Artificial Intelligence for finance start-ups – opportunities and challenges

# Introduction

This report discusses the potential value of Artificial Intelligence (AI) in fintech. The client is a consulting start-up which helps other start-ups build their financial models and secure funding.

AI refers to technology aimed at conducting tasks that typically require human intelligence, or replicating human or rational thinking and/or behaviour, without explicit instructions on how to do so (Russel and Norvig, 2021). Although first mentioned in 1956 (Russel and Norvig, 2021), AI has recently entered mainstream public discourse following the release of generative AI tools, such as Chat-GPT or DALL-E, that can process and/or produce text or images closely resembling those created by humans (Kneusel, 2023).

By leveraging large datasets, AI may help increase efficiency and foster innovation by either replacing or enhancing human-based work (Jyoti and Schubmehl, 2023; Hubert, Awa and Zabelina, 2024). Indeed, AI-based technology is being rapidly adopted across many industries (Loukides, 2021), including finance (Buchanan, 2019), but also in government (National Audit Office, 2024).

# Artificial intelligence in fintech: use-cases and implementation strategies

Many large companies are already using AI, including leading management consulting firms (Veloso, Balch, Borrajo, Reddy and Shah, 2021; Foy, 2024). The opportunities and potential benefits within fintech are significant, given both the availability and need of processing large volumes of data, and the importance of rapid and accurate decision making (Wamba-Taguimdje, Fosso Wamba, Kala Kamdjoug and Tchatchouang Wanko, 2020).

Successful AI implementation requires focusing not on the intricacies and capabilities of specific models, but which steps in the business cycle they can contribute to (Davenport and Ronanki, 2018; Kahn, 2022, 2022; Westenberger, Schuler and Schlegel, 2022). The Cross-Industry Standard Process for Data-Mining (CRISP-DM) procedure, the *de facto* standard for developing and deploying data-based projects, is a well-established and comprehensive approach (Schröer, Kruse and Gómez, 2021). The first stage involves understanding the business purpose and potential use-cases, followed by development work on data exploration and preparation, including feature engineering (i.e. selecting and transforming data in order to extract the most information possible) (Duboue, 2020). Of note, CRISP-DM emphasizes the importance of an iterative approach, so that earlier stages may be revisited if needed. A model or solution is then built and its performance evaluated against the desired objectives, with iterative improvements undertaken as needed (including improvements to the data collection approach). The process concludes with the deployment phase, including product monitoring and maintenance.

The potential benefits of AI in business are varied, but can generally be aggregated into process automation (replacing or improving routine procedures), cognitive insight (extracting enhanced information from data), or cognitive engagement (facilitating interactions with employees or customers) (Davenport and Ronanki, 2018). Below we discuss a potential use-case in each of these areas.

## Process automation

Document abstraction and summarisation is an onerous part of routine workflows in most organisations. AI algorithms such as natural language processing (NLP) and voice recognition may be harnessed to parse and abstract text documents or audio recordings, and produce accurate summaries (Bardelli, Rondinelli, Vecchio and Figini, 2020; Gao, Zhao, Yu and Xu, 2023; Van Veen et al., 2024). These can quickly extract relevant information from lengthy documents to streamline complex bureaucratic processes, take meeting minutes, or facilitate recruitment. Successful examples include implementation within management consulting (Foy, 2024) and accounting (De Kok, 2023), or multiple off-the-shelf solutions.

Development of such tools requires access to large volumes of text/audio data from publicly-available and/or internal documents directly relevant to the company’s business, such as financial reports, grant calls, regulatory documents, or legal contracts. A purpose-specific large language model (LLM) can be built using these data, either in-house or through integration with existing platforms such as ChatGPT, Google Gemini, or Microsoft Copilot. Importantly, the model may need training on multiple examples for each specific document type, given the different sentence structure and lexicons (e.g. legal, regulatory, and scientific). This approach has some important limitations, namely the possibility of “hallucination” (i.e. the model makes a wrong prediction of the text output it is expected to produce, resulting in false statements or made-up facts) (Hicks, Humphries and Slater, 2024). LLMs may also struggle processing very lengthy documents, such as contracts and regulatory documents (Ding et al., 2024).

## Cognitive insights

Complex datasets can be harnessed using AI to extract advanced insights for myriad purposes. These include development of financial models to predict cash flows, future company growth, or likelihood of success, and are already in widespread use by management consulting firms and others (Coad and Srhoj, 2020; Dellermann, Lipusch, Ebel, Popp and Leimeister, 2021; Veloso, Balch, Borrajo, Reddy and Shah, 2021; Zhao and Bai, 2022). Such information can guide executive decisions around client selection, financing, or recruitment, and the models produced can be sold as a product themselves. Potential benefits include accelerating and scaling up assessment of potential clients, and improved forecasting by extracting information integrating multiple and complex data sources in real-time. Importantly, model performance would be expected to increase with new data as the business grows, and particularly as proprietary data accumulates (Bessen, Impink, Reichensperger and Seamans, 2022).

Predictive AI models require large amounts of training data. These data may be obtained via web-scraping or from structured online databases (such as Crunchbase or Kaggle) (Kim, Kim and Geum, 2023; Potanin, Chertok, Zorin and Shtabtsovsky, 2023), and eventually proprietary data. Supervised machine learning (ML) models can be trained to predict an outcome (e.g. sales, or funding success) based on observations related to the company (attributes) and the outcome (labels). Candidate models include simple logistic regression, decision trees, random forest, and gradient boosting and support vector machines (SVMs) (Kim, Kim and Geum, 2023). Alternatively, unsupervised ML could be used to reveal hidden patterns, groupings, or outliers in the data without specific instructions on what to predict. Importantly, no single model can be considered superior a priori, and many may need to be developed and tested for each particular scenario of interest (while also considering which ones can best handle the available data) (Henrique, Sobreiro and Kimura, 2019). Potential drawbacks include high computational demands and lack of explainability of some models, which may become particularly problematic if used to support financial decision-making or recruitment (Černevičienė and Kabašinskas, 2022).

## Cognitive engagement

Finally, AI may be used not only to process information or text (as outlined in the first example), but also to generate outputs such as documents or slide presentations (Veloso, Balch, Borrajo, Reddy and Shah, 2021). These may include strategy or financial reports, grant applications, legal documents, or pitch scripts. These tools can help scale up operations and facilitate production of complex documents required for day-to-day activities, helping to break “writer’s block” by providing an initial outline that humans can build upon. Relevant examples include drafting legal documents (Cui et al., 2023; Musumeci, Brienza, Suriani, Nardi and Bloisi, 2024) and scientific research grants (Van Noorden and Perkel, 2023), as well as AI-powered chatbots to support staff workflows in financial consulting (such as to query company documentation, or write statistical programming code) (Foy, 2024), or customer management in energy firms (Gosden, 2023).

Development of such tools requires access to large troves of proprietary documentation, or to documents from publicly-available resources (such as regulatory, legal, or scientific documents). While the end goals and applications are different, the development approach could be similar to that outlined in the first example, but with LLM development and tuning focused on output generation. However, a single model could be developed to support both applications (Veloso, Balch, Borrajo, Reddy and Shah, 2021). Appropriate development and efficient use may require prompt engineering (i.e. the process of designing optimal inputs for generate AI), and delivering specific training for company staff. The major limitation inherent to this application is the potential for hallucination (as outlined above) (Foy, 2024), so that any outputs would require proof-reading by humans. Moreover, some individuals may be able to identify AI-generated text (particularly if experienced in the specific area), potentially generating resistance if model outputs are used in externally facing documents.

# Challenges of implementing AI solutions

Despite its many advantages, AI poses broad challenges that transverse any particular algorithm. First, development requires large amounts and diversity of high quality data. Finding and curating such data may be troublesome, but potential solutions include AI-generated synthetic data or data purchases. AI paradigms such as semi-supervised learning, self-supervised learning, and transfer learning may also facilitate development in sparse data conditions (Russel and Norvig, 2021). Second, in-house AI engineering may be lengthy and costly, given its complexity, high computational demands, and scarcity of specialised AI engineers (Westenberger, Schuler and Schlegel, 2022; Jyoti and Schubmehl, 2023). While off-the-shelf solutions may be useful, the full value of AI likely comes from tailored development and training using proprietary data (Bessen, Impink, Reichensperger and Seamans, 2022). However, it is possible to start with existing products, or repurposing general purpose applications like ChatGPT, Google Gemini, or Microsoft Copilot, as a stepping stone to generate confidence and advance towards in-house development. For some ML tasks, low- or no-code solutions like WEKA (Waikato Environment for Knowledge Analysis) may also facilitate early development and implementation (Frank, Hall and Witten, 2016). Third, the data used for AI applications must to be stored securely and privately, which may prove challenging as data volume, complexity, and speed increase (Leslie, 2019). Fourth, integration of AI tools with legacy systems may be troublesome, together with the need to adapt existing user workflows (Davenport and Ronanki, 2018). Finally, increasing allocation of important tasks to AI algorithms may raise concerns about job destruction or unethical uses. Development and implementation of AI technology must therefore strictly comply with relevant ethical principles and the evolving regulatory guidance landscape (Leslie, 2019).

# Conclusion

AI is an established technology with great potential for increased efficiency and returns, and wide adoption across multiple enterprises, particularly in data heavy sectors such as finance. Successful implementation of AI technology requires an appropriate understanding of its capabilities, but also of its limitations, requirements, and challenges.

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