies, and digitization of business assets. This has led to the emerging field called financial technology or simply FinTech. In this editorial review, we first provide an overview on relevant technological, pedagogical, and managerial issues pertaining to FinTech teaching and research, with a focus on market trading, artificial intelligence, and blockchain in finance. And then we introduce the articles appearing in this special section. We hope that our discussions of potential research directions and topics in FinTech will stimulate future research in the fields of information systems and finance toward making their unique marks in the FinTech evolution and the associated business and societal innovations.

Keywords: FinTech • financial service • blockchain • AI

1. Introduction

It is not a stretch to say that financial technologies (FinTech) are transforming every corner of financial services. The list goes from deposits, loans, credit, fundraising, leasing, wealth management, investment, insurance, risk assessment, compliance, payment, clearing and settlement, securities, and trade finance to financial advising, among others. As summarized by Tapscott (2020), financial services are fundamentally about authenticating identity and value, transferring value, storing value, lending value, exchanging value, funding and investing value, managing and insuring value, and accounting for value. All these areas have experienced FinTech innovation or disruption. Contemporaneous and emerging information technologies, such as artificial intelligence (AI), blockchain, big data analytics, IoT, cryptography, and cloud computing, have gradually become an integral and indispensable part of today's financial services.

Finance industry transformations, as a result of FinTech, are evident. We are seeing many financial businesses being digitized and tokenized, information asymmetry being mitigated, middlemen being eliminated, human beings being replaced by machines, services becoming more intelligent, governance being decentralized, trust becoming coded and protocolized, security being strengthened, and compliance being enforced. Along with the creative destruction of FinTech, it has spawned new ways of providing financial services. Robo-advising, neobank, decentralized finance, open finance, Secured Automated Lending Technology, digital currency, micropayments, insurance technology (InsurTech), regulation technology, and token economics (Voshmgir 2019) are some of the examples.

In the meantime, the boundary between a finance company and a technology company is becoming blurred. Traditional financial institutes are becoming information technology (IT) companies, whereas IT companies are offering financial services. Many financial-service businesses have been transforming themselves into IT businesses. Lloyd Blankfein, the former chief executive officer of Goldman Sachs, holds that Goldman Sachs is more of a cutting-edge technology firm, rather than a grey-haired investment bank (Oran 2015). As a matter of fact, among the 33,000 employees of Goldman Sachs, more than 9,000 were engineers and programmers.[1] As Lloyd succinctly put it, "We are a technology firm. We are a platform."[2] Goldman Sachs is not alone. Barclays created a global community for FinTech innovation, including opening an accelerator in New York. The company used machine learning to reduce the number of mundane, repetitive tasks performed by banks to prepare for client meetings. Capital One and Liberty Mutual's Alexa solution (a voice-activated personal assistant) allows customers to check balances, pay bills, and track spending through these devices.

Financial services are likely going to be around and be needed, but they may not necessarily be offered by

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traditional financial institutions. Bill Gates famously said in 1994, "Banking is necessary, banks are not." IT firms are encroaching into this area. Google, Apple, Facebook, Amazon, and Microsoft, collectively known as GAFAM, are already active investors in the payments industry; they're quickly penetrating into the core businesses of legacy financial service providers.[3] This trend is best summarized by Alibaba's Chairman, Jack Ma, "If banks don't change, we will change them." In 2019, Apple debuted its credit card; in 2020 Google launched consumer bank accounts; Facebook is consolidating its payment product under Facebook Pay. Facebook is also introducing a potentially game-changing digital currency, Libra.[4] This list is much longer. Uber is issuing Uber Money housed in one's digital wallet. Amazon has already been in the business of lending for years, setting up student loans. Amazon's foray into small business lending aligns it more closely with traditional financial institutions. Since 2011, it has been leveraging the data generated by small businesses that use Amazon Marketplace, which helped Amazon to identify loan candidates for amounts ranging from $1,000 to $75,000. Amazon reported that it has issued over $1 billion in loans to 20,000 small businesses.[5] Based on its superb data analytics capability, Amazon Web Services is able to provide services to dozens of finance companies, including Aon, Capital One, Carlyle, Nasdaq, Pacific Life, and Stripe.

The trend of tech giants stepping into the finance service territory is worldwide. Rakuten, Japan's largest online retail marketplace, issues credit cards and offers mortgages and securities services. China's Alibaba is another big e-commerce company that acts as an asset manager, lender, and payment firm.[6] Its affiliated Ants Financial, valued at over $200 billion, has become one of the biggest FinTech companies in the world. Besides its core payment service, Alipay, it has expanded into products, such as wealth management and loans.[7] WhatsApp rolled out its payments feature to select users across India, providing a strong boost to India's digital payments ecosystem. Brazil's Banco Bradesco Facebook app allows customers to conduct day-to-day banking from Facebook, using the social network's customer data analytics to target users. Singapore and Hong Kong are also in the process of introducing new digital bank licenses to make it easier for tech businesses to offer financial services. Likewise, in Europe, technology-enabled banks from Monzo to N26 have emerged, targeting the wallets of younger, tech-savvy consumers.

FinTech has been evolving since the early days of ATMs in the 1970s. To understand the business value of technology to finance, one needs to trace the journey of financial innovation from the early days of FinTech to its present frontiers, such as the fusion of AI and blockchain with finance. Taking financial circulation as an example, financial technology has gone through three stages of development.

1. As an early financial technology, the traditional ATM machine realized the automation of cashier work and improved the operational efficiency of banks. However, ATMs have not changed the basic business model of the bank. This stage can be regarded as "the stage where financial technology helps traditional business models," which we term as the "+tech" era.

2. In the mobile internet era, mobile payment technology has created brand-new technology-based financial institutions (such as Alipay, etc.) and new financial business models. This stage is "the stage where financial technology subverts the traditional business model." We term this era the "tech+" era because the financial service is spawned from the new technology.

3. Entering the era of digital currency, some fiat currencies have begun to undergo digital transformation. At this stage, changes not only occur in business models but even the national governance system is undergoing major innovations. This stage is "the stage where financial technology promotes major and potentially game-changing business ecosystems." We term this era as "tech^2," as the technology and business ecosystems cohere.

It is clear that FinTech not only has changed the way we do business but also the way we live our daily lives. Given its growing importance, this editorial review aims to provide a deeper anatomy on FinTech with research directions. As FinTech itself has become a huge area, we do not want this editorial review to be all-encompassing. Rather we first zoom in on one of the most prevalent applications of FinTech on financial market trading as an illustration of FinTech application and then proceed to elaborate the role of two of the most important technologies in FinTech, AI and blockchain. We lastly discuss how FinTech education can be improved and provide a brief introduction to the papers included in this special section.

2. Application: Technology in Financial Market Trading

One area where the technology impact in finance is most evident is the transformation of securities trading and other financial instruments. Before the substantial automation of the past few decades, trading was conducted by humans on physical trading floors. Human clerks in back offices ensured proper processing of transactions. Over time, both the back office and the actual trading process have been transformed by automation.

Many financial markets have moved beyond human intermediation in floor trading or on the telephone, replacing human intermediaries with electronic limit order books and other automated trading systems.[8] In response to the automation of the exchanges, investors and traders developed trading algorithms. Many of these algorithms were designed to replicate the behavior of humans involved in the trading process, such as agency floor brokers or proprietary market makers. Over the past decade or two, these trading algorithms have improved, computing technologies have advanced, and buy and sell orders are arriving and matching faster than ever before.

A form of algorithmic traders referred to as high-frequency traders (HFTs) exemplifies the innovating role of FinTech in trading. The SEC (2010) described HFTs as "professional traders acting in a proprietary capacity that engage in strategies that generate a large number of trades on a daily basis." HFTs are often characterized by their use of (1) high-speed and sophisticated computer programs; (2) colocation services and individual data feeds to minimize network and other types of latencies; (3) very short time frames for establishing and liquidating positions; (4) the submission of numerous orders that are cancelled shortly after submission; and (5) ending the trading day in as close to a flat position as possible. These characteristics are used for both arbitrage and market making and are only made possible with new technologies. A central question is whether HFTs improve the functioning of financial markets in terms of informational efficiency and liquidity.

Significant theoretical and empirical literature has focused on HFTs' role in the incorporation of information into price, often called price discovery (see Brogaard et al. 2014, 2019). If HFTs' investment in technologies and algorithms is primarily to react to public information faster than other traders, then HFTs can increase information asymmetry.[9] This can increase adverse selection and reduce liquidity because HFTs "pick off" other investors' "stale orders." For example, when the S&P 500 futures increase in price on the Chicago Mercantile Exchange, HFTs race to buy stocks in New York. Slow investors who cannot cancel their orders fast enough will sell stocks to HFTs unwillingly before prices rise. Anticipating this possibility, slower investors (or even other HFTs) will demand greater compensation for providing liquidity in terms of a wider bid-ask spread (Budish et al. 2015, Shkilko and Sokolov 2020).[10] The simple ETF-futures arbitrage illustrates potential tensions between statistical arbitrage and market making. However, it is important to note that the distinction between arbitrage and market making is often simpler to see in theoretical models than in practice. Market makers trying to avoid being picked off by arbitrageurs can become arbitrageurs themselves if other liquidity providers are slower.

Although HFTs have grown as a percentage of volume, liquidity has improved (see Jones 2013 and Menkveld 2016). Transaction costs for small investors, as measured by bid-ask spread, have declined. Transaction costs for large institutional investors, as measured by implementation shortfall, have also declined substantially. Algorithmic trading is generally thought to have been responsible for this liquidity improvement (Hendershott et al. 2011). However, it can be challenging to separate the causal effects of increases in agency algorithmic trading from the increases in HFTs.

Menkveld (2013) examines the entry of a single HFT market maker into the trading of Dutch stocks in July 2007 and finds a decline in bid-ask spreads and adverse selection. Brogaard et al. (2017) use an instrumental variables approach exploiting differences in the 2008 short-sale ban's cross-sectional impact on HFTs and non-HFTs to find that some HFTs' activities are harmful to liquidity during the extremely volatile short-sale ban period. One way HFTs could harm institutional investors is by "front-running" non-HFTs' orders by detecting large non-HFT orders that are split over time (van Kervel and Menkveld 2019, Korajczyk and Murphy 2020, Yang and Zhu 2020). Beyond the impact of HFTs on average market liquidity, HFTs' impact during volatile market conditions has been an important area of study (Kirilenko et al. 2017, Bogousslavsky et al. 2020).

HFTs raise important concerns for financial market design. Concerns about the possible deleterious effects of HFTs have led to many proposals to curb HFTs' actions. Some of the most prominent are (1) transaction taxes, (2) frequent batch auctions, and (3) speed bumps. Colliard and Hoffmann (2017) find that the French transaction tax lowers trading volume and reduces liquidity. Budish et al. (2015) and Baldauf and Mollner (2020) theoretically study how frequent batch auctions and speed bumps can improve liquidity by reducing adverse selection. Aoyagi (2020) shows how speed bumps can actually worsen adverse selection by increasing HFTs' investment in speed.

Future research opportunities on HFTs and technologies in financial markets include (1) the study of regulatory interventions designed to impact HFTs; (2) the analysis of HFTs' behavior across markets and securities; (3) the study of HFTs that move beyond the stock market; (4) the examination of market data's impact on HFTs and other investors; (5) analyzing the impact of HFTs on different types of investors, for example, retail versus institutions and passive versus active; (6) the impact of high-quality investor tools and low-cost trading by brokerage firms; and (7) better understanding of the impact of agency algorithms.

3. Technology: Blockchain as a New Frontier of FinTech

Blockchain technology is considered to be one of the most disruptive technological innovations since the invention of the internet (Zhao et al. 2016). The essence of blockchain is a *consensus system* involving multiple parties and a strong security mechanism under an open architecture (Cai 2018). It relies on ingenious distributed algorithms of cryptography and mathematics and uses network computing to enable participants to reach consensus on the internet where trust cannot be easily established.

In recent years, blockchain has become a new subject of widespread studies in both financial industries and academia (Lacity et al. 2019) on such topics as cross-border payments, cryptocurrencies (Ilk et al. 2021), supply chain finance, insurance (Gomber et al. 2018, Goldstein et al. 2019), and new financial organizations and processes (Biais et al. 2019). In this section, we drill down the technical nature of blockchain and its implications for financial businesses (Chiu and Koeppl 2019).

Blockchain is, from the data management perspective, an innovative data structure that includes two basic features, blocking and chaining. Blocking is the process that collects data records within a certain time, such as 10 minutes in the case of Bitcoin (a public chain). Chaining is a process that hashes the block to generate a unique identification number for a given block. This block ID or hash value will in turn be included in the next block, thus creating a chain of blocks. As a basic tool of modern cryptography, a hash function (or, simply, hash) is a mathematical algorithm that maps data of arbitrary size to a bit array of a fixed size (the hash value). The ideal hash is deterministic, meaning that the same message always results in the same hash, and unique, that is, it is (close to) impossible to find two different messages with the same hash value.

The much-talked-about immutability feature of blockchain as an innovative data structure stems from these two basic properties of hash, being deterministic and unique. The data structure resulting from blocking and chaining enables several new properties of data management that are very different from the relational data structure that are broadly in use in business. In a relational database, removing or modifying one record will not affect the basic database operation. As such, it is not possible for relational databases to be tamperproof, even though one may rely on the system log to track unauthorized operations, which could be compromised. In contrast, blockchain is tamperproof because any slight modification to the existing records in a blockchain will render the blockchain useless because of the built-in tamperproof features. Of course, blockchain does allow correction of data entry errors by adding new records, just as in typical bookkeeping operations.

3.1. Trends of Blockchain Applications in Finance

As is well known, finance is the earliest field of blockchain practice. The original Bitcoin white paper by Nakamoto (2008) advocates a peer-to-peer payment system that prevents double spending. The timeliness and immutability of blockchain are especially meant to help resolve financial credit problems. Not surprisingly, financial institutions are actively endorsing blockchain for digital currency and asset custody transactions. Stock trading, financial audit, cross-border finance, electronic bills, clearing, and supply chain finance are some of the many fields that have harnessed blockchain to solve the problems of complicated credit verification, high cost, long process, and data transmission errors in financial transactions.

So far, many blockchain application projects have begun to move from proof of concept to production. For example, IBM and Ripple launched cross-border payment services based on blockchain technology; Hong Kong Monetary Authority, HSBC, Bank of China, Bank of East Asia, and Hang Seng Bank cooperated with Standard Chartered Bank and Deloitte to establish a blockchain trade financing platform in the Guangdong-Hong Kong-Macao Greater Bay Area; Facebook's cryptocurrency Libra, tries to establish a borderless currency and the financial infrastructure to serve billions of people.

Blockchain technology is still in its early stage. Major risks must be prevented at the technical and application levels. This is because of the following: (1) At the technical level, it is still difficult to fulfill the safety, function, and performance requirements of some financial scenarios. (2) At the governance level, relevant arrangements for supervision, standards, and talents need to be further improved. (3) There are still ambiguities at the business level, and application innovations lack authoritative third-party evaluation. At the same time, digital currency, digital identity, and broader financial security (regulatory) infrastructure will be the three important hurdles to cross for many financial applications.

3.2. Killer Finance Applications of Blockchain

Supply chain finance (SCF) has been widely regarded as a killer finance application of blockchain technology. Core companies in SCF, including logistics companies, warehouses, and banks, act as computing nodes in a blockchain financial platform, maintaining the stability of the system. Other companies, as users of the system, only participate in financial services but do not participate in blockchain computing. The main functions of a blockchain SCF platform include (1) managing customer permissions—review user information and assess user credit risk, and authorize user operating permissions accordingly; (2) managing digital assets—transfer users' offline assets, audit, and manage online assets; and (3) provide users with various functions for digital asset transactions.

In a typical digital asset issuance process, a user confirms the physical asset application as a digital asset and the platform audits the physical asset. It needs to be connected to the logistics system (e.g., a warehouse) to verify the information on the digital notes (e.g., a warehouse receipt) generated though the logistics system. Common notes transacted in SCF include bill of lading, warehouse receipts, accounts receivable, accounts payable, and invoices. The digital asset application process and the generated digital assets are recorded on the blockchain. Through the platform, users can list digital assets for trading and other users can purchase digital assets on the platform. Digital asset transactions (e.g., in the form of factoring and reverse factoring) are automatically executed through smart contracts, and transaction information is recorded on the blockchain (Cong and He 2019). Enterprise production capacity can also be converted into digital assets and presold on the platform. Companies can also issue digital assets for financing through the platform's smart contract template and redeem the assets within the agreed period.

In the SCF operation, blockchain and smart contracts can be regarded as credible workflows— this requires the application of data verification technology to ensure data reliability. Its authenticity verification technology may include physical tracking to ensure the accuracy of digital assets. Of course, blockchain anticounterfeiting is not a panacea; relevant laws and regulations are still needed to reduce crimes, such as selling the same thing more than once. SCF with blockchain technology (Du et al. 2020) has given rise to blockchain platforms such as those being marketed by IBM, Tencent, and Ant Financial.

Blockchain can also be used to solve the pain points of business links in payment and settlement, such as interbank joint loan business. The PeerSafe Corporation uses blockchain to build a trustworthy interagency fund reconciliation platform. Smart contracts are used to realize quasi-real-time reconciliation processing, which greatly saves reconciliation time and improves reconciliation efficiency. The reconciliation platform is the most common middle and back office business between financial institutions and customers and is a critical link in fund payment and settlement. Under the traditional reconciliation mode, the two involving institutions generate business records by asynchronous processing, compare them on a case-by-case basis, and deal with the differences in accordance with the previously agreed upon processing method. Generally, it takes T+3 days (e.g., SWIFT) to complete the reconciliation on day T, which is deficient in timeliness and risk prone. In contrast, blockchain reconciliation helps achieve (1) quasi-real-time reconciliation, which improves processing efficiency; (2) reduced error rate; and (3) ensured data security.

There is no doubt that blockchain has promoted the rapid development of fiat digital currency. At present, the People's Bank of China is vigorously exploring RMB digital currency and electronic payment (DCEP). There are five main reasons: (1) substitute banknotes to further reduce currency issuance and circulation costs; (2) promote inclusive finance and improve payment diversity and convenience; (3) facilitate internationalization of RMB; (4) respond to the upcoming challenge of private digital currency (such as Facebook's Libra); and (5) enhance the effectiveness of governance and prevent crimes, such as money laundering and terrorist financing.

Under the current financial system, issuing fiat digital currency needs to consider several issues. (1) Fiat digital currency cannot be directly issued to the public at present and needs to be indirectly distributed with the help of commercial banks, nonbank financial institutions, and other financial institutions. (2) Fiat digital currency cannot accrue interest. (3) While developing fiat digital currency, cash payments should also be retained for a long time. (4) The implementation of fiat digital currency must be boldly envisaged and carefully verified. In short, fiat digital currency is a supplement to the existing currency circulation system. In practice, digital currency promotion should be gradual to prevent risks, so that it can be integrated with cash in this process.

The large-scale development of blockchain applications requires blockchain platforms to support the vast number of small and medium-sized enterprises to develop blockchain applications. Under these conditions, the Blockchain-based Service Network (BSN) came into being. It is a public infrastructure network that can provide low-cost development, operation and maintenance, and supervision of alliance chain applications. Using BSN, users can directly build their own blockchain operating environment and rent shared resources on demand. BSN is led by the National Information Center and was jointly prepared by China Mobile, China UnionPay, and others in 2020. BSN is a global infrastructure network based on blockchain technology and consensus mechanisms. It is a credible, controllable, and scalable alliance chain for industry, enterprise, and government applications. The purpose is to increase the popularity, development, and application of the blockchain technology. Currently, BSN has established 40 public nodes in China; the new nodes are being expanded to operators in Southeast Asia and Europe. The successful promotion of BSN will establish a new type of internet space, which is a value internet based on blockchain. Its economic and political significance is self-evident.

3.3. Blockchain as a Catalyst of Societal Changes in Finance

As an emerging technology, the most basic characteristics of the blockchain technology are tamper resistance and traceability. The use of blockchain technology in the financial industry can promote information sharing (Wang et al. 2021). Further, social accountability can be enhanced through blockchain technologies. The traceable characteristics of the blockchain can better regulate financial organizations and individuals and reduce the occurrence of illegal financial activities.

As an example of large-scale implementation of blockchain in public service, in 2018, Shenzhen Metro enabled the use of mobile phones for users to scan-and-ride subways and retrieve reimbursement documents. This kind of information sharing improves the efficiency of information flow and reduces the cost of information use. This retransformed the relevant financial processes. Shenzhen Metro's use of blockchain to realize the autonomy of customer reimbursement on the chain greatly simplified the reimbursement process, improved efficiency, and reduced operating costs. At the same time, it also thwarted false reimbursement documents.

Because financial information recorded on the blockchain is difficult to tamper with and traceable, people will be more careful about what they say and do, which will strengthen financial accountability, enhance trust, and better regulate all organizations and financial behaviors. When a financial contract is signed on the blockchain, people have to be more scrupulous in checking the terms and conditions, be more responsible for the implementation process, and avoid possible risks. Accordingly, blockchain can help reduce the occurrence of illegal financial activities and improve individuals' and organizations' consciousness of financial accountability.

Blockchain technology enables financial innovations in three aspects. The first is the quality of information. After the application of blockchain technologies, there is a higher demand for data quality. With its tamperproof and traceability characteristics, if the information itself is wrong, the execution result must be wrong. Therefore, enterprises and individuals will have to greatly increase the quality requirements for financial information, which will lead to changes in financial information management. The second is the efficiency of information circulation. At present, each enterprise in a society locks its own financial data behind the firewall; the flow of financial information is replete with manual interventions, which not only incurs low process efficiency but also creates privacy concerns. For example, using blockchain technology to replace manual monitoring and operation with machines in financial processes will not only improve quality and efficiency but also greatly increase people's trust in the information. The third is the governance reform of the financial industry. Blockchain technology has changed people's understanding of the quality of information, communication efficiency, and trust. While bringing new changes, it also requires new regulations to keep up with the blockchain-triggered financial innovation.

3.4. Blockchain Is No Panacea to Financial Fraud

Although blockchain has the advantages of being tamper resistant and easy to trace, it cannot prevent financial fraud completely and automatically, simply because, as a ledger technology, it does not break the principle of garbage-in-garbage-out. Consequently, the development of blockchain technology and applications will be accompanied by the development of authentication techniques, such as face recognition, voice recognition, and chemistry signature (Leng et al. 2019). Because of the large variety of financial assets, many different authentication and tracking techniques will be necessary to ensure the accuracy, quality, and reliability of blockchain data, leading to a great demand in this line of techniques and tools. Many of these hardware and software will become part of the Internet-of-Things for the financial industry.

Blockchain-based identification is another relevant area of development for financial applications, particularly in international settings where national identification is hard to authenticate and use. For instance, Microsoft's decentralized identity creates a blockchain identity that changes the way people trust each other on the internet. This has the potential for people to make deals with one another across borders with a new identity that is not issued by their home countries. Recently, Tencent developed a blockchain identity for its WeChat users. As a national endeavor, Estonia's blockchain-based national identity project is another prominent example in this regard.

Even with the development and implementation of authentication and identification tools in finance, there will inevitably be fraudulent activities. That is, blockchain is a new technology for improving trust in finance, but fraudsters will also become more capable with new types of fraud that will require new government regulations and law enforcement, just as shown by the new blockchain-related policies issued by governments around the world. This shows again that new regulations must go hand-in-hand with the new technologies in order to ensure healthy installation of new financial changes.

Blockchain technologies and applications in finance are still experiencing dramatic changes in order to meet the needs in complex financial situations and government regulations. For instance, in order to improve the efficiency of blockchain operations in large-scale financial applications, braided blockchains have been developed to integrate multiple blockchains into a blockchain system so that parallel updates and queries can be done to speed things up dramatically. Although it is not feasible to do parallel operations in Bitcoin or other cryptocurrencies, it is possible to do so in other financial applications, such as purchasing goods or healthcare records. An obvious area of blockchain technology development is cross-chain operations because a customer may need to use multiple blockchains from different business sectors and companies. Another area of blockchain development has to do with the requirements of governments to monitor blockchain information, which leads to a backdoor for the government, although this is clearly in opposition to the security principles of blockchain.

Blockchain-enabled financial innovations will change the order and rules of the game in many business sectors and should be studied at the intersection of information systems (IS) and finance. Such research topics include, but are not limited to, the following. (1) What is the impact of fiat digital currencies, such as China's DCEP, on banking and business processes and societal governance? (2) How will blockchain technology help securitize business assets that are hard, if not impossible, to digitize otherwise, and how do we balance the benefits of improved business liquidity and the increased financial risks? (3) Will the blockchain technology reshape supply chain finance toward enabling better capital financing for SMEs? (4) Will blockchain technology enable value tokenization (token economics) in enterprise and across-enterprise processes so that future economic systems will be much more value-driven?

4. Technology: Artificial Intelligence in Finance

No magic wand is needed to see that artificial intelligence is revolutionizing the financial market. According to the new International Data Corporation spending guide, worldwide spending on AI is expected to reach $110 billion in 2024,[11] a big portion of which is in the finance sector.[12] AI's application encompasses wide-ranging settings from trading and brokerage (Robinhood), portfolio management (Aladdin Wealth), robo-advising (Betterment), and alternative data (Quandl, KENSHO, Dataminr, etc.) to clearance (PeerNova), Know Your Customer (KYC) (VeraFin, Contego, etc.), risk management (Riskalyze), and compliance (AQMETRICS).

Behind the excitement and hype, academic research has established some important insights regarding the power of AI in finance. Depending on the degree of abstraction, we can classify research papers into three categories. The first category focuses on theoretical and methodological aspects of AI in finance. The corresponding research topics deal with technical challenges, such as overfitting, handling false discovery, selecting features, and AI-assisted hypothesis testing. The second category addresses the modeling aspects of AI in finance. The focus in this category is on asset pricing (Zhang and Zhang 2015). These studies build AI-informed models of either asset pricing or behaviors of market participants. The research topics include return prediction, market microstructure modeling, robust decision making, partially observable Markov decision process, and fuzzy reasoning agent. The third category centers on the direct applications of AI in finance using news, social media, and word of mouth data (Xu and Zhang 2013). Some direct applications of AI in finance can be predicting company performance, finding new customers, learning customer demands, studying corporate culture, classifying patent innovations, understanding the effects of news and word of mouth, detecting fake news, and estimating emotions in social media.

In these research papers, the AI techniques with proven performance include neural networks and tree-based methods, such as gradient boosting regression trees and random forests. Deep learning models, such as convolutional neural network (CNN), recurrent neural network (RNN), and generative adversary network (GAN), are rarely explored in the literature.

4.1. Theoretical and Methodological Applications

There are several theoretical/methodological issues related to applying AI in finance. These issues include overfitting prevention, false discovery prevention, feature selection or dimension reduction, and hypothesis testing using machine learning. Much progress has been made in recent years.

One most exciting advancement brought about by AI-based models is the freedom to capture previously hard-to-find linear and nonlinear relations. However, the associated downside of this progress is the possibility of overfitting. Numerous studies have been dedicated to overcoming this problem. Ban et al. (2018) propose a new type of regularized linear regression to deal with the issue of overfitting. The authors add a regularization term (a sample variance operator) to the objective function of the classical mean-variance analysis and call the method *performance-based regularization.*

Another important theoretical/methodological challenge arising from the application of machine learning in finance is false discovery, also known as data dredging, data snooping, or p-hacking. If a researcher mines the same data set over and over again, he or she is increasingly likely to find some spurious statistical significance, even though the finding may be due to coincidence. Recently, some progress has been made in dealing with this issue, such as Giglio et al. (2020). The authors adapt the techniques of Benjamini and Hochberg (1995) to the context of linear factor models to find assets with strictly positive alpha. The authors show that after adopting this "alpha screening," there is a significant improvement in the performance of the linear factor model.

Feature selection, or dimensionality reduction, is also an important theoretical/methodological consideration. Thousands of pricing factors can be the candidates for features. Many of them are highly correlated with each other, whereas the majority of them are not effective. We need to reduce the number of factors and figure out the few most effective ones. Feng et al. (2020) propose a feature selection method by combining the double selection least absolute shrinkage selection operator (LASSO) method of Belloni et al. (2013) and Fama-MacBeth regression. Kozak et al. (2020) propose a dimensionality reduction method by adding a shrinkage factor into the traditional generalized method of moments estimator of the stochastic discount factor.

What machine learning can do for hypothesis testing is another promising area. Polk et al. (2006) introduce a linear model to forecast equity premium. The predicting factors in their model have both autocorrelation and correlation with equity returns. The authors develop a machine learning method to test the hypothesis that the correlation between the predicting factor and the equity return is zero. To do so, the authors build a neural network approximating the probability of generating certain data by the model. Jackwerth and Menner (2020) apply machine learning to test the Ross recovery theorem. The basic idea is the same, that is, using machine learning to estimate the probability of generating certain data by a model. After adding a few reasonable economic constraints, it is shown that the Ross recovery theorem is rejected. These two papers demonstrate that machine learning can help test statistical hypotheses.

4.2. Asset Pricing Models

Applications of AI in asset pricing typically involve estimating model parameters of statistical models with machine learning techniques. Such models are found in return prediction, market microstructure, portfolio choice, game strategy, and investors' behavior modeling.

Feng et al. (2018) apply deep learning (long-short-term-memory (LSTM)) to predict asset returns, and then Feng et al. (2021) develop a characteristics-sorted factor model based on deep learning (non-reduced-form neural network) for asset pricing. Iwasaki and Chen (2018) propose a deep neural network model to conduct sentiment analysis and incorporate this knowledge into asset pricing and portfolio construction. Gu et al. (2020) present a comparative study of using different machine learning methods in stock return prediction. The authors study three categories of machine learning methods: linear regressions, tree-based models, and neural networks. For the linear regressions category, the methods include ordinary least squares (OLS; directly running linear regression with many factors), applying OLS with Fama-French 3 factors (OLS-3), partial least square (OLS with a feature selection technique), principal component regression (OLS with another feature selection technique), OLS with elastic net regularization (ENet), and generalized linear models (including nonlinear features). For the tree-based models, the methods include gradient boosted regression trees (GBRT) and random forest (RF). GBRT applies the gradient boosting technique to regression trees. It first fits a shallow regression tree, then uses another shallow regression tree to fit the residual, and lastly adds forecasts of these two trees together after multiplying the second tree's forecast by a shrinkage factor. RF is a method of adding forecasts of many regression trees together using the bootstrap aggregating and dropping techniques. For neural networks, the authors compared neural networks with different numbers (one to five) of hidden layers. Overall, the authors find that tree-based models and neural networks with three or four hidden layers perform the best. Bianchi et al. (2020) perform a similar comparative study for predicting bond returns.

Easley et al. (2020) argue that machine leaning can help us better understand market microstructures, and this understanding is profitable. Inspired by the market microstructure models, the authors build several machine learning models (including a random forest model and a neural network model) to predict multiple market microstructure measures with six input variables. These six input variables are the Roll measure, the Roll impact, a volatility measure (the CBOE Volatility (VIX) index), Kyle's λ, the Amihud measure, and the volume-synchronized probability of informed trading. The output market microstructure measures include the signs of change in terms of the bid-ask spread, realized volatility, Jacques-Bera statistic, sequential correlation of realized returns, absolute skewness of returns, and kurtosis of realized returns. Ruf and Wang (2020) review the literature on the use of neural networks in option pricing and hedging.

When financial market participants make decisions, model uncertainty and strategy robustness are important considerations. The problem of portfolio choice can be written as an optimization problem. In Lim et al. (2012), the authors introduce the concept of *relative regret* and model the original optimization problem as a maximin problem to increase robustness and deal with model uncertainty. The optimal strategy can then be obtained by using a learning algorithm. Although the authors consider only the single-period case in their paper, it is not hard to model a multiperiod case as a Markov decision process or one of its variants and adopt techniques of reinforcement learning to deal with multiperiod cases.

There is increased attention to the application of reinforcement learning in the financial market. Repetitive decision making, such as portfolio position adjustment, and production volume, usually can be modeled as a Markov decision process or a partially observable Markov decision process (POMDP). Aviv and Pazgal (2005) model the change of customer demands and the process of revenue-maximizing dynamic pricing as a POMDP. In this model, there are a few hidden states in the Markov chain. Each hidden state corresponds to a probability distribution of the demand for a given price in a given period. The authors develop an approximation method for solving their POMDP model and obtain the pricing rules. The POMDP model, although highly useful, is also overly simplistic. Lovejoy (1991) shows that application of the POMDP model to more realistic and complex situations is computationally intractable in general. With new developments in the machine learning theory, simulation-based methods may help address this issue. For example, DeepMind used Monte Carlo tree search to solve the intractability problem when they developed AlphaGo (Silver et al. 2016). Given the complexity of the financial market, such approximation- and simulation-based solution methods are highly useful.

Decision theory models (such as a Markov decision process) are single-agent models. Game theory models can be viewed as decision theory models generalized to multiagent cases. Techniques of reinforcement learning used to learn the optimal strategy of a Markov decision process can be adapted to the context of learning the optimal strategy of game theory models. Camerer et al. (2019) propose a game-theory model of bargaining and use machine learning techniques to obtain the players' optimal strategy. The model can be used to explain observed behaviors of all agents and to predict the result of the bargaining.

Fuzzy logic is a mathematical tool that can be incorporated into reinforcement learning. Linn and Tay (2007) build an investor model based on the assumption that investors do reasoning according to fuzzy logic. This leads to a unified stock market model that describes both investors' behavior and stock price movements.

4.3. AI and Firm Value

With the penetration of AI into various industries, can we measure and capture its value?

Understanding when and how firms should use AI is of great importance. It gives researchers insights into the effectiveness of AI on firm performance and helps managers decide the timing and resources for AI development. Anand et al. (2020) theoretically and empirically show how and when firms leverage business intelligence and analytics (BI&A) to conduct searches and improve performance. They examine problemistic search, which is the process of managers' learning from performance feedback. In the proposed theory of performance-driven search, they consider the individual and joint effects of failures in operational performance and financial performance. They find that when a joint failure of operational and financial performance occurs, organizations leverage BI&A systems to search with the objective of improving the performance. Their findings are confirmed by longitudinal data from seven U.S. hospitals. This study points out a potential problem of AI investments: when firms invest in AI to enhance their search and analytics abilities, they tend to use such abilities only when facing performance failures.

In the financial market, information processing is probably the most important task of all participants. Machine learning can be used to extract information from traditional data sources, such as news, user-generated content (UGC), experiments, and firm reports. Many studies show how firms can apply AI in various settings. These settings may not be limited to the financial market, but they can inspire studies in the financial environment.

Brown et al. (2020) use a Bayesian topic modeling algorithm to improve detection of financial misreporting. Bao et al. (2020) utilize ensemble learning to build a fraud prediction model. Zheng et al. (2018) propose a model using generative adversarial network (GAN) to detect telecom fraud.

Text mining and natural language processing (NLP) is a field significantly pushed forward by deep learning models. We are now able to process huge amounts of unstructured text data, such as daily news. This development enables studying the relationship between news and stock performance. With market frictions, stock prices may not reflect all available information instantaneously when they arrive. Hence, can news content predict stock returns in the short or long run? Frank and Sanati (2018) use AI (Naive Bayes, k-nearest neighbor, random forest, and neural network models) to categorize news from the *Financial Times* into different topics (earnings reports, governance stories, restructuring stories, etc.). Then they conduct an event study to compare the average cumulative abnormal returns over the next month/quarter after news arrival. They find the market overreacts to good news and underreacts to bad news on the news day. They also provide evidence that the interaction between retail investors with attention bias and arbitrageurs with short-run capital constraints can explain the findings. Manela and Moreira (2017) find that information from front-page articles of *The Wall Street Journal* can predict high future stock returns even in the long run. They rely on machine learning techniques to reveal the volatility implied from the news (NVIX). The authors find high NVIX is followed by high stock returns in a period. The predictability is statistically significant from 5 months to 24 months in the postwar U.S. stock market. Further, by classifying the disasters reported in news into different categories—such as wars, financial intermediations, government policies, stock markets, and natural disasters—they find the predictability power of NVIX comes from the news coverage of wars and government policies.

There exists much fake news in the financial market. Clarke et al. (2020) tackle this issue by studying the news stories on Seeking Alpha. AI can also help examine human traits and behaviors. Adamopoulos et al. (2018) show machine learning algorithms can identify individuals' personality traits from their activities in social media. Chau et al. (2020) provide a machine learning–based system to detect depression emotions on social media. In business, AI can help firms target customers and make good pricing strategies based on customer demands. Leveraging machine learning methods, Simester et al. (2020) target prospective customers by analyzing field-experiment data of promotions from a large U.S. retailer. They compare the performance of different targeting methods and find model-driven methods perform better than distance-driven methods and classification methods with ideal training data. In addition, they deal with four general data challenges, that is, covariate shift, concept shift, information loss through aggregation, and imbalanced data. Levina et al. (2009) develop an approach for online learning in markets where price is dynamic and customers are strategic. Based on an aggregating algorithm, Vovk (1990) is able to dynamically learn consumer purchase probability with any demand model. Costello et al. (2020) propose a new feature for an AI-based credit scoring platform. These studies show the great potential of leveraging the power of AI to understand consumers. Financial firms can apply such techniques to promote their products and services with more accurate targeting, improve risk management with reliable credit systems, and even develop new business models.

Similarly, AI has been used to understand firm characteristics by analyzing firm activities. Li et al. (2020) measure corporate culture using the word embedding model. Because of the nebulosity of corporate culture, there are many measurement issues. Leveraging machine learning, the authors score the five corporate cultural values of innovation, integrity, quality, respect, and teamwork from earnings call transcripts. The word embedding model generates a dictionary relating words to the five cultural values. The scores are generated by counting the words. The innovation culture is broader than the usual measures, such as the research and development expenses and the number of patents. The authors report strong correlations between firm culture and firm performance.

Chen et al. (2019) implement machine learning techniques to classify and identify the exact underlying technologies of innovations from patent filings data. Neural network and support vector machine (SVM) models outperform other algorithms in this classification task. The authors advocate blockchain technology to be the most valuable FinTech innovation for innovators. In the financial sector, Internet-of-Things, robo-advising, and blockchain are the most valuable innovation types.

Another AI application in finance is using it to gauge the performance of trading algorithms and hedge funds. Allen and Karjalainen (1999) use genetic algorithms to learn technical trading rules and test if these rules earn consistent excess returns. Previous literature on the effectiveness of technical trading rules all use ad hoc specifications of trading rules, which suffer from the problem of data snooping. The authors show that genetic algorithms avoid such problems. By finding and evaluating ex ante optimal trading rules, they find technical trading rules cannot bring excess returns when factoring in transaction costs. Wu et al. (2020) leverage machine learning to predict the cross-sectional returns of different hedge funds. It is hard for investors to compare and select hedge funds because of the confidentiality of their investment strategies. The authors present a machine learning–based approach to predict future hedge fund returns for 23,762 hedge funds recorded in the Hedge Fund Research (HFR). By utilizing four machine learning algorithms (least absolute shrinkage and selection operator, random forest, gradient boosting, and deep neural network), they run a cross-sectional forecast model with a set of idiosyncratic, return-based variables. Their forecast model outperforms the HFR index in most aspects, including annualized return, Sortino ratio, and alpha. In this setting, neural network is the most effective among the four machine learning methods.

4.4. Discussion

We find there is a growing interest in AI in finance. AI has provided new tools for solving a wide spectrum of problems in the financial industry. The progress is very promising; but compared with the fast development of AI as a technology, AI's application in the financial market and research on AI in finance are still in the infancy stage. The main applications of AI are in asset pricing, return prediction, and sentiment analysis. Naive Bayes, *k*-nearest neighbor, random forest, SVM, and neural network models are among the most frequently used AI models in finance. Textual analysis is used broadly for identification and classification tasks. AI's outstanding ability to capture nonlinear relations is one of the most important aspects of its use in financial research. It can provide new insights beyond traditional linear regressions.

However, very few studies examine the newly developed deep learning algorithms in finance. Neural network algorithms are used and have shown good performance in predicting returns under certain circumstances (Easley et al. 2020, Gu et al. 2020, Wu et al. 2020) with the basic feed forward algorithm. Advanced algorithms like CNN, RNN, and GAN are seldom seen in the literature. These algorithms have specific advantages in dealing with different financial market problems. For example, CNN is good at object detection and classification on images. It may be used to detect patterns in stock charts. RNN has demonstrated advantages in processing contextual and temporal data, and it is suitable to learn price trends. Besides deep learning algorithms, reinforcement learning is also a good candidate for generating financial insights. It dynamically optimizes a task to get the best outcome under preset conditions. One example is Jiang et al. (2017), which proposes a financial-model-free reinforcement learning framework, using a convolutional neural network, a basic recurrent neural network, and an LSTM, respectively, for portfolio management in a cryptocurrency market. Such methods can be utilized to find novel solutions to optimization problems that previously were prohibitively costly.

Deep learning, on the other hand, faces severe challenges when implemented in finance. One of these challenges is the overfitting problem. Overfitting occurs when there are too many degrees of freedom in a model and the model captures only noises. To overcome this problem, some restrictions need to be set up. However, it is difficult to do so when one does not know much about the system (the financial market). Another challenge is the interpretability of deep learning models. Adding hidden layers may generate good predicative results, but we cannot learn about the mechanism underlying the results from the algorithm. A better way to use deep learning is to build a theoretical model first, but it is quite hard to do so in complex systems.

Toward a successful application of AI in finance, it is also important to understand issues such as the potential bias AI may bring (Fu et al. 2021), AI fairness (Satell and Abdel-Magied 2020), interpretability/explainability of AI (XAI),[13] and how humans and AI may interact (Ge et al. 2021) to augment human intelligence. For example, Ge et al. (2021) find that allowing humans to intervene in the use of robo-advising may lead to inferior return on investments; that is, having humans in the AI application loop can be counterproductive.

Other future research opportunities on AI in finance may include (1) custom-made AI algorithms specifically targeted at finance settings (e.g., financial neural networks); (2) investor-AI interaction; (3) financial intelligence extraction and augmentation; (4) how methods such as heterogeneous treatment effect, deep counterfactual learning, federated learning, and capsule networks can offer new insights; (5) algorithm aversion and manipulation in financial settings; (6) AI and risk management and compliance; and (7) how the respective models in AI and econometrics can be integrated to expand the frontier of both prediction and explanation.

There is a long way to go to get deeper understandings and better implementations. Concerted efforts on theory and methodology should be made by researchers from multiple disciplines, including IS, finance, and computer science.

5. A Word on FinTech Teaching

With the global frenzy about FinTech, the demand for FinTech education blossoms. What classes should we offer in FinTech? What areas should be involved in offering FinTech courses? How can the finance and IS areas collaborate to offer a strong FinTech curriculum? We provide our thoughts on these questions.

We first tabulate 10 representative FinTech programs currently being offered in Table 1. Most of these FinTech programs started very recently. The first program of this kind we know of is New York University's (NYU) FinTech MBA program, launched in 2017. Almost all of these FinTech programs target master students or executives. However, as of now, only a handful of them are offering a formal master's degree.

Table 1. A Sample of FinTech Programs at 10 Universities

Number	University	School	Format	Degree	Fee	Length	No. courses/ credits	Main courses in curriculum	Year start	Link
1	University of Pennsylvania	The Wharton School	Online	Nondegree	$79/month	4–6 Weeks per course	4 Courses	Payments & Regulation, Crypto currency and Blockchain, Lending, Application of AI, Insurance	2019	https://online.wharton.upenn.edu/fintech-specialization/
2	Harvard University	B-school	Online	Nondegree, certificate	$3,600	6 Weeks, 8–10 hours per week	3–4 Courses	Banking and Payment, Raising Money, AI and Machine Learning, Personal Finance, Blockchain and Cryptocurrency, FinTech Future	2018	https://harvardx-onlinecourses.getsmarter.com/presentations/lp/harvard-fintech-online-short-course/
3	UC Berkeley	B-school	Online	Certificate	$2,600	8 Weeks, 4–6 hours per week	8 Modules	Fintech Revolution, Economic Foundation of FinTech, Data Science, Analytics Tools, Financial literacy, FinTech Execution, FinTech Strategy	2018	https://em-executive.berkeley.edu/fintech
4	Columbia University	B-school	Online	Certificate	$2,800	6 Weeks	6 Courses	Demystifying Machine Learning (ML) and AI, Blockchain and Digital Tokens, Regulation and Data	2019	https://online1.gsb.columbia.edu/fintech
5	New York University	B-school	On campus	FinTech MBA	$76,780	2 Years	10–12 Courses	FinTech Analytics, Digital Currency, Blockchain, Financial Information Systems, Robo-Advisors, Risk Management for FinTech	2017	https://www.stern.nyu.edu/programs-admissions/full-time-mba/academics/specializations/fintech
6	Imperial College of London	Finance department	On campus	MSC Fintech	37,500	1 Year	6–8 Courses	R, database, Python, Big Data in Finance, Blockchain and Applications, Financial Econometrics in R/Python, Mathematics for Finance	2019	https://www.imperial.ac.uk/business-school/programmes/msc-financial-technology/

Table 1. (Continued)

Number	University	School	Format	Degree	Fee	Length	No. courses/credits	Main courses in curriculum	Year start	Link
7	University of Texas at Dallas	B-school	On campus	MS in Fintech and Analytics	$44,100 (nonresident)/ $ 38,000 (resident)	3 Semesters	12–15 Courses/ 36 credits	Financial Information and Analytics, FinTech I & II, Cloud Computing, Statistics for Finance, Cybersecurity, Machine Learning	2019	https://fin.utdallas.edu/ms-ftec/
8	National University of Singapore	School of Computing	Online/on campus	FinTechSG certificate	$1,600	2 Months	6 Courses	FinTech, Blockchain, Programming, AI/ML, Database, Risk Management	2020	https://fintechlab.nus.edu.sg/nus-fintechsg-programme/
9	Duke University	Pratt School of Engineering	On campus	MS engineering in Fintech	$83,910	3 Semesters	30 Credits	Secure Software Development, Financial Engineering, Quantitative Financial Analysis, Robo-Advising, Machine Learning for FinTech, Blockchain, Mobile Application Development, Fundamentals of Data Science, Data Visualization	2019	https://pratt.duke.edu/fintech-masters-degree
10	Chinese University of Hong Kong	Engineering School	On campus	MS in Fintech	HK$140,000	1 Year full time	8–10 Courses	Financial Markets and Instruments, Advanced Financial Infrastructure, Blockchain and Cryptocurrency, Computational Finance, Database, Machine Learning, Big Data Analytics, Algorithm Trading, Security	2020	http://fintech.erg.cuhk.edu.hk/programme-information/programme-structure

This list includes NYU, Imperial College of London, Duke University, the Chinese University of Hong Kong (CUHK), and the University of Texas at Dallas (UTD). Many of these programs (e.g., Wharton, Harvard, Columbia, and University of California, Berkeley, among others) offer online certificate programs as part of their executive education. Most of these programs are hosted by business schools, whereas a few of them are offered by engineering schools, such as the MS engineering in FinTech at Duke University and the MS in FinTech program at CUHK.

An examination of the main courses offered in the FinTech curriculum shows that most programs combine a set of technical courses with finance classes. Common technical classes include subjects on artificial intelligence and machine learning, blockchain and cryptocurrency, cybersecurity and cryptography, and big data analytics. Common finance subjects include risk assessment, digital payment, algorithm trading, wealth management, robo-advising, InsurTech, and regulation. Full-fledged FinTech programs (i.e., those offering an MS in FinTech) tend to also cover several foundational courses such as programming, database, mathematics, statistics, and data visualization.

Notably missing is the engagement of the information systems area in the FinTech program. Although a big portion of the curriculum involves technical classes that the IS area offers, very few FinTech programs are initiated or even cohosted by IS departments. From the curriculum perspective, the opportunity and the need for the IS and finance departments to collaborate is obvious. AI, machine learning, big data analytics, cybersecurity, and blockchain technologies are some of the classes in which the IS area is well poised to play a role. In the near future, we expect more IS faculty members to retrain themselves to be knowledgeable in the relevant subject, while more finance professors will retool themselves to be proficient on the technology side.

6. Introduction to the Special Section

In view of the upcoming FinTech disruption, *Information Systems Research* rolled out a timely call for papers for the FinTech special section in 2017 (Hendershott et al. 2017). This special section received 90 submissions by July 2018. In August 2018, the four coeditors went through every paper together and selected 33 papers for further review. Among them, eight went into the second-round review process. Eventually four of them were accepted. These four papers cover different aspects of FinTech, including crowdfunding in education (Gao et al. 2021), mobile money (Dong et al. 2021), machine learning augmented decision making in lending (Fu et al. 2021), and fake financial news identification (Clarke et al. 2021).

Gao et al. (2021), "Educational Crowdfunding and Student Performance: An Empirical Study," study how to leverage new funding channels enabled by financial technologies to improve public education (K–12 education). The paper finds that when teachers receive donations through crowdfunding platforms, such as DonorsChoose.org, students' academic performance improves. Further donations from parents and the local community make an impact. Interestingly, the simple act of seeking funding helps: those teachers who made an attempt but failed to raise funds also witnessed better student performance. The study attributes the improvement to the effect of personalized funding. Teachers need to "make a case" to potential donors to justify the usage and expected outcome of the funds, such as the purpose and intent of the fund use, the detailed activities they intend to carry out, and how the activities fit the curriculum as well as the intended goal of academic performance. All these activities help validate the use of the funds and motivate students and teachers to work harder to achieve the intended goal. Teachers then need to report the realized results back to donors, which effectively forms a closed-loop monitoring system. This shows that online education crowdfunding can help match educational outcomes with donors' outcome-oriented funding for specific projects. The authors explained the improved academic performance from the perspective of social bonds (when students receive parental and community support), planning effect (when teacher and students engage in planning), and specificity (more targeted use of funding). This study sheds light on how to improve educational financing when public funding may not be sufficient.

Dong et al. (2021), "Mobile Money and Mobile Technologies: A Structural Estimation," examine the interplay between wireless technology and financial services in terms of mobile money services. Mobile money, a form of electronic money, allows mobile phone users to deposit, transfer, and withdraw funds without having formal bank accounts. Mobile money services critically hinge on the underlying mobile technology infrastructure. However, in the market, different generations of telecommunication technologies, such as 1G, 2G, 3G, and 4G, coexist. This study investigates the price elasticity between different generations of mobile technologies and mobile money. By examining the mobile-money service providers of various mobile network operators (MNOs) from 2000–2014, it is found that offering mobile money services differentiates the market and mitigates competition between these mobile service providers. The paper considers a variety of mobile money services, including bill pay, person-to-person (P2P), government-to-person (G2P), and microinsurance. Using a structural estimation with the Berry-Levinsohn-Pakes (BLP) approach, the paper is able to estimate the impact of price of technology and mobile money on demand using aggregate data. One of the novel findings is that providing mobile money can help increase MNOs' market share by 0.4%. That is, providing financial services can help a technology firm increase market share.

Fu et al. (2021), "Crowds, Lending, Machine, and Bias," investigate how to use big data and machine learning to improve investors' decisions in crowd lending. Using an intelligence augmentation method originally proposed by Kleinberg et al. (2018), the study shows that machine learning approaches can be combined with human decisions to achieve better lending performance. The approach addresses the "selective label problem" where only the default outcome of the funded loans is known, whereas the outcome of unfunded loans is not observed. It also tackles time-varying unobserved variables, such as the changing risk preference of individual lenders. Finally, the paper proposes a method to debias the gender and race biases incurred in machine learning.

Clarke et al. (2021), "Fake News, Investor Attention, and Market Reaction," demonstrate that fake news in the financial market attracts more investor attention but may not necessarily exhibit a significant impact on stock price. Using 251 fake news articles identified by the SEC as the ground truth, the paper examines financial analysts' reaction to fake news at Seekingalpha.com and subsequently the fake news' impact on stock price. It is found that fake news generates more attention than legitimate articles. Article commenters and editors at Seekingalpha.com do not seem to have the ability to discern fake news. In contrast, machine learning methods such as NLP can help identify fake news by analyzing the linguistic features of the news articles. The stock market is found to have priced in fake news correctly. There is an abnormal trading volume increase around the release of fake news, but not the stock price. In other words, fake news attracts attention but does not yield abnormal returns.

7. Conclusion

Every new advancement in technology inevitably pushes forward the progress of individuals, organizations, economies, and societies. FinTech has demonstrated tremendous power in fundamentally changing how the financial market is run.

With the fast development of FinTech in business applications, exciting research opportunities arise. In this editorial review, we provide an overview of relevant technological, pedagogical, and managerial issues concerning FinTech research and teaching. We first give one specific example of how high-frequency trading as an application of FinTech is transforming trading itself and discuss the recent academic works that deepen our understanding of this technology. Then we focus on two most important technologies that supercharge the FinTech revolution: blockchain and artificial intelligence. We review pioneering works in these two fields and conclude that they are both in their infancy. Given the immediate importance of such technologies in practice, academic work in this direction can lead to both theoretical breakthroughs and practical relevance. We also review top FinTech education programs and call for further collaboration between IS and finance.

Endnotes

[1] See https://www.businessinsider.com/goldman-sachs-has-more-engineers-than-facebook-2015-4.

[2] See https://digital.hbs.edu/platform-digit/submission/goldman-sachs-a-technology-company/.

[3] See https://medium.com/macoclock/why-big-tech-firms-want-a-piece-of-finance-deb375bcf1bb.

[4] See https://www.cnbc.com/2020/01/03/big-tech-will-push-into-finance-in-2020-while-avoiding-bank-regulation.html.

[5] See https://thepeninsulaqatar.com/article/09/06/2017/Amazon-lent-$1bn-to-merchants-to-boost-sales-on-its-marketplace.

[6] See https://medium.com/macoclock/why-big-tech-firms-want-a-piece-of-finance-deb375bcf1bb.

[7] See https://www.cnbc.com/2020/07/21/alibaba-ant-group-ipo-hong-kong-shanghai-explained.html.

[8] The largest electronic trading system in the United States in the 1990s, Instinet, was founded in 1969. In 1995, Instinet's trading volume was over 10 billion shares, accounting for over 20% of Nasdaq volume. By 2000, numerous electronic trading systems together captured roughly 40% of the volume in Nasdaq stocks (Barclay et al. 2003). Fully electronic trading came later to the New York Stock Exchange (Hendershott and Moulton 2011). Electronic trading also became significant in other asset classes; see Weber (2006), Chaboud et al. (2014), Hendershott and Madhavan (2015), and Fleming et al. (2018) for studies of electronic trading in stock options, FX, corporate bonds, and government bonds, respectively.

[9] HFTs may have an advantage because of other types of information, for example, O'Hara (2015) discusses order related information.

[10] Other theoretical models analyzing speed include Hoffmann (2014), Biais et al. (2015), Foucault et al. (2016), Jovanovic and Menkveld (2016), and Du and Zhu (2017).

[11] See https://www.idc.com/getdoc.jsp?containerId=prUS46794720.

[12] See https://www.statista.com/statistics/940783/ai-spending-by-industry-group/.

[13] See https://en.wikipedia.org/wiki/Explainable_artificial_intelligence.

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