

**Testimony of Dr. Bonnie Buchanan**

Head of Department of Finance and Accounting,  
Full Professor of Finance, Surrey Business School.  
The University of Surrey  
Guildford, Surrey, GU2 7XH UK

before the

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## **Biography**

Professor Bonnie Buchanan is the Head of the Department of Finance and Accounting at the Surrey Business School, University of Surrey, UK. In 2018-2019, Professor Buchanan served as the Fulbright Distinguished Chair in Business and Economics at the Hanken School of Economics, Finland (her project was titled Fintech in the Nordic Countries). She has also served as the Bosanko Professor of International Economics and Finance at Seattle University as well as the George Albers Professor. She has taught university courses on Financial Institutions and Markets, International Finance and the History of Financial Crises. Dr Buchanan is the Editor in Chief of the Journal of Risk Finance.

Professor Buchanan conducts research in Fintech, Artificial Intelligence in Finance, Securitization and International Finance. She is the author of the book, *Securitization and the Global Economy*.

Professor Buchanan holds a Ph.D. in finance from the Terry College of Business, University of Georgia, a M.AppSc. in statistics from RMIT and a BSc. (Hons) in mathematics from the University of New South Wales.

Distinguished members of the Subcommittee, thank you for the opportunity to appear before you and provide testimony today to help inform discussion about artificial intelligence in the financial services sector. I am Dr Bonnie Buchanan, Professor of Finance at the Surrey Business School, University of Surrey. In this testimony I will provide some background on AI, its applications in finance as well as challenges and opportunities facing the financial services industry. I hope we can all work together to address the challenges and opportunities that artificial intelligence provides to the financial services industry.

## **Overview**

Artificial Intelligence (AI) is rapidly transforming the global economy and the way we think about our financial future. Global revenues in the AI market grew from \$126 billion in 2015 to \$482 billion last year and are forecast to increase to \$3.061 trillion by 2024<sup>1</sup>. In 2017, 84.2% of cards and payments in the banking sector used AI techniques, mainly in online payment and credit card usage<sup>2</sup>. In 2017 AI was ranked as the key trend in financial services and Fintech<sup>3</sup>. AI, cloud computing and big data have created an affordable infrastructure to spur innovation in the financial services sector. There are two explanations for AI's impressive growth in a relatively short period of time. First, exponential advances in computing power have contributed to declining processing and data storage costs. Second, data availability is now more widespread.

Outside of the IT sector the financial services industry is experiencing the fastest growth and is in turn the biggest spender on AI services<sup>4</sup>. Until recently hedge funds and high frequency trading (HFT)<sup>5</sup> firms were the main users of AI in finance, but usage has now spread to other areas including banking, insurance, wealth management, personal financial planning and regulation. More specifically, AI financial applications include: algorithmic trading, portfolio composition and optimization, model validation, back testing, robo-advising, virtual customer assistants, market impact analysis, regulatory compliance and stress testing models.

AI is both disrupting and refining existing financial services. AI is not straightforward to define as there is no generally agreed upon definition. However, AI can be broadly thought of as a group of related technologies including machine learning and deep learning. Machine learning (ML) is concerned with general pattern recognition and universal approximations of relationships in data in cases where no a priori analytical solution exists. ML is best suited for situations that require extracting patterns from noisy data or sensory perception – or what is termed, a “data-up approach”. ML is primarily derived from sources such as experience,

practice, training and reasoning. A typical ML application is based on a problem, a data source, a model, an optimization algorithm and validation and testing.

ML uses algorithms to automatically optimize through experience with limited or no human intervention (or in other words, supervised versus unsupervised learning). An example of supervised ML in a banking context entails teaching an algorithm to learn from past regulatory breaches and to predict new breaches such as insider trading or cartel detection. In unsupervised learning, ML can help issue alerts such as low balance warnings. It can also be applied to bank overdraft charges to help assess what is happening to individual customers and what might be the causes of their current situation. Clustering algorithms help accomplish this objective. Regulators can use clustering algorithms to better understand trades and categorize business models of banks in advance of regulatory examinations. Topic models help us understand the behavioral drivers of different market participants and includes text mining and natural language processing (NLP). NLP links human language with computing. For example, the SEC has used topic models to detect accounting fraud.

The term “robo-advisor” was virtually unheard-of five years ago but is now commonplace in the financial services jargon. Chatbots and robo-advisors powered by NLP and ML algorithms have become powerful tools which provide a personalized and conversational experience to users in the financial services sector. For example, in September 2017 Allstate Insurance deployed Amelia, an AI powered chat bot, to assist employees. Amelia is trained in 40 insurance related topics and uses deep learning and NLP as well as data analytics to understand the intent of the user’s text and offer precise answers. To date, Amelia has helped call center representatives with more than 3 million customer conversations<sup>6</sup>. In another example, Lemonade is a platform providing property and casualty insurance to home owners and renters. Lemonade uses ML and chatbots for its customers. On average, it takes 90 seconds to get insured and 3 minutes to get paid for a claim.

Deep learning (DL) algorithms automate routine tasks, mitigate risk, help prevent fraud and assist in generating new insights. DL uses neural networks (NN) which are based on mimicking the way multiple layers of the brains’ neurons work (hence the term ‘deep’). For example, the Deutsche Bundesbank’s risk management area is already using NN to assess financial market soundness. NN have also been widely used in predicting financial distress and bankruptcy likelihood. NN, clustering and decision trees are AI techniques that assist financial institutions study customers’ buying behaviour, comparing it against other indicators to create a more complete picture of a transaction. Two primary advantages of DL are: (1) it is more resilient than machine learning to overfitting and (2) DL can address non-

linear events such as market volatility, which in standard quantitative models must usually be adjusted manually. However, one of the challenges with DL is model opacity, or the “black box” nature of its predictions. It is called “black box” because of the user’s limited ability to fully understand how the DL processes derive their predictions.

### **AI and Accountability**

AI is continuing to become more sophisticated and complex. But as we saw with the last financial crisis, financial markets are already very complex. This rapid growth and complexity in both AI and the financial system presents major new challenges regarding regulation and policy making, risk management as well as ethical, economic and social hurdles.

Like other Fintech product areas, AI should enhance financial inclusion. There are approximately 1.7 billion adults (or about 31% of adults) who are “unbanked”<sup>7</sup>. In these countries, cash economies are being supplemented by mobile access to digital funds. The increased application of AI technology to financial markets is likely to reduce barriers to entry for many individuals and business models that might not have previously had access to financial markets.

However, ML algorithms can potentially introduce bias and discrimination. Deep learning techniques provide predictions, but they do not provide insight into how the variables are being used to reach these predictions. This is especially important for trying to prevent discrimination in lending models. Hiring and credit scoring algorithms can exacerbate inequities due to biased data. Applications such as facial recognition can be inaccurate and biased. This can be demonstrated in the P2P lending industry. P2P business platform models depend on proprietary and complex algorithms. The interest rates applied are often based on credit e-scores (and sometimes other optional information provided). In the US, P2P platforms have come to represent an important market for debt consolidation. There is already a literature on P2P lending that investigates possible bias and discrimination in the industry. Duarte et al (2012) find that borrowers who appear more trustworthy (they have provided a photo on the platform) have a higher probability of getting funded. Online friendships of P2P borrowers can act as a signal of credit quality (Lin et al., 2013). They find that friendships increase the probability of successful funding and lower interest rates on funded loans. Unverifiable information affects lending decisions above and beyond the influence of verifiable and objective information with P2P loans (Herzenstein et al, 2011). Finally, Pope and Snyder (2011) find evidence of discrimination based on race, age and

weight. They find the market favors those listings that signal military involvement, being female or a desire to pay down credit card debt.

To combat potential bias in the mortgage lending market, Zest Finance applies AI models and big data. Through its ZAML Fair tool, Zest Finance reduces the impact of discriminatory credit data by excluding signals that tend to result in bias.

AI is also being applied to debt collection agencies. Consider the Chinese P2P lending market which has experienced platform failures in the last few years. After mid-2017 many P2P lenders shut down due to new lending controls and additional required licenses. Ziyitong launched an AI platform to help recover an estimated Rmb150 billion in delinquent loans<sup>8</sup>. The AI platform helps recover delinquent loans for approximately 600 debt collection agencies and over 200 lenders (including the Postal Savings Bank of China and Alibaba). A dialogue robot utilizes information about borrowers and their friends' network, and then uses the information to determine the phrasing with the highest likelihood of compelling the borrower to repay the loan. The dialogue robot will also call the borrower's friends, encouraging repayment of the loan. Ziyitong claims its recovery rate is 41 percent for large clients and loans that are delinquent up to one week, a rate that is twice that of traditional debt collection methods.

As financial services become increasingly automated, it remains unclear as to whether all borrowers will benefit from AI. If poor inputs are provided, then the biased outputs will be produced by the algorithms. In other words, bias in, bias out. This will have huge repercussions for low-income and minority consumers. Existing inequality could be exacerbated by ML algorithms that single out borrowers who are already disadvantaged as poor credit risks. In this scenario, borrowers might seek out alternative financial providers such as payday lenders and end up paying much higher interest rates than a traditional lender. Cathy O'Neil (2017) characterizes "weapons of math destruction" as being important, secret and destructive. This could be said of biased and discriminatory algorithms in financial services: they affect large numbers of people, are entirely opaque and destroy lives.

Resolving issues such as discrimination and bias requires being grounded in ethics and understanding what causes the bias in the algorithm in the first place. When it comes to AI in the financial services industry and a fairer future, policymakers need to be concerned about explainability and accountability of AI models. To overcome discriminatory bias, there needs to be robust oversight to ensure that AI applications in the financial services industry remains accountable to all members of society. An April 2018 UK House of Lords report<sup>9</sup> suggests that the AI sector's full potential would only be realized if potential risks such as

algorithmic bias and the opaqueness of "black box" systems that we see in DL techniques can be mollified.

### **Fraud and Cybersecurity Issues**

The use of AI in the financial sector can assist in identifying fraud and cybersecurity crimes. A 2019 World Economic Forum report ranks the inappropriate use of customer data as one of the top two risks facing the global financial system. In banking, IT governance, fraud and cybersecurity are now equally important as capital and liquidity requirements. Online financial crimes have become more sophisticated and cost countries significant economic losses each year. Cybercrime costs the global economy over US\$400 billion annually with credit card fraud accounting for a large portion of this cost.<sup>10</sup> Due to massive fines imposed upon banks for failing to stop illegal financing, many banks have turned to AI techniques to improve their operations. For example, Feedzai uses real time ML to identify fraudulent transactions by recognizing behavioral patterns that could indicate fraudulent payment activity.

Another example of financial fraud is the voice phishing scam that recommends low interest loans to financially strained citizens. For example, last year in South Korea voice phishing scams entailed losses equivalent to \$391 million. As a regulatory response, the National Information Society Agency, the Financial Supervisory Service and the Industrial Bank of Korea co-developed "IBK Phishing Stop"<sup>11</sup> which is an AI-based voice phishing detection app. The algorithm is trained to detect stipulated keywords, special phrases and speech patterns. If at least 80 percent of the phone call is perceived to be fraudulent then an alert is sent before any significant financial transactions are made.

Another example of successful fraud detection involves Estonian company Transferwise, which moves nearly \$4 billion across borders every month. Multiple ML models instantly score each transfer, and Transferwise also uses ML to detect fraudulent behaviour and money laundering attempts. Another Estonian company, Veriff, uses ML applications for automation and fraud detection. Veriff achieves this in a cost-efficient manner by scanning 3200 different document types that are issued around the world. Human intervention only occurs when a more thorough examination of the transaction is needed.

Other challenges exist in this area, such as transactions wrongly declined due to suspected fraud, known as the "*false positive*". This works against the issuer because a false-positive declined transaction can result in erosion of customer loyalty and retail losses. False positives account for \$118 billion in retail losses and nearly 39 percent of declined

cardholders report that they abandoned their card after being falsely declined (Buchanan, 2019). ML methods can substantially reduce false declines and improve credit card approvals<sup>12</sup>.

### **AI and the future of work in the financial sector**

In the financial services industry, AI has the potential to disrupt jobs across many levels. In 2017 Opimas LLC estimated that AI would result in approximately 230,000 job cuts in financial firms worldwide by 2025, with the hardest hit area being asset management (with an estimated 90,000 job cuts)<sup>13</sup>. In 2016, the GIS-Liquid Strategies group was managing \$13 billion with only 12 people. A major issue confronting the financial industry is how to balance the rapid deployment of AI, ML and DL against developing the best talent pool and skillsets. If algorithms struggle to distinguish the signal from the noise, then one really needs a person to step in and recalibrate ML models. Human talent and skills will become even more critical to sustaining competitive advantage in the financial services industry.

Robotic Process Automation (RPA) is being widely utilized in the banking industry. RPA enhances productivity, reduces transaction costs, eliminates manual errors and redeploys staff to higher skilled roles. One example of RPA is used by the UK Serious Fraud Office (SFO). In a typical year the SFO processes over 100 million documents in fraud and corruption cases. One notable case is the Rolls Royce bribery case, which resulted in the largest ever fine imposed in the UK for criminal conduct<sup>14</sup>. The SFO used the RAVN robotic system, which ended up costing £50K, and saved UK taxpayers hundreds of thousands of pounds. RAVN is referred to as a Legal Professional Privilege (LPP) robot and sifts documents into “privileged” versus “non-privileged” piles, indexes and compiles summaries. In the Rolls Royce case, RAVN processed 30 million documents at a rate of up to 600,000 per day (compared with a team of lawyers that would have processed 3,000 per day). Law clerks were deployed to other areas of the case.

As AI becomes more pervasive in the financial services industry there will need to be a shift towards appropriately educating workers. Graduates with tech and finance skills are in high demand. But as we move forward, and AI models become more ubiquitous in the finance, students will need to integrate other skills such as philosophy, economics, psychology, anthropology and sociology.

## **Risks and Regulatory aspects**

AI is viewed in the financial services sector as a technique that has the potential to deliver huge analytical power, but many risks still need to be addressed. Many AI techniques remain untested in a financial crisis scenario. There have been several instances in which the algorithms implemented by financial firms appeared to act in ways quite unforeseen by their developers, leading to errors. In 2012 Knight Capital lost \$440 million in 45 minutes after deploying unverified trading software. The “Flash Crash” on May 6, 2010 was noteworthy for another reason. Procter and Gamble swung in price between a penny and \$100,000, but the problem wasn’t caused by bugs or computer malfunctions that verification could have avoided. It was caused by expectations being violated: automatic trading programs from many companies found themselves operating in an unexpected situation where their assumptions were not valid (i.e., they were operating in “out-of-the-box” situations). In 2013, during a 17-minute computer glitch, Goldman Sachs flooded the US market with orders to purchase 800,000 contracts linked to equities and ETFs. During the same week, Chinese brokerage firm Everbright Securities, suffered a malfunction which resulted in it purchasing nearly \$4 billion worth of shares on the Shanghai market<sup>15</sup>. After the Brexit referendum in June 2016, Betterment LLC (a robo advisor that relied heavily on algorithmic trading) suspended trading in response to market volatility to spare its clients higher transactions costs. MIT economist, Andrew Lo has called for developing more robust AI technology capable of adapting to human foibles so that users can employ these tools safely, effectively and effortlessly.

AI and ML developments are moving fast to such an extent where it is almost outstripping the current legal and regulatory framework. The European Union and UK have adopted a more government-led approach to developing AI principles. In 2018, the UK’s introduction of Open Banking gave consumers the ability to compare product offerings and exchange data between providers in a secure way. Other countries such as Singapore, Canada and Iran are also considering adopting some form of open banking regulation.

In 2018, the General Data Protection Regulation (GDPR) also came into force. Under GDPR, EU citizens have the right to receive an explanation for decisions based solely on automatic processing. Furthermore, GDPR stipulates that companies must first obtain consent from an EU citizen before using consumer data. If the EU citizen data is stored on servers located outside of the EU region, GDPR rules apply. Failure to comply to GDPR can result in substantial fines (either up to \$22 million or 4% of a company’s revenues).

As of 2018, the European MIFID II<sup>16</sup> requires firms that apply AI and ML algorithmic models to have a robust development plan in place. Firms should also ensure that potential risks are included at every stage of the plan. In February 2018 the Financial Conduct Authority and Prudential Regulatory Authority released consultation papers on algorithmic trading which lists key areas of supervisory focus in relation to MIFID II.

Last month, 42 countries came together to support a global governance framework for AI. Singapore's AI governance structure is based on a "human-centric" approach, which emphasizes explainability, transparency and fairness to establish public trust in AI<sup>17</sup>.

### **Other emerging trends that relate to AI.**

Banks are spending massive amounts of money on AI. For example, JP Morgan has invested in COiN, an AI technology that reviews documents and extracts data in far less time than a human. UBS has used AI to trade volatility and JP Morgan uses AI to execute equity trades. JP Morgan, Wells Fargo, Bank of America and Citigroup have increased their IT budgets to pursue AI innovation.

There is also a vibrant merging of financial services and tech companies that specialize in AI. For example, S&P acquired Kensho in 2017 for \$550 million in the biggest AI acquisition to date. Kensho was founded in 2013 with the intention of replacing bond and equity analysts. Its Warren algorithm<sup>18</sup> can process 65 million question combinations by scanning over 90,000 events such as economic reports, drug approvals, monetary policy changes and political events and its impact on financial assets. Google has purchased DeepMind Technologies and Intel has acquired Nervana Systems.

### **Conclusion**

AI is becoming more ubiquitous in the financial services industry. This will present more legal, ethical, economic and social challenges. AI will also continue to bring new complexities to the global financial ecosystem. As more and more data become available and computing power increases, AI programs will become more complex. In response, AI in financial services needs to be technically robust, secure, protect privacy, be ethically sound and regulation compliant. Ultimately, AI in financial services needs to promote and maintain financial inclusion.

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<sup>1</sup> Source: Statista and Transparency Market Research.

<sup>2</sup> Source: Statista, 2018

<sup>3</sup> Future Today Institute (2017).

<sup>4</sup> Citi (2018).

<sup>5</sup> HFT is the most recognizable form of AT and use high-speed communications and algorithms in financial market transactions. In 2011, HFT firms accounted for 45-50% of US equities trading.

<sup>6</sup> Allstate's Digital Colleague Amelia Answers Questions for Call Center representatives. Sara Castellanos, WSJ. March 30, 2018.

<sup>7</sup> Worldbank (2017)

<sup>8</sup> China's debt collectors focus in on \$200 billion P2P debt pile", Don Weinland, FTimes. June 5, 2018.

<sup>9</sup> Britain urged to take ethical advantage in artificial intelligence. John Thornhill. FTimes. 04/15/2018.

<sup>10</sup> [https://csis-prod.s3.amazonaws.com/s3fs-public/legacy\\_files/files/attachments/140609\\_rp\\_economic\\_impact\\_cybercrime\\_report.pdf](https://csis-prod.s3.amazonaws.com/s3fs-public/legacy_files/files/attachments/140609_rp_economic_impact_cybercrime_report.pdf)

<sup>11</sup> Korea introduces AI app that auto-detects 'voice phishing' scams

<sup>12</sup> Citi (2018).

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<sup>13</sup> Robots in Finance Bring New Risks to Stability, Regulators Warn. Silla Brush. Bloomberg Magazine. Nov 1, 2017. Available at: <https://www.bloomberg.com/news/articles/2017-11-01/robots-in-finance-bring-new-risks-to-stability-regulators-warn>.

<sup>14</sup> Serious Fraud Office CEO Ben Denison reveals how AI is transforming legal work, Thomas Macaulay, CIO, January 3, 2018.

<sup>15</sup> “17-minute trading glitch put Goldman’s reputation on the line”, Arash Massoudi and Tracy Alloway, FTimes. August 22, 2013.

<sup>16</sup> MiFID II or Markets in Financial Instruments Directive came into effect early 2018 and is designed to offer greater protection for investors and inject more transparency into all asset classes: from equities to fixed income, exchange traded funds and foreign exchange.

<sup>17</sup> How governments are beginning to regulate AI, Madhumita Murgia and Siddarth Shrikanth, Financial Times, May 30, 2019.

<sup>18</sup> Named after Warren Buffett.