Journal of Business Economics (2023) 93:1451–1461
https://doi.org/10.1007/s11573-023-01181-5

EDITORIAL

Recent trends in the digitalization of finance and accounting

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Published online: 16 October 2023

JEL Classification G1 · M4 · M15 · M21

1 Digitization, digitalization, and the rise of fintechs

The concept of digitalization for firms is generally associated with the extensive use of digital technologies (e.g., Balsmeier and Woerter 2019); however, this definition, at most, is related to digital transformation as an output rather than a process (Schildt 2022). Therefore, there is a clear distinction between digitization and digitalization. Digitization involves the automation of processes through the use of information and communication technologies (Hess et al. 2020), where mostly incumbent firms using their "survival instincts" have to embrace technological change because even though they might not be focusing on competitive advantage, the inability to adopt this change might lead to competitive failures. On the other hand, digital transformation or digitalization is a holistic process that is associated with changes in business processes, products, organizational structure, and business models (e.g., Hess et al., 2016). Therefore, certain researchers look at digitalization as not a mere exploitation of digital technologies but also the evolution of infrastructures, organizational practices, and managerial beliefs around such technologies (e.g., Schildt 2022). According to Gartner's glossary for information technology (IT), "Digitalization is the use of digital technologies to change a business model and provide new revenue and value-producing opportunities; it is the process of moving to a digital business." First empirical evidence suggests that engaging in digitalization positively affects firms' financial performance (e.g., Abou-foul et al. 2021).

Digitalization has transformed financial markets primarily by improving information dissemination across market participants and by providing various digital platforms to ease the execution of financial transactions (e.g., Feyen et al. 2021;

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Goldstein et al. 2023). In this context, among many other factors, the development of Electronic Data Gathering, Analysis, and Retrieval (EDGAR) in April 1993, has enhanced the information dissemination process by reducing information asymmetries among market participants. Unlike in the past, where retail investors and most of the small institutional investors used to refrain from accessing corporate filings due to high information costs (e.g., Chang et al. 2023), with the implementation of EDGAR, investors can now enjoy reduced information processing costs by easily accessing and analyzing firms' public disclosure information (e.g., Gao and Huang 2020). Moreover, for firms, the implementation of EDGAR has resulted in a decrease of the cost of capital, an increase in operating performance and an increase of the extent of equity financing (e.g., Goldstein et al. 2023). However, due to the enhanced use of machine learning (ML) techniques and natural language processing, firms now also take into account the preferences of this new target audience, namely 'machines', by adjusting their disclosure filings (e.g., Allee et al. 2018; Cao et al. 2023).

The proliferation of digital financial products and services is another major aspect of digitalization in the financial industry. These digital products and services better meet customers' demands regarding around-the-clock availability, personalized treatment, zero errors, and global consistency (e.g., Markovitch and Willmott 2014). Similarly, digitalization improves the efficiency of financial products and services (e.g., Wang et al. 2020). As a consequence, digital financial products and services elevate the quality of life for those segments of society that previously had limited access to financial products and services (e.g., Chen and Zhao 2021; Peric 2015).

When practitioners and academics refer to "digitalization" in finance and accounting, the term "fintech" is often used. It generally refers to innovative concepts that utilize computer and IT in the financial industry. As Zavolokina et al. (2016) explain, there is however no universal understating of the term "fintech".

Fintechs can be "born digital" or incumbent firms digitally transformed. The incumbent firms try to use IT to secure their market positions through "incremental innovations". Or conversely, the new "born digital" firms may provide unique products and services with greater efficiency, flexibility, and security (e.g., Chiu 2016; Gomber et al. 2017). Examples include (but are not limited to) PayPal (for payment and remittances), Robinhood (for personal finance and investment), Binance (for cryptocurrency), Revolut, and Chime (for digital banking), and Transferwise (for cross-border payments and remittances).

Evidently, the various advancements driven by the digitalization of business processes are significantly impacting the economy. In this editorial, we aim to illuminate several crucial facets of this economic transformation, with a particular emphasis on matters related to finance and accounting.

The remaining structure of this article is as follows: Section 2 addresses the use of big data in finance and accounting. Section 3 explains the impact of digitalization on portfolio management. Section 4 discusses decentralized finance. Section 5 refers to the use of artificial intelligence (AI) and ML in finance and accounting research. Section 6 deals with the black-box problem of machine learning and explainable AI as a solution to the black-box problem. Section 7 presents algorithm aversions as one of the causes of why the market penetration for AI is still low and Sect. 8 concludes with a concise glimpse into future developments in the realm of digitalization in finance and accounting.

2 Big data in finance and accounting

The widespread use of advanced technologies with high computational powers results in so-called "big data". Due to firms' increased computing powers, they tend to use big data to their advantage. For instance, since most people around the world use social media in one form or another (e.g., Poushter et al. 2018), firms exploit this reality to engage in direct contact with end users at a lower cost and with a broader influence (Kaplan and Haenlein 2010). These firms use social media analytics to understand the behavior and preferences of their customers for more targeted marketing campaigns. Innovative firms take advantage of this big data to make informed decisions. A good example of this is the alliance between ZestFinance and Baidu in China. Baidu offered small loans to customers who buy products from its platform. However, most of them had no credit profiles which could be used for lending decisions. In such a case, ZestFinance used (with permission) the search and purchase histories of the customers who had no credit profiles otherwise, to make more informed lending decisions. As a consequence, the lending volume increased by 150% with no increased credit losses in just two months (Aziz and Dowling 2019).

One instance of big data that has received a lot of attention in the finance and accounting literature is the use of textual analysis. A particular challenge of analyzing texts, like firms' public disclosure documents, lies in the unstructured nature of this kind of data. *Benjamin Clapham, Micha Bender, Jens Lausen*, and *Peter Gomber* address this issue for the problem of regulatory impact assessment (RIA). They develop a methodological RIA framework for unstructured data using textual analysis or natural language processing (Clapham et al. 2022).

3 Traditional portfolio management and social trading

Digitalization has also revolutionized the finance industry due to various other emerging and drastic trends. For example, several digital platforms have taken over the traditional roles of asset allocation, portfolio rebalancing, and the generation of performance evaluation reports (e.g., Beketov et al. 2018). Some robo-advisors (algorithmic platforms providing different types of finance-related services), like Wealthfront, Betterment, and Schwab Intelligent Portfolios, include considerations regarding tax and risk optimization. Such advisors rely on core theoretical knowledge like Markowitz's modern portfolio theory and the use of highly sophisticated procedures, for instance, simulations, neural networks, neuro-fuzzy models, evolutionary methods, and support vector machines.

Another trend in stock market investing is called "social trading". The idea of social trading revolves around the "wisdom of the crowd" of online communities. One of the online platforms for the exchange of valuable financial information is Seeking Alpha, which is the largest crowd-sourced social information forum, based on third-party financial analyses of public firms. Out of about 16,000 registered authors who contribute to the forum, 400 are investment firms (Ding et al. 2023). Empirical evidence suggests that views expressed on social platforms like Seeking Alpha can predict future stock returns and earnings surprises (e.g., Chen et al. 2014; Da et al., 2011; Ding et al., 2022). Other platforms provide the opportunity for social trading by observing, imitating, and replicating investment strategies (e.g., Gomber et al. 2017). Examples of such platforms include eToro, Zulu Trade, NAGA, Ayondo, and Covesting. They are characterized by "copy trading" which allows community members to imitate successful investment strategies. While this "mirror trading" yields positive abnormal returns, however, it is also risky (e.g., Pan et al. 2012). Even though social trading is considered relatively transparent, investors who follow successful trades are still unable to identify whether the good past performance of the so-called "finfluencers" is a result of luck or skill (e.g., Doering et al. 2013; Huddart 1999).

4 Decentralized finance

Yet another breakthrough in digital finance is the emergence of decentralized finance, mainly characterized by cryptocurrencies and security tokens. The overall market capitalization for cryptocurrencies is around 1.19 trillion USD as of July 2023. These currencies act as an alternative to the conventional fiat currencies where consumers can utilize them for payments without the role of intermediaries, hence serving as a medium of exchange, while the problem of double-spending is resolved through networked authentication (e.g., Doran 2004; Elwell et al. 2014; Nakamoto 2008). These currencies are characterized by decentralized peer-to-peer transaction systems, lower transaction costs, high security, ease of use, compatibility with other mobile devices, and limited supply (e.g., Baur et al. 2015; Brito and Castillo 2013; Fang et al. 2022; Halaburda et al. 2022).

Likewise, security tokens now enable small investors to gain fractional ownership in illiquid assets such as real estate which traditionally require high initial investments. Since such assets are issued and traded on a blockchain, the need for intermediaries like clearing houses and banks diminishes in this context (e.g., Kreppmeier et al. 2023). In the current issue, *Julia Kreppmeier* and *Ralf Laschinger* explore the impact of positive signals including a pre-sale and the announcement of token transferability on the success of security token offerings (STOs). They find that these factors are positively related to the STOs' success (Kreppmeier and Laschinger 2023).

5 AI and machine learning in finance and accounting

The High-level Expert Group on Artificial Intelligence (AI HLEG) of the European Commission defines artificial intelligence as systems that are characterized by a behavior that aims at "analyzing their environment and taking actions – with some degree of autonomy – to achieve specific goals" (High-Level Expert Group on Artificial Intelligence 2019). Machine learning, on the other hand, is a subset of AI, which is described as "a diverse collection of high-dimensional models for statistical prediction, combined with so-called 'regularization' methods for model selection and mitigation of overfitting, and efficient algorithms for searching among a vast number of potential model specifications" (Gu et al. 2020). Machine learning is used to remove computational barriers and to replace "traditional, low-dimensional, hand-crafted models" with models which utilize a much larger number of parameters to account for potential, complex relationships (Cohen et al. 2021, p. 2).

Machine learning based on algorithmic approaches can be characterized by several advantages over traditional stochastic data models. Firstly, ML approaches can work with larger volumes of data as compared to traditional statistical models. Secondly, these techniques enable the handling of unstructured data that exist in a variety of formats, for example, images, videos, sound, and texts. Thirdly, machine learning approaches are characterized by "feature engineering" which means that unlike traditional econometric models, where different forms of data processing like monotonic transformation, normalization or only adding a specific interaction term are manually considered, ML approaches make it possible to take different transformed forms, including binned form, high orders, and interactions, all as an input at the same time, hence ML approaches are specialized in using complex, nonlinear, noisy data which results in relatively accurate predictions (e.g., Chen and Hao 2017; Ma and Sun 2020). In the finance and accounting literature, ML models have been utilized to achieve better predictive outcomes in the fields of asset pricing (e.g., Bryzgalova et al. 2019; Chen et al. 2023; Freyberger et al. 2020; Gu et al. 2021; Moritz and Zimmermann 2016), bankruptcy predictions (e.g., Barboza et al. 2017; Nanni and Lumini 2009), and fraud detection (e.g., Hobson et al. 2012; Throckmorton et al. 2015), to name only a few.

6 Black-box and explainable AI

Machine learning can however also have serious downsides. One of them is a lack of transparency, which is often referred to as the "black box character" of ML models. It is associated with the opaqueness and complexity of machine learning models where it is hard to explain how the machine learning model has arrived at a specific conclusion or prediction.

This black-box feature is a particularly strong concern in academia, where its users are not only interested in the predictive power of models, but even more in the reasons leading to a result or a prediction (e.g., Christoph Molnar 2022). The lack thereof reduces replicability and hence implies less generalizability of results. For example, ML techniques like Naïve Bayes in textual analysis, rely on numerous unpublished filters; therefore, replication of results is difficult for other researchers (e.g., Loughran and Mcdonald 2016).

Traditionally, researchers may take on two alternatives to mitigate the black-box problem. Firstly, they may use white-box approaches like simple Bayesian models or regressions which are easily interpretable (e.g., Barredo Arrieta et al. 2020).

Secondly, researchers may use explainable AI (XAI) techniques which transform complex and opaque black-box approaches, like support vector machines and deep neural networks, into more transparent approaches (for a detailed review, see Ali et al. 2023). Barredo Arrieta et al. (2020) synthesize various goals of XAI from the literature which include trustworthiness, causality, transferability, confidence, informativeness, fairness, interactivity, accessibility, and privacy awareness. One such example is the use of "Multinomial Inverse Regression" (MNIR) from Taddy (2013, 2015), to model the relationship between words or n-grams (i.e., expressions consisting of combinations of n words) and an outcome variable (e.g., Breuer et al. 2023; García et al. 2023; Kelly et al. 2021).

Indeed, this issue thus features four papers on explainable AI in finance and accounting. Firstly, these studies add to the existing literature on the supremacy of non-linear machine learning approaches in contrast to linear models, and secondly, they contribute to the emerging strand of literature on the use of explainable AI in finance and accounting.

Lars Beckmann, *Jörn Debener*, and *Johannes Kriebel* investigate the predictors of bond excess returns using machine learning approaches. They utilize SHAP (SHapley Additive exPlanations) to open the black-box features of machine learning models (Beckmann et al. 2023). The authors estimate bond excess returns for different maturities in the US and the German bond markets. They find that the slope of the yield curve is an important predictor of excess bond returns, where steeper yield curves represent higher excess returns, while variables related to the housing market are relevant to the US but not to the German bond market.

Similarly, *Moritz Schneider* and *Rolf Brühl* use different machine learning models to investigate CEO characteristics in relation to accounting fraud. They establish the supremacy of machine learning approaches over linear models (Schneider and Brühl 2023). Additionally, they utilize model-agnostic techniques, in particular permutations-based feature importance and SHAP dependence plots, to overcome the black-box features of machine learning.

Tobias Götze, *Marc Gürtler*, and *Eileen Witowski* add to the literature on the superior use of machine learning approaches in catastrophe (CAT) bond premia forecasts (Götze et al. 2023). They show that random forest forecasts are significantly more precise as compared to linear regressions and artificial neural networks. In order to mitigate the black-box phenomenon, they use the feature or variable importance tool of XAI.

Last, not least, *Christian Lohmann*, *Steffen Möllenhoff*, and *Thorsten Ohliger* demonstrate the superior performance of Generalized Additive Models (GAM) as compared to Generalized Linear Models (GLM) while taking into account the non-linear relationships between accounting-based predictors and bankruptcy (Lohmann et al. 2022). The authors use estimated spline functions to improve the reader's understanding of the underlying cause-effect relationships. Furthermore, they show that taking into account non-linearities among independent variables results in higher statistical validity.

7 Algorithm aversion

Ample research in the literature supports the notion that algorithms outperform their human counterparts in various fields (e.g., Dawes and Corrigan 1974; Dietvorst et al. 2015). In the context of delegated investment decisions, algorithms provide concrete information with high accuracy (as discussed by Logg et al. 2019).

Despite superior algorithmic forecasts, cost efficiency, and the option of customized products and services, the share of investors using algorithms is still rather low (e.g., Merkle 2020). This tendency to prefer human inaccurate forecasts over superior algorithmic predictions is called "algorithm aversion" (e.g., Dietvorst et al. 2015), while the opposite, the preference to take advice from algorithms rather than humans is known as "algorithm appreciation" (Logg et al. 2019).

The literature contains support for both aspects of algorithm recognition, i.e., algorithm aversion (e.g., Dietvorst et al. 2015; Filiz et al. 2021) and algorithmic appreciation (e.g., Holzmeister et al. 2023; Logg et al. 2019). Various factors besides demographics are associated with this divergence in results, for instance, decision-making in an ethical setting (e.g., Dietvorst and Bartels 2022), desire for control (Candrian and Scherer 2022), the extent of uncertainty (e.g., Dietvorst and Bharti 2020), and punishment evasion (Feier et al. 2022). Beyond the uncertainty embedded in the decision setting, algorithm aversion could also be associated with the uncertainty involved in modeling caused by the black-box character of ML approaches in particular. Solving the black-box problem could thus also add to managing algorithm aversion to some extent.

Maximilian Germann and *Christoph Merkle* investigate algorithm aversion in the context of delegated investing in an experimental setting (Germann and Merkle 2022). They do not find any evidence of algorithm aversion. Participants in the experiment seem to care about returns regardless of whether these returns are intermediated by human fund managers or investment algorithms.

Algorithms can only assist users in terms of quantitative and qualitative estimations. Traditional financial advisors on the other hand are generally considered "well-being managers" rather than mere "wealth managers". Anecdotal evidence in this regard was seen in the financial crisis when "the phones of wealth managers did not stand still" and human wealth managers were constantly providing emotional support to their investors (e.g., Merkle 2020). Overall, algorithms can aid human advisors rather than compete with them. That is why the existence of hybrid solutions is justified, where algorithms offer concrete estimations, while human advisors provide the basis for trust (e.g., Sironi 2016).

8 What else and what next?

Apparently, this brief overview of important recent developments in the digitalization of finance and accounting must remain incomplete. We did not cover other types of digital assets such as stablecoins, non-fungible tokens (NFTs), and the Digital Euro in this editorial. Additionally, we also did not delve into applications of the blockchain technology in auditing and tax accounting as well as peer-to-peer lending and crowdfunding as alternative financing methods among others.

Overall, we should expect an even more deepened integration of IT applications in finance and accounting in the future. One medium for such enhanced penetration could be the use of smart contracts which are characterized by self-executing agreements with predefined rules. Smart contracts could potentially transform the whole landscape in finance and accounting with its over-arching implications on corporate governance, regulatory compliance, and auditing. Certainly, such issues and related topics will be extensively discussed in upcoming issues of the Journal of Business Economics!

Acknowledgements We would like to express our gratitude to Mr Sami Uddin for his invaluable assistance in the preparation of this editorial.

Funding Open Access funding enabled and organized by Projekt DEAL. Apart from Open Access funding enabled and organized by Projekt DEAL, no funds, grants, or other financial support was received. Open Access funding enabled and organized by Projekt DEAL.

Declaration

Conflicts of interest The authors have no relevant financial or non-financial interests to disclose.

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