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From Crisis to Prosperity:

AI and Open Finance for Holistic Financial Health and Smart Future Planning

FRIL
Financial Regulation Innovation Lab

FinTech Scotland

University of Glasgow

University of Strathclyde Glasgow

in collaboration with

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From Crisis to Prosperity: AI and Open Finance for Holistic Financial Health and Smart Future Planning

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Financial Regulation Innovation Lab

Who are we?

The Financial Regulation Innovation Lab (FRIL) is an industry-led collaborative research and innovation programme focused on leveraging new technologies to respond to, shape, and help evolve the future regulatory landscape in the UK and globally, helping to create new employment and business opportunities, and enabling the future talent.

FRIL provides an environment for participants to engage and collaborate on the dynamic demands of financial regulation, explore, test and experiment with new technologies, build confidence in solutions and demonstrate their ability to meet regulatory standards worldwide.

What is Actionable Research?

FRIL will integrate academic research with an industry relevant agenda, focused on enabling knowledge on cutting-edge topics such as generative and explainable AI, advanced analytics, advanced computing, and earth-intelligent data as applied to financial regulation. The approach fosters cross sector learning to produce a series of papers, actionable recommendations and strategic plans that can be tested in the innovation environment, in collaboration across industry and regulators.

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Executive Summary

The financial services industry stands at a critical inflection point. Traditional credit-score-centric frameworks, rooted in historical repayment data and broad demographic categories, are increasingly incapable of capturing the full spectrum of consumers' financial health. The COVID-19 pandemic, successive cost-of-living crises and wider economic shocks have exposed deep vulnerabilities in reactive, one-dimensional risk models. Consumers and institutions require proactive, resilience-focused insights that span day-to-day cashflow management, medium-term debt servicing, and long-term wealth accumulation.

Open Finance - the consent-driven sharing of a comprehensive array of financial data (current accounts, mortgages, loans, savings, investments, pensions, insurance, government benefits), combined with advanced Artificial Intelligence (AI) and Machine Learning (ML) techniques, offers a transformational route to truly holistic financial health evaluation. By ingesting rich, multi-dimensional data and applying explainable models, financial firms can transition from static credit assessments to dynamic, personalised guidance and recommendation engines. These engines empower consumers to build financial resilience, make informed decisions and pursue life goals with confidence.

Building on Sopra Steria and Glasgow University's joint whitepaper "*Consumers at the Heart of Innovation: Financial Health Evaluation in the UK Regulatory Landscape"* and inspired by R&D collaboration between Sopra Steria and Oxford University, this whitepaper:

Examines the scope and expected data architecture of Open Finance, extending from Open Banking to full-spectrum data sharing.

- **Presents a robust data modelling framework**, encompassing data acquisition, cleansing, feature engineering, supervised and unsupervised modelling, scorecard design and persona segmentation. It culminates in a composite financial health score that blends aspects like credit risk and resilience evaluation.

- **Explores explainability and consumer engagement**, employing data science techniques to ensure transparency and mapping various persona archetypes to tailored, sequential optimisation plans.

- **Demonstrates regulatory alignment**, showing how non-product-specific, persona-driven guidance and recommendation can fit within the Financial Conduct Authority's (FCA) Advice and Guidance Boundary (FG15/1) and the Consumer Duty framework.

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1. Introduction

1.1 Context & motivation - shifting financial landscape

Over the past decade, digital transformation, fintech innovation and economic volatility have radically changed consumers' financial lives. Typically, traditional credit-scoring frameworks are heavily reliant on repayment histories and demographic proxies. These can therefore often fail to reflect complex, dynamic realities such as fluctuating gig-economy incomes, irregular self-employment cashflows or sudden macroeconomic shocks. The COVID-19 pandemic exposed the fragility of many households, while the following cost-of-living crises have underscored the imperative for financial resilience – more specifically, the ability to absorb income shocks, maintain essential spending and avoid harmful debt spirals.

The financial sector's balance sheets as a proportion of GDP, and share in economy value added, have been rising in many economies. From the resulting financial depth, such "financialisation" can boost growth and productivity, especially in developing countries. However, too much of a good thing can be a concern: financial intermediation costs continue to rise, calling into question the industry's efficiency. The relationship between financial depth and productivity and growth is possibly U-shaped. Thus, it is pivotal to acknowledge these factors and to question the financial system's contribution to economy and society [6].

More contemporary evidence casts further scrutiny upon finance's societal value. Sentiment positivity from a huge corpus of finance literature (captured, for example, in multiple languages and over multiple decades) has been shown to be positively correlated with financial market participation and negatively with income inequality [1],[2]. The former is represented by equity percentage of total assets for households (from the Organisation for Economic Co-operation and Development – OECD), total loans to households and non-financial private sector, as percentages of GDP. The latter is measured with national accounts data using the Gini coefficient, reported by the World Income Inequality Database.

In light of the above, global and UK concerns surrounding the role of such income and wealth inequality and concentration merit acknowledgement and consideration, alongside alternate solutions such as better corporate and wealth taxation. Specifically, from macroeconomic data in [3], researchers investigate substantial profit reductions for nations from profit shifting strategies of multinational companies to tax havens.

At the same time, rising consumer expectations demand proactive support. Rather than simply deciding on creditworthiness, households seek insights into essential buffer levels, optimal debt-repayment strategies, saving trajectories for medium- and long-term goals (homeownership, education, retirement) and timely nudges when life events (job loss, family expansion, rate resets) threaten financial stability.

1.2 Problem statement

This whitepaper addresses the urgent challenge of improving holistic financial health and resilience in an increasingly complex and shifting financial landscape. While traditional financial guidance often focuses narrowly on creditworthiness or savings, many consumers still struggle to manage everyday finances, absorb shocks and plan effectively for their futures [5],[6]. Our work situates financial health as a multi-dimensional concept, integrating spending, saving, borrowing and financial planning, with resilience as a cross-cutting capability that supports wellbeing through life's uncertainties.

This approach aligns closely with the FCA's Advice Guidance Boundary Review (AGBR), which explores new regulatory frameworks to better support consumers in making financial decisions [6]. The AGBR focuses on bridging the gap between generic guidance and full advice by introducing "targeted support" (see **Figure 1**) – tailored suggestions developed for groups of consumers with similar circumstances, designed to improve access to timely and affordable financial help. This emerging model aims to empower more people to navigate pensions and investments with confidence, addressing the persistent "advice gap" where only around 8% of UK adults currently receive financial advice [8].

Ideally, such targeted support ought to be provided at a minimal cost to vulnerable parties. Fairness should be considered for delivery of targeted support to ensure maximal efficacy. For instance, AI's potential in improving learning outcomes and promoting diversity, equity, and inclusion should be considered [8]. Further, blended human-AI delivery behoves consideration especially for complex problems in the context of targeted support, as research indicates hybrid human-AI interaction yields better performance in interactive reasoning tasks, driven by the latter's correct reasoning [9].

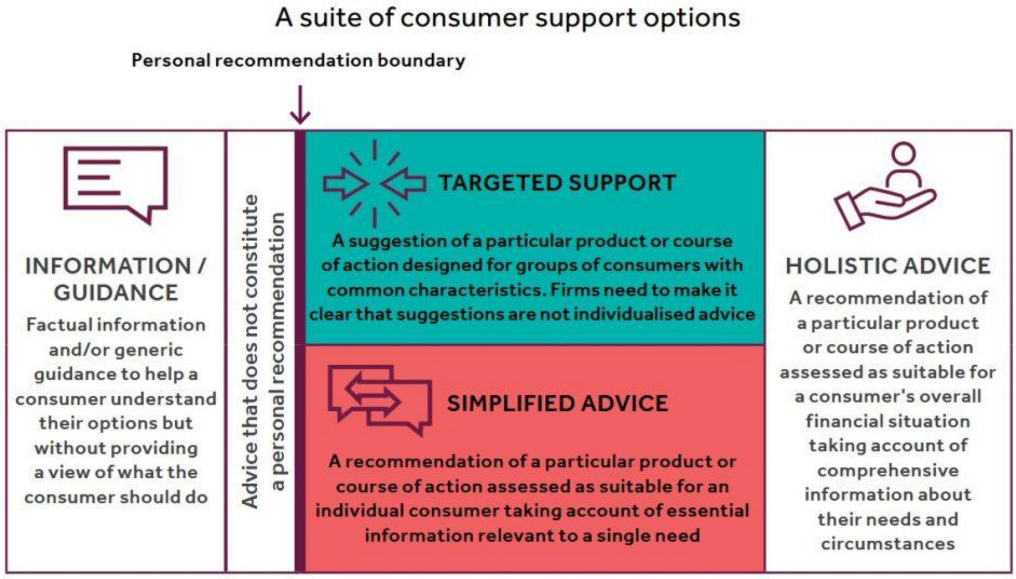

Figure 1: Consumer Support Options. Source: The FCA's plans to bridge the advice gap - The Lang Cat

Our Smart Personalised Finance Management Framework presents a tangible and actionable methodology to tackle this. By integrating Open Finance data, AI and data-driven predictive analytics and behavioural insights, our framework can help drive personalised, scalable support consistent with the AGBR's targeted support approach. This can enable firms and innovators to provide meaningful, timely financial guidance that helps consumers improve their financial health and resilience sustainably.

1.3 From Open Banking to Open Finance

The EU's Payment Services Directive 2 (PSD2) and the UK's Competition and Markets Authority (CMA) Open Banking mandate required banks to expose payment-account data and payment-initiation services via secure Application Programming Interfaces (APIs). Open Banking proved a powerful opportunity: fintech apps now offer budgeting, expense categorisation and streamlined credit applications. Yet its scope is limited to current accounts and payment flows, leaving mortgages, savings, pensions, investments and insurance data aside.

It is worth noting data breaches and risks on privacy, fraud and exploitation fronts exist from a risk perspective: we address these in more depth later in the paper. Another concern is bias or misuse of such data. This in turn can result in vulnerable consumer exploitation due to conflicts of interest in the use of such data, depending on who is providing targeted support and can arise in both human and AI support. For example, contemporary analysis on hotel pricing algorithms showcases price setting frictions due to adjustment costs of human decision makers, which induce a conflict of interest with the algorithmic advisor. Such costly price adjustments lead to suboptimal pricing by human decision makers and the losses from this strategic bias can be avoided with a full shift to automated algorithmic pricing [10].

Open Finance extends the API-driven paradigm to a full spectrum of financial products (see **Figure 2**). Under customer consent, it enables:

- **Credit products**: mortgages, personal loans, credit cards.
- **Savings & investments**: deposit accounts, ISAs.
- **Pensions & retirement products**: Defined Contribution (DC) pot valuations, contribution histories.
- **Insurance policies**: life, home, auto; coverage, premiums, claims history.
- **Government benefits & incentives**: Universal Credit, Child Benefit, pension credit.

This richer dataset allows a truly holistic view of financial health and underpins advanced AI-driven guidance engines.

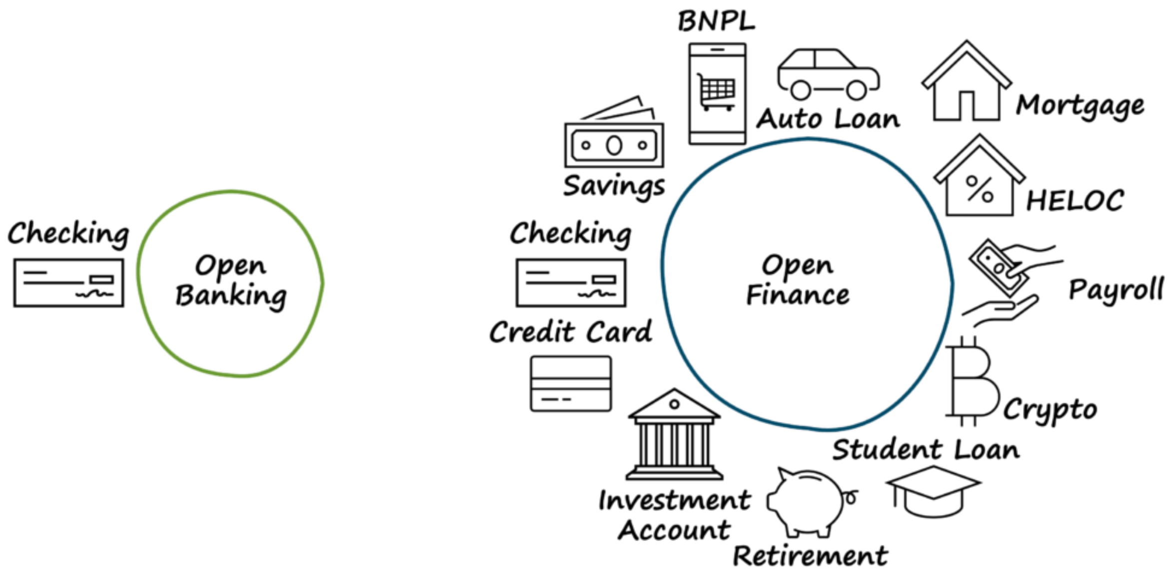

Figure 2: Open Finance as an extension of Open Banking. Source: How to Survive Open Banking - Fintech Takes

1.4 Defining financial health and resilience

In our work, financial health is considered not merely as credit worthiness but as a multi-dimensional construct combining ability to meet day-to-day obligations, capacity to absorb shocks, and readiness for future goals. The FCA, in its 2021 guidance, identifies four primary drivers of vulnerability: low financial resilience, poor health, recent negative life events and low capability. Of these, low financial resilience (the inability to hold out against unexpected expenses without falling into difficulty) was the most common, affecting approximately one quarter of UK adults in 2022 (12.9 million people) [12].

Financial health encompasses four pillars [13], [14]:

Pillar	Descriptor	Example Financial Products
Spend	Covering essential needs without overextending.	Current accounts, credit cards, store cards
Save	Building buffers for planned and unplanned events.	Savings and investment accounts, ISA
Borrow	Accessing and managing credit sustainably.	Credit cards, short term loans, car finance and more
Plan	Setting and pursuing financial goals.	Insurance, retirement products

Financial health is not just about having a good credit score or being able to pay the bills – instead, it is about balancing everyday spending, saving for a rainy day, borrowing sensibly, and planning ahead for the future. At the heart of all these elements lies financial resilience – the capacity to cope when circumstances change unexpectedly.

Figure 3: Main pillars of Financial Health. Source: [What is Financial Health? – Financial Health Network]

Financial resilience is the thread running through each pillar of financial health. Being able to spend wisely relies on having reserves to fall back on in an emergency. Saving and borrowing work best when people can manage cashflow and debt without resorting to costly credit. And effective financial planning depends on being prepared for both personal and economic uncertainties.

Regulators like the FCA increasingly highlight resilience as a key factor in financial vulnerability. It is not just about having financial wellbeing at a single point in time but also about sustaining that wellbeing in the face of change – whether that is an unexpected expense, income fluctuation or larger economic shifts.

Examples of key resilience metrics can be illustrated with the following:

- **Buffer ratios**: liquid assets (current + savings) divided by essential monthly outflows.
- **Cashflow volatility**: the rolling standard deviation of net inflows over recent periods.
- **Debt-service coverage**: ratio of income to scheduled debt payments under stress scenarios.
- **Days-to-buffer-breach:** estimated number of days before liquid assets fall below the minimum required buffer threshold.

Integrating financial resilience into the holistic assessment of financial health provides a more dynamic and practical framework. It ensures that interventions and innovations in finance support people, not only in maintaining financial wellbeing today, but also in adapting and prospering for the future.

As holistic financial data becomes central to improving financial health and resilience, it is crucial to use such data ethically and avoid bias [14],[15]. The aim must be to support individuals, not to allow firms to benefit at their expense.

1.5. Industry & Regulatory perspectives

Studies on Alternative Credit Scoring and Financial Resilience

Global institutions like the World Bank and the International Monetary Fund (IMF) have highlighted the potential of alternative credit scoring methods that go beyond traditional credit histories. These approaches often incorporate behavioural indicators, psychometrics and non-financial data to evaluate creditworthiness more holistically and inclusively, especially for underserved populations. For example, the World Bank's Entrepreneurial Finance Lab developed psychometric credit scoring [17] to better assess small business owners in emerging markets, improving access without raising default risk. The IMF has further explored how ML and alternative data enhance risk assessment, supporting fairer credit access [18]. Parallel to credit scoring innovation, frameworks focused on financial resilience have emerged – such as the Financial Health Network's model that measures individuals' capacity to absorb shocks and manage financial wellbeing over time, moving beyond simple balance sheet assessments [19].

Individual differences that predict success and achievement in all professional domains may offer another approach to alternative credit scoring and determining financial resilience. For example, grit, defined as perseverance and passion for long-term goals, has been shown to account for an average of 4% of the variance in success outcomes, and is highly correlated with conscientiousness. It supports the idea that achievement of difficult goals entails the sustained and focused application of talent over time [19]. This Grit scale measurement can be achieved via Short Grit Scale (Grit–S) [20], an improved version of the original.

It is important to acknowledge the impact of financial technology, through channels such as peer-to-peer lending and "shadow banks". For instance, research shows that due to the trust-intensive nature of peer-to-peer lending, borrowers that appear to be more trustworthy have higher probabilities of having loans funded [21]. Indeed, such borrowers are likely to have better credit scores as well. Overall, impressions of trustworthiness matter in financial transactions as they predict the investor's, as well as the borrower's, behaviour. Likewise, a study on the supply of financial services to small businesses found FinTech is disproportionately used in ZIP codes with fewer bank branches, lower incomes and more minority households, and in industries with fewer banking relationships [22]. Further, its use was also greater in counties where the economic effects of the COVID-19 pandemic were more severe and financial services expanded.

FinTech lenders are major suppliers of credit to small businesses and played an important role in the recovery from the 2008 financial crisis. Furthermore, some argue that reduced bank lending did not have substantial effect on employment, wages and new business creation by 2016, due to its substitution by FinTech lenders [23].

Finally, researchers explore connections between bank capital regulation and the prevalence of lightly regulated, often technology-enabled, nonbanks (i.e. shadow banks) in the U.S. corporate loan market. It is found that at times when capital is scarce, such shadow banks step in and provide credit or funding for loans with higher capital requirements, which are offloaded by less-capitalised banks subject to Basel III requirements [24].

Regulations and Policy Making

Consumer protection remains a cornerstone of regulatory efforts as financial data sharing and AI-based advisory tools expand [25], [26]. Sopra Steria's recent research emphasises the importance of safeguarding consumer interests in this evolving landscape, highlighting transparency, fairness and data privacy as key enablers of trust [28]. Furthermore, the FCA (through its AGBR) is actively redefining how financial support is delivered. The AGBR focuses on innovative regulatory frameworks that enable "targeted support", offering tailored guidance to groups with shared characteristics, bridging the gap between generic guidance and full advice and thus, improving access and outcomes [6], [29]. On the international stage, the Organisation for Economic Co-operation and Development (OECD) advocates advancing financial literacy and inclusion through integrated technology and policy approaches, empowering consumers globally [30]. Meanwhile, Open Finance initiatives, potentially accelerated by the forthcoming Payment Services Directive 3 (PSD3) in Europe, seek to standardise and broaden data sharing while embedding strong consumer rights protections [31].

Industry Perspectives

Industry stakeholders recognise the transformative power of Open Finance for personalised financial wellness. Market reports observe a rising trend in dynamic, AI-driven financial planning tools, delivering real-time insights and tailored recommendations [32], [33]. Firms like Cleo and MoneyHub demonstrate this shift by integrating Open Finance data with ML to enhance budgeting, debt management and forward-looking planning for consumers [34], [35]. MoneyHub's recent expansions (e.g. partnering with Experian to accelerate debt repayment [36] and with Pennyworth to democratise financial planning [37]) showcase practical deployments of personalised financial management at scale. Additionally, AI-driven digital platforms are increasingly engaging consumers who live paycheck to paycheck, offering support customised to their needs [38]. Such initiatives, embedding Open Finance capabilities, demonstrate clear industry momentum toward closing the financial wellness gap and promoting resilience.

Contrasting Viewpoints

Despite these advances, persistent concerns exist around data privacy, algorithmic bias, and consumer trust [39]. The aggregation of personal financial data raises risks of misuse and unintended discrimination unless managed through ethical AI frameworks and transparent governance [40]. Consumer scepticism toward data sharing further challenges adoption, underscoring the need for clear communication and robust protections to build confidence in emerging financial tools.

2. Open Finance: Data integration and customer segmentation

The transition from traditional banking to Open Finance represents one of the most significant paradigm shifts in the financial services industry [11]. This evolution moves far beyond the foundational concepts of Open Banking to encompass a comprehensive ecosystem that integrates diverse financial data sources including mortgages, insurance, investments, pensions and government incentives into a unified analytical framework.

2.1 The Open Finance data revolution

Open Finance fundamentally transforms how financial institutions access and utilise customer data. Traditional banking systems operated in silos, with each institution maintaining isolated datasets that provided only fragmented views of customer financial health. The Open Finance framework will break down these barriers through consent-based APIs and trusted third-party frameworks, enabling the creation of comprehensive financial profiles that span multiple institutions and product categories [40].

The scope of data available through Open Finance extends significantly beyond transactional information. Modern implementations can capture income patterns, expenditure categories, debt obligations across multiple products, savings behaviours, pension contributions, insurance coverage details and participation in government financial incentives such as Individual Savings Accounts (ISAs). This rich data environment can also incorporate event-driven disclosures that capture life-changing events, dependency changes and employment transitions that significantly impact financial circumstances [42].

Category	Examples / Data Types
Credit Products	**Mortgages**: outstanding balances, amortisation schedules, rate resets.
	Personal loans & credit cards: credit limits, utilisation, minimum payments.
Savings & Investments	**Deposit accounts & ISAs**: balances, interest rates, contribution histories.
	Brokerage accounts: holdings, asset valuations, transaction histories.
Pensions & Retirement	Defined-contribution pots, contribution rates, projected retirement income.
Insurance	Policy details, coverage limits, premium schedules, claims records.
Government Benefits & Incentives	Universal Credit, Child Benefit, Pension Credit, ISA allowances, tax relief data.

Credit Products

Open Finance is reshaping access to credit information by enabling lenders to supplement traditional bureau data with live account-level insights [43]. The democratisation of data is lowering entry barriers for fintechs, encouraging competition and innovation in consumer lending [44]. At the same time, consumers' credit product usage is diversifying, with many households managing a mix of mortgages, loans and revolving credit [45].

- **Mortgages:** Data on outstanding balances, amortisation schedules and rate resets is gathered via the FCA's Mortgage Lending and Administration Return (MLAR), submitted quarterly by mortgage lenders in the UK [46]. Such integration supports both lenders and regulators in monitoring repayment risks and borrower resilience.

- **Personal Loans & Credit Cards:** Open Banking is already deployed to improve lending decisions by giving providers real-time access to loan affordability, credit limits, utilisation and minimum repayment histories. This dynamic visibility allows for more accurate credit risk profiling and prevents overextension.

Savings & Investments

Open Finance expands beyond transactional accounts into the broader realm of wealth and asset management [41],[47].

- **Deposit Accounts & ISAs:** Access to balances, accrued interest, and contribution histories provides a dynamic view of liquidity and savings capacity.

- **Brokerage Accounts:** With Open Finance frameworks, historical data on investment holdings and valuations can be made portable across platforms, enhancing consumer choice and advisory services.

Pensions & Retirement

Pensions are among the most significant assets for many households, yet they are traditionally fragmented and opaque. For example, as an individual's employment changes, their pension providers may do as well. For an individual, these changes can be unclear and difficult to track. Structured access to defined-contribution pots and retirement income projections is highlighted in [47], [48]. This shift would allow individuals to view contribution rates, investment performance and projected retirement income in one place, significantly improving retirement planning.

Insurance

Insurance data remains at an early stage in the Open Finance journey. Future phases outlined by the OBIE envision access to policy details, coverage limits, premium schedules, claims records and others [41]. Incorporating such datasets into financial health models can allow consumers to understand their protection gaps, while enabling insurers to personalise offerings based on holistic financial profiles.

Government Benefits & Incentives

A forward-looking extension of Open Finance lies in the integration of government benefits and tax-related incentives. Universal Credit, Child Benefit, Pension Credit, ISA allowances and tax reliefs all play a material role in financial wellbeing. Incorporating such data into Open Finance ecosystems would give households comprehensive visibility of their entitlements and improve the ability of financial advisors and digital tools to deliver tailored guidance [47].

2.2 Data structures

The technical infrastructure supporting Open Finance relies on standardised data schemas and temporal structuring[1] approaches [32],[48]. Account-customer relationships are mapped through sophisticated data models that maintain event timeline tagging and spending categorisation systems. These structures enable both time-series analysis and static attribute analysis for demographic and behavioural segmentation [40]. Integration with external data sources, including census data, house price indices, and regional deprivation indices, further enriches the analytical potential of Open Finance datasets.

Designing the data architecture[2] compatible with Open Finance involves careful schematic structuring to accommodate data streams from multiple financial products. This may involve relational or graph-based schemas[3] (see **Figure 4**) that associate customers with multiple account entities spanning different providers and product types. Each account is tagged with a timeline of events (e.g. transactions, contributions, expenditure, and facilitating temporal structuring). Transactions and financial behaviours are categorised hierarchically to reflect spending patterns (for example rent, discretionary spending, utilities), debt servicing, and income sources.

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[1] *Temporal data* is information that involves time – data points that have timestamps or durations, such as records of events, changes, or states occurring at different moments. Read more: Three Aspects of Temporal Data - DATAVERSITY

[2] *Data Architecture* – a blueprint for how data is collected, stored, managed and used. Read more: What Is a Data Architecture? | IBM

[3] *Relational schemas* organise data into tables with rows and columns, while *graph-based schemas* connect data like a web of relationships using nodes and links (like social networks). Read more: What is A Graph Database? A Beginner's Guide | DataCamp

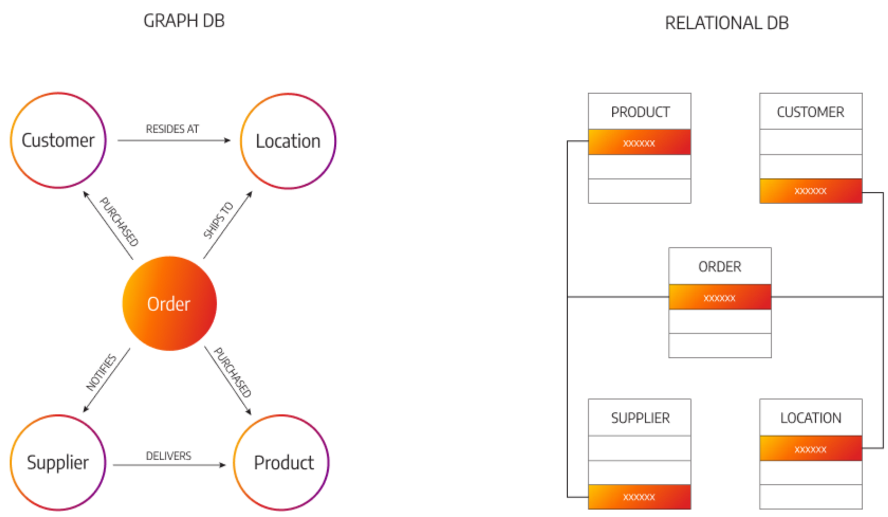

Figure 4: Graph vs Relational schema. Source: [Graph Database vs Relational Database]

Temporal structuring is fundamental to capturing both static attributes (e.g. date of birth, region, occupation) and evolving time-series data, such as monthly cash flows or investment portfolio valuations [48]. This dual approach supports both cross-sectional snapshots and trend-based analyses, enabling dynamic risk scoring and forecasting.

Integration with external data sources augments the internal financial dataset. Linking to census data, house price indices (HPIs), regional deprivation indices or labour market statistics enriches demographic and behavioural context. Such linkages improve accuracy where data gaps exist, enhance segmentation models and enable robust benchmarking against population-level trends.

2.3 Data sharing mechanisms

Central to Open Finance's architecture are consent-based APIs, which empower consumers to authorise specific data access between financial institutions and authorised third party providers (TPPs).

TPPs operate as intermediaries facilitating data aggregation and service delivery across multiple financial institutions, giving consumers a consolidated financial view beyond siloed accounts. Their role is critical for seamless data ingestion and delivering personalised recommendations. By leveraging secure APIs and consent arrangement platforms, TPPs enable customers to benefit from comprehensive insights without compromising data security.

In summary, this framework of consent-driven APIs, robust regulatory support and trusted intermediaries lays the foundation for Open Finance to deliver holistic financial management and proactive future planning.

2.4 Advanced customer segmentation through AI-driven analytics

The wealth of data available through Open Finance will enable unprecedented sophistication in customer segmentation approaches. Traditional demographic segmentation based on age, income, geography etc will be superseded by behavioural and financial health-based clustering methodologies that provide much more actionable insights for financial service providers [40], [49].

Modern segmentation approaches leverage ML techniques to identify patterns in transactional data that reveal spending periodicities, savings capacity assessments and predictive indicators of future financial behaviour. These algorithms can detect subtle patterns such as seasonal spending variations, response to economic shocks, and propensity for financial product adoption that would be impossible to identify through traditional analytical methods [40]. It is important to note that ML techniques can perform better than traditional economic forecasting methods in many settings and are especially useful when financial markets are uncertain or behave in non-linear ways. With proper tuning and testing, these models can offer clearer and more accurate predictions. However, in some cases, simpler models like factor models work just as well or even better, especially when the data is stable and the relationships are mostly linear. Not every ML application improves results, and overly complex models can perform worse if not carefully managed. The key is to use ML when it adds real value, while still keeping traditional models as strong benchmarks. More in-depth scientific discussion can be found in [50] and [51].

The implementation of clustering techniques such as K-means, DBSCAN and hierarchical clustering on Open Finance data reveals distinct customer archetypes that align with different financial health profiles and advisory needs. Sopra Steria & Oxford University's collaborative research demonstrates that effective clustering can identify groups such as "Emerging Professionals with Debt", "Disciplined Debt Navigators", "Established and Secure Homeowners", "Vulnerable and Delinquent Renters" and others, each requiring tailored financial guidance strategies [52].

Advanced clustering methodologies incorporate both demographic features and behavioural indicators derived from transaction analysis. Financial prudence scores, debt management patterns, discretionary spending volatility and investment allocation preferences all contribute to more nuanced customer understanding. These multidimensional approaches enable financial institutions to move beyond simple income-based categorisation toward truly personalised service delivery [53].

2.5 Privacy-preserving data enhancement

The sensitive nature of financial data requires sophisticated approaches to data privacy and often the use of synthetic data generation for development. Privacy-preserving techniques, particularly those compliant with GDPR and other regulatory frameworks, are essential for enabling innovation while protecting customer interests [54],[55].

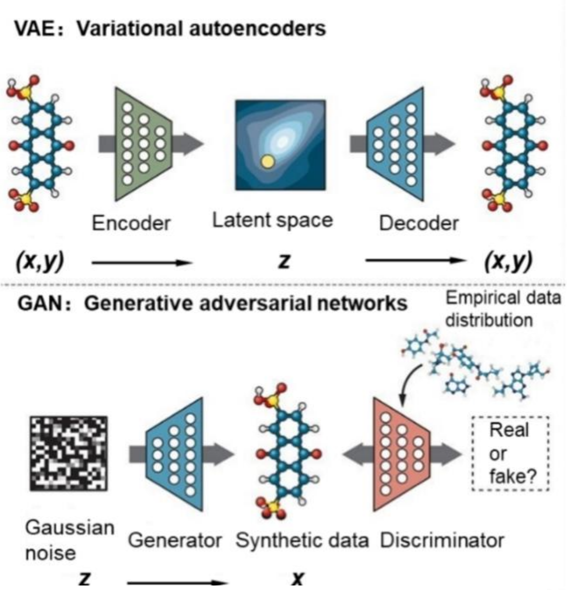

Figure 5: Technical schematic representations of VAEs and GANs. Source: Chemistry Europe

Synthetic data generation techniques using advanced ML models, including Generative Adversarial Networks (GANs)[4] and Variational Autoencoders (VAEs)[5] (see **Figure 5**), enable the creation of realistic financial datasets that maintain statistical properties of original data while eliminating direct personal identifiers. These approaches are particularly valuable for model development, testing and research collaboration [56].

Statistical imputation methods, e.g. Bayesian inference[6] approaches, provide robust frameworks for enhancing existing datasets with additional demographic and behavioural attributes. These techniques leverage publicly available distributional data from sources such as the Office for National Statistics (ONS) to enrich synthetic datasets while maintaining realistic correlation structures between variables [52]. The implementation of diverse privacy techniques ensures that synthetic data generation processes provide mathematically rigorous privacy guarantees. These approaches inject carefully calibrated noise into data generation processes to prevent individual record identification while preserving overall dataset utility for analytical purposes [54].

[4] *Generative Adversarial Networks (GANs)* are a type of AI that generates new, realistic data, like images or music, by pitting two neural networks against each other in an iterative competitive game. One network ("generator") creates fake data, while the other ("discriminator") tries to tell the difference between the fake data and the real data it was trained on. Read more: Generative Adversarial Networks Explained | AWS

[5] *Variational Autoencoders (VAEs)* are AI models that learn to generate new, similar data like images or text by understanding the underlying "rules" or patterns in existing data. They contain an encoder that maps input data to a "fuzzy" representation and a decoder that takes a sample from this space and reconstructs new, similar data. Read more: What is a Variational Autoencoder? | IBM

[6] *Bayesian inference* is a learning technique that uses probabilities to define and reason about our beliefs. Read more: Bayesian inference | Introduction with explained examples

2.6 Regulatory compliance and ethical considerations

Open Finance implementation must navigate complex regulatory landscapes that balance innovation enablement with consumer protection. The Data (Use and Access) Bill and evolving regulatory guidance from the FCA provide frameworks for responsible data utilisation while encouraging technological advancement [57]. Consent-based data sharing mechanisms ensure that customers maintain control over their financial information while enabling them to benefit from improved service personalisation. These frameworks require clear transparency about data usage purposes, retention periods and sharing arrangements with third parties.

The role of intermediaries and trusted third parties becomes crucial in maintaining data security and privacy while enabling innovation. These entities must demonstrate robust data governance and cybersecurity capabilities as well as compliance with evolving regulatory requirements [59].

Ethical considerations extend beyond regulatory compliance to encompass fairness, transparency and inclusivity in algorithmic decision-making. Open Finance systems must actively address potential biases in data collection and model development, to ensure unbiased outcomes across different customer segments [60]. Bias can arise from incomplete, imbalanced or historically skewed data. If left unchecked, it risks entrenching inequalities rather than reducing them. Literature emphasises the need for ongoing checks, transparent algorithms and active human oversight to ensure fair outcomes in financial decision-making [61], [62], [63].

Ethical frameworks should always be incorporated to prioritise consumers' financial health over business opportunity identification. Recommendations focus on improving customer financial health and resilience rather than product sales or revenue optimisation. Such a customer-centric approach builds trust and supports long-term relationship development.

Transparency and explainability requirements demand that consumers understand the basis for recommendations and can see how their specific circumstances influence the guidance provided. Explainable AI techniques (e.g. SHAP[7]) bring insights to life and deliver recommendation rationales [63]. Proper use of data means prioritising positive impact on people's financial wellbeing, with fairness and transparency at the core. This approach builds trust in technology and ensures that advancements serve everyone, not just financial institutions.

[7] *SHAP - (SHapley Additive exPlanations)* is a game theoretic approach to explain the output of any ML model. Read more: An introduction to explainable AI with Shapley values — SHAP

2.7 Beyond Open Finance: inclusion, smart data and cross-border portability

While this paper places primary emphasis on Open Finance, it is important to recognise that financial health is not defined solely within the boundaries of formal financial products. Hence, Open Finance may not go far enough in addressing the full spectrum of financial inclusion. Smart Data and Open Data initiatives, such as those being advanced under the UK Smart Data schemes [65], can enrich the picture, particularly for those without bank accounts or who interact only minimally with financial products (e.g. those who hold only a single basic bank account with no available credit facilities). Utility bills, rent records, mobile phone usage and other non-financial sources can provide crucial signals of discipline and resilience. In practice, this broader approach can help ensure that individuals who are financially inactive, underserved or "off-grid" are brought into the fold, as a key part of inclusion efforts.

To ensure inclusion, modelling frameworks should anticipate dedicated clusters for the "financially invisible". These individuals may not receive highly tailored recommendations due to limited data, but they can still benefit from generalised, yet actionable, advice that safeguards against exclusion. By recognising varied levels of data richness, personalised and group-based advice can be delivered at scale, ensuring that the benefits of financial technology reach as many people as possible. This addresses social equity and supports smarter risk management.

Looking beyond national boundaries, financial health frameworks (when built on verifiable and transferable data) hold promises for supporting mobility across borders. The ability to 'carry' one's credit score, resilience metric or financial health indicators internationally could empower individuals to access fair financial products wherever they choose to live or work, removing a longstanding barrier for those relocating. With initiatives such as PSD3 in Europe [66], which aims to expand and harmonise access to financial data across borders, there is an opportunity to embed verification and interoperability mechanisms into Open Finance architectures. Such portability would generate Pareto-optimal[8] benefits: consumers retain recognition of their financial discipline internationally, while institutions reduce onboarding risks and open new opportunities for responsible growth.

[8] Pareto optimality (efficiency) describes a situation where resources are allocated in the best possible way, making it impossible to improve one person's situation without negatively affecting another. Read more: [Pareto Efficiency Examples and Production Possibility Frontier]

3. Predictive analytics & cash flow modelling

The foundation of effective financial guidance and tailored recommendations in the Open Finance era rests on sophisticated cash flow modelling capabilities that can accurately predict and analyse individual customer financial trajectories. These modelling approaches must capture the complexity of modern financial lives, whilst providing actionable insights for both short-term stability optimisation and long-term wealth building strategies.

3.1 Comprehensive data sourcing

Effective modelling requires robust and comprehensive data sourcing that reflects the complexity of modern personal finance.

- **Open Finance Data:** Core financial data is aggregated from multiple providers within the Open Finance ecosystem. Collectively, these datasets offer an extensive view of consumers' financial positions and behaviours, surpassing the limited scope of Open Banking transactional data. Note: cash transactions outside the digital ecosystem cannot be tracked and hence, cannot form part of data-driven predictive modelling.

- **Consumer-Disclosed Information:** Supplementary data directly reported by consumers plays a crucial role. Such event-driven disclosures provide critical context for adaptive and personalised modelling.

- **Publicly Available Data:** External datasets enrich individual financial profiles by embedding them within broader socio-economic frameworks. Integrating external data informs risk assessments and ensures models account for environmental variables affecting financial resilience.

Furthermore, modern cash flow modelling extends far beyond simple income-expense calculations to encompass a holistic view of financial health that includes housing costs, essential expenditures, debt service obligations, discretionary spending patterns and allocation toward savings and investments. This comprehensive approach recognises that financial health cannot be assessed through any single metric but requires integrated analysis of multiple financial dimensions [66], [67].

Housing cost modelling, for example, must account for regional variations, tenure types (rental, mortgage, owned outright) and the relationship between housing expenses and income levels across different demographics. Research demonstrates significant variation in housing cost ratios based on regional economic conditions [69],[70], with London and Southeast England showing markedly different patterns compared to other UK regions (see **Figure 6**). Wealth and assets concentration in these regions plays a key role.

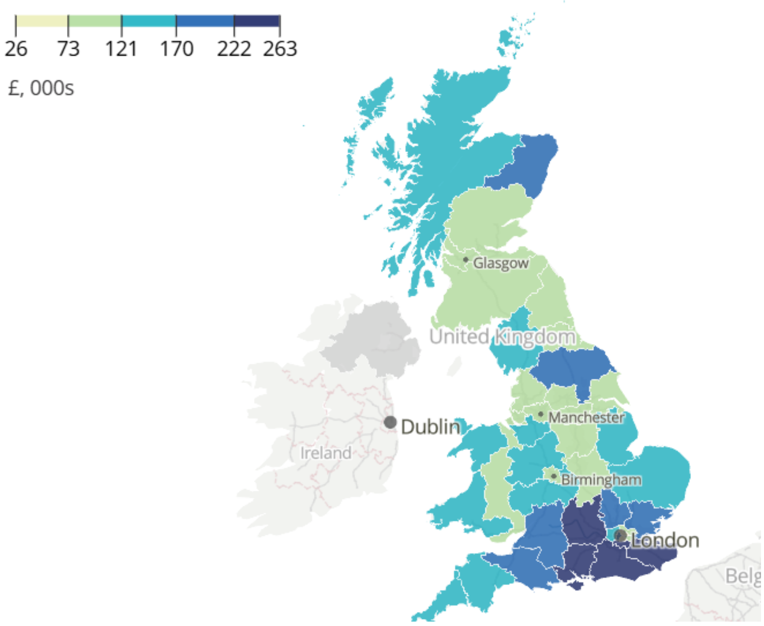

Figure 6: Wealth & Assets Medians – 2018-2020.
Source: [Distribution of individual total wealth in Great Britain - Office for National Statistics]

Essential expenditure modelling beyond housing presents additional complexity, as spending on food, transportation, and utilities varies not only with income levels but also with regional cost structures and individual lifestyle choices. Advanced modelling approaches use techniques like Iterative Proportional Fitting[9], Propensity ScoreMatching[10], and Counterfactual Identification[11] to generate realistic joint distributions that respect both regional and income-based marginal constraints while introducing appropriate stochasticity to capture individual variation.

Debt service modelling requires sophisticated understanding of different credit product types, interest rate structures, payment timing patterns etc. The framework must distinguish between revolving credit (credit cards, overdrafts) where payment obligations vary with utilisation and fixed credit products (personal loans, mortgages) with predetermined payment schedules. Integration of late payment patterns and associated penalty structures provides crucial insights into financial stress indicators.

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[9] *Iterative Proportional Fitting techniques* – mathematical methods that adjust a dataset, such as a table of data, to make its row and column totals match a known set of target marginal totals from a different source. Read more: Iterative Proportional Fitting | TF Resource

[10] Propensity score matching (PSM) – statistical method used in observational studies to reduce selection bias when estimating the effect of a treatment. Read more: Understanding the Propensity Score: A Guide to Reducing Bias | DataCamp

[11] Counterfactuals help to identify which aspects of the input data are most influential in the model's decisions, aiding in model debugging, fairness analysis and improving model performance. Read more: Counterfactual Explanations: The What-Ifs of AI Decision Making

3.2 Dynamic risk assessment and behavioural prediction

Advanced cash flow modelling incorporates predictive analytics capabilities that can anticipate future financial stress, identify emerging opportunities for financial improvement and adapt recommendations based on changing circumstances. These capabilities rely on ML techniques that can identify subtle patterns in financial behaviour that precede significant financial events [49], [70].

Transaction pattern analysis reveals cyclicality in financial behaviour that can inform both short-term cash flow forecasting and long-term financial planning. Algorithms capable of detecting spending seasonality, income volatility and irregular financial events enable more accurate prediction of future cash flow challenges and opportunities [40].

Behavioural risk assessment leverages advanced analytics to ultimately identify early warning indicators of financial distress. These may include increasing credit utilisation rates, growing payment delays, changes in discretionary spending patterns or shifts in savings allocation behaviours. ML models trained on historical patterns can identify customers at risk of financial difficulty with sufficient advance warning to enable proactive intervention.

Such models may also add potential monitoring benefits in other contexts. For example, undiagnosed memory disorders in early stages impact a broad range of financial outcomes, such as: credit card account payment delinquency and amount of delinquent balance, credit utilisation among credit card account holders, mortgage delinquency and delinquent balance amount, and credit scores. These effects are seen across seniors in single and coupled households, racial/ethnic minorities and non-minorities, and older adults living in areas with higher and lower education levels [71]. Clinically informed lead indicators of dementia, extended to include money management difficulty (which emerges as the most important lead indicator), can inform a high-performance AI model to predict a clinical diagnosis [72]. Armed with this knowledge, financial institutions can enhance their protection of vulnerable customers with dementia and, potentially, inform the intergenerational transfer of financial control. Likewise, mergers of large regional banks leading to branch closures and tighter credit constraints in counties harm the mental health of lower-income individuals [73]. Conversely, regulatory reforms that improved credit conditions reduced mental depression, boosted labour market outcomes, eased access to mortgage debt, and reduced the ranks of the “unbanked” [73]. Lastly, permissive laws deputising financial professionals to screen for misbehaviour without providing explicit incentives are shown to result in fewer reports of abuse by financial professionals and, separately, in financial crimes against the elderly, with a stronger impact for isolated elders [74]. This showcases how financial professionals can prevent financial fraud and combat social problems, an important contribution of finance to society.

3.3 Feature selection & engineering

Identifying the most explanatory variables essential for accurate predictions and insightful customer segmentation involves multiple analytical techniques, alongside careful ethical considerations.

In order to extract data features that capture both the static attributes and dynamic financial behaviours driving individual financial health and trajectories, the following techniques can be used:

Technique	Description
Correlation Analysis & Mutual Information	Measures linear and non-linear relationships between features and target variables.
Chi-squared Binning	Evaluates categorical variables' predictive power and enables effective discretisation.
Principal Component Analysis (PCA)	Reduces dimensionality by extracting orthogonal components explaining variance.
Stepwise Regression	Iteratively adds or removes features to find the best predictive subset.
LASSO Regression	LASSO (Least Absolute Shrinkage and Selection Operator) uses regularisation to penalise less important features, promoting model sparsity.
Time-Based Feature Engineering	Creates temporal variables such as spending volatility, seasonal trends, late payment counts.
Permutation Feature Importance	Measures a feature's importance by calculating the decrease in a model's performance after shuffling the feature's values.

In addition, the following ethical considerations must be embedded in the data processing:

- **Protected Characteristics:** Features relating to sensitive personal attributes, including but not limited to race, gender, disabilities etc. Their inclusion requires clear justification and transparency, to avoid bias and discrimination.

- **Fairness Constraints:** The modelling framework should apply fairness-aware principles to ensure that selected features do not inadvertently conserve historical biases or result in unfair outcomes for protected groups [75], [76], [77]. Continuous monitoring and adjustment are required to uphold ethical standards in financial decision-making.

3.4 Predictive modelling & clustering

Building on carefully engineered features, a suite of AI/ML models can be utilised to generate personalised financial health scores, and customer segmentation.

Technique	Examples	Description
Logistic Regression	N/A	Baseline model for binary classification, valued for interpretability.
Ensemble Learning Methods	XGBoost, LightGBM, Random Forest	Handles complex relationships, reduces overfitting, suitable for classification and regression.
Neural Networks	LSTM	Captures temporal dependencies and seasonality in sequential financial data.
Unsupervised Learning	k-means, DBSCAN, SOMs	Identifies clusters or segments within customer data for personalised insights.
Reinforcement Learning	Q-Learning, Deep Q-Networks (DQN), Proximal Policy Optimisation	Enables dynamic planning and real-time adaptive recommendations, based on feedback.
General-to-Specific (GETS) Modelling	Autometrics, Hendry's Classical, Dynamic GETS Models	Used for variable selection by starting with a general model and simplifying it step-by-step. Retains only statistically significant variables, ensuring models are both data-driven and economically meaningful. Helps identify key determinants in large datasets while avoiding overfitting.

Typical Model Outputs:

- **Financial Health Scorecard:** A composite metric that provides a holistic measure of an individual's current financial health and risk exposure. It reflects cashflow stability, debt management, sustainable growth in savings & investment and others.
- **Resilience Index:** This index quantifies an individual's capacity to withstand adverse macroeconomic shocks, incorporating scenario analysis informed by economic indicators such as unemployment rates, inflation levels and housing market trends. Monte Carlo simulations[12] and stochastic modelling techniques can be used to achieve this.
- **Clustering Results:** Customer clusters derived from unsupervised methods identify typical financial personas and segments, informing tailored recommendation strategies and product offerings. Clustering outcomes are usually validated via silhouette scores[13] and external benchmarking. Other methods that may be considered within this context include Linear Discriminant Analysis[14] and Support Vector Machines[15].

3.5 Model explainability vs performance

The success of AI-driven financial models rests on balancing predictive performance with interpretability. While high predictive accuracy metrics (such as Precision, Recall, F1 Score, and Log-loss) demonstrate model effectiveness in classifying or forecasting financial behaviours (e.g. probability of default or cash flow stability), these alone are insufficient for transparent customer engagement and regulatory compliance.

- **Precision** quantifies the correctness of positive predictions (in our case correctly identifying at-risk customers).

- **Recall** captures the model's ability to detect all relevant positive cases.

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[12] *Monte Carlo simulations* – computational method that uses repeated random sampling to generate a distribution of potential outcomes for an uncertain event or process. Read more: [Monte Carlo Simulation: What It Is, How It Works, History, 4 Key Steps]

[13] *Silhouette score* – a metric used to evaluate the quality of clustering in unsupervised machine learning. The silhouette score assesses both cohesion (how similar a point is to its own cluster) and separation (how dissimilar a point is to neighboring clusters).

[14] *Linear Discriminant* Analysis – a supervised ML technique used for dimensionality reduction and classification by finding a linear combination of features that maximizes the separability between known classes. Read more: [What Is Linear Discriminant Analysis? | IBM]

[15] *Support Vector Machine* – a supervised ML algorithm that finds the best line or "hyperplane" to separate different classes of data. Read more: [What Is Support Vector Machine? | IBM]

- **F1 Score** harmonises precision and recall into a single metric.

- **Log-loss** evaluates the confidence of probabilistic predictions, penalising overconfident errors.

Other measures for practical applicability and predictive power such as proportion of variation (R^2), Mean Squared Error, Root Mean Squared Error, Mean Absolute Error, other loss functions (e.g. quasi-likelihood function, asymmetric loss function) and more [78],[79],[80].

In financial health contexts, where trust and accountability are most important, explainable AI (XAI) techniques such as **SHAP** (SHapley Additive exPlanations) and **LIME** (Local Interpretable Model-agnostic Explanations) play a pivotal role. These tools dissect complex AI models to provide:

- Data feature-level insights showing how individual inputs (such as income volatility, discretionary spend etc) influence predictions.

- Local explanations that clarify a specific decision for an individual customer, essential for personalised recommendations.

There is a trade-off between interpretability and predictive power. Simpler models like logistic regression offer clear rationales but may miss compound patterns, while complex ensembles or neural networks may capture deeper relationships at the cost of harder interpretability. This paper acknowledges the trade-off at a high level - detailed exploration is reserved for works focused on AI fairness and regulatory explainability.

3.6 Stochastic modelling and scenario analysis

The inherent uncertainty in financial planning requires stochastic modelling approaches that can capture the range of possible financial outcomes and their associated probabilities. Monte-Carlo simulation techniques enable comprehensive scenario analysis that accounts for variability in income, expenses, investment returns etc.

Investment modelling incorporates sophisticated stochastic processes including Geometric Brownian Motion[16] (see **Figure 7**) for risky asset evolution and deterministic modelling for risk-free savings growth. These approaches account for market volatility and risk tolerance preferences.

[16] **Geometric Brownian Motion** – a mathematical model used to describe asset prices such as stocks, that follow a pattern of random (but generally upward) movement. A key feature is that the asset's value cannot go below zero, and its changes are proportional to its current price. Read more: How to use Monte Carlo simulation with GBM

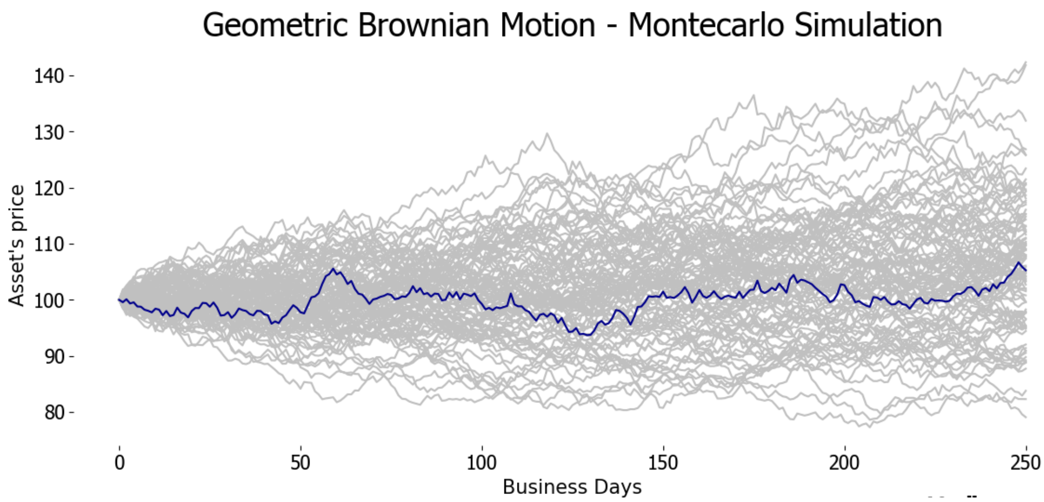

Figure 7: Geometric Brownian Motion Simulation. Source: Montecarlo simulation for Geometric Brownian Motion

Wealth accumulation trajectories are widely held to be based upon either S-shaped or inverted-L shaped curves shown below for the relationship of income today and tomorrow (and by extension wealth as a function of income) [81] – see **Figure 8**.

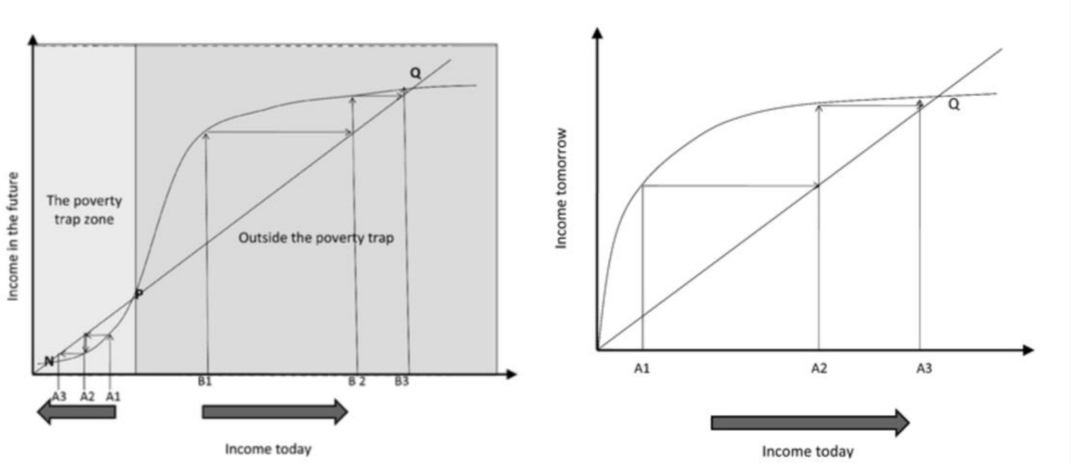

Figure 8: The S-Shape Curve and the Poverty Trap (left); the Inverted L-Shape: No Poverty Trap (right). Source: [81]

Age groups and income-based risk appetite modelling recognises that appropriate investment allocation varies significantly across different life stages and wealth levels. Glide path methodologies can adjust risk exposure based on time horizon and financial capacity, ensuring that investment recommendations remain appropriate as circumstances change.

Scenario analysis capabilities enable exploration of various "what-if" situations including job loss, health events, housing market changes, economic recession scenarios and so on. These analyses help customers understand the resilience of their financial plans and identify areas where additional protection or flexibility might be beneficial [82],[83].

3.7 Adaptation and continuous learning

Modern cash flow modelling systems must provide real-time adaptation capabilities that can respond immediately to changing financial circumstances. This requires regular data refresh capabilities that can incorporate new transaction information, economic data updates and customer-reported life changes into ongoing financial assessments [70]. As discussed earlier in this paper, potential non-financial benefits can result from this approach, e.g. diagnosing memory disorders, mild cognitive impairment, dementia, mental health deterioration and others [71],[72],[73].

ML models enable continuous improvement in prediction accuracy through ongoing training on new data patterns [49]. These systems can identify shifts in customer behaviour, adapt to changing economic conditions, and refine their understanding of the relationships between different financial variables over time.

The integration of feedback loops from customer interactions and outcomes (see **Figure 9**) enables model validation and improvement [40]. When customers report satisfaction with recommendations, experience financial improvements or deteriorations, this information feeds back into model refinement processes.

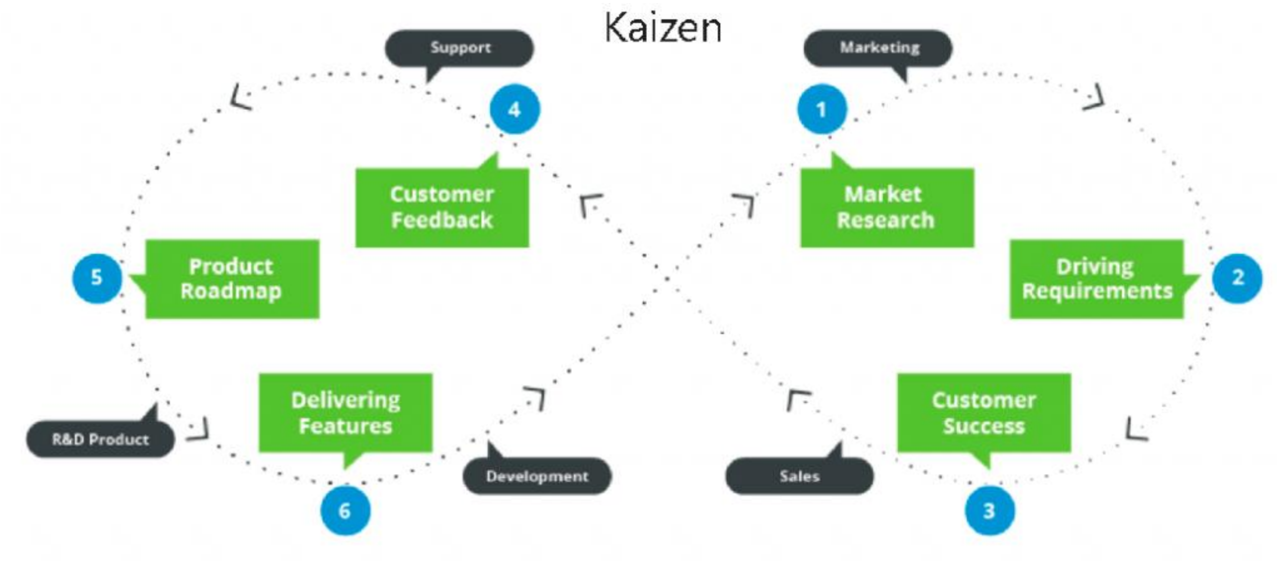

Figure 9: An example of continuous feedback loop structure. Source: Zeda.io

4. Smart Personalised Finance Management Framework

The culmination of Open Finance data integration and sophisticated cash flow modelling enables the development of comprehensive smart personalised finance management systems that can provide tailored, actionable financial guidance and recommendations at scale. These systems must balance automated efficiency with personalised relevance while maintaining regulatory compliance and ethical standards.

4.1 Hierarchical financial needs framework

Effective personalised financial management recognises that financial needs exist in a hierarchical structure, similar to Maslow's hierarchy of human needs (see Figure 10). This framework prioritises fundamental financial stability before progressing to more advanced wealth optimisation objectives [84],[85],[86].

The foundational level focuses on basic financial survival through cash flow stability optimisation. Customers experiencing negative cash flow or inadequate emergency savings require immediate attention to essential expense management, income stabilisation and basic safety net establishment. This level corresponds to the physiological and safety needs in Maslow's hierarchy and must be addressed before any higher-level financial planning can be effective [84].

The second level addresses financial security through debt management and risk mitigation. Once basic cash flow stability is achieved, attention turns to managing debt service ratios, eliminating high-interest debt, and establishing appropriate insurance coverage [85]. This level provides the foundation for more advanced financial planning by eliminating major financial vulnerabilities.

The third level focuses on financial independence through strategic wealth accumulation. With stability and security established, customers can pursue long-term wealth building through investment optimisation, tax planning and goal-based savings strategies [86]. This level corresponds to self-esteem and belonging needs as customers work toward financial goals that enable lifestyle choices and social participation.

The highest level encompasses financial self-actualisation through legacy planning and value-aligned financial strategies. This includes estate planning, charitable giving and investment approaches that reflect personal values and long-term societal impact.

Figure 10: Application of Maslow's theory in a financial needs' context.
Source: [Visualizing the Hierarchy of Financial Needs]

4.2 Sequential optimisation engine architecture

The implementation of hierarchical financial guidance requires sophisticated sequential optimisation engines that can systematically address financial needs in appropriate priority order while avoiding premature advancement to higher-level objectives before foundational needs are met.

Layer 1 optimisation focuses exclusively on cash flow stability and emergency fund adequacy. The system evaluates current cash flow patterns, identifies potential expense reductions through discretionary spending optimisation and essential expense rebudgeting, and calculates feasible timelines for emergency fund accumulation. For young renters, this may include recommendations for temporary housing arrangement changes to dramatically reduce housing costs.

The optimisation engine incorporates constraint handling that recognises practical limitations on expense reduction while identifying all feasible improvement strategies. If cash flow cannot be made positive through reasonable expense modifications, the system provides recommendations about the need for professional financial counselling or income enhancement strategies.

Layer 2 optimisation addresses debt management and service ratio optimisation only after Layer 1 stability is achieved. This layer prioritises elimination of payment arrears, reduction of high-interest debt balances and optimisation of debt service ratios to sustainable levels. The system calculates optimal debt paydown strategies that balance interest cost minimisation with cash flow sustainability.

Advanced debt optimisation incorporates understanding of different debt product characteristics, interest rate structures, and penalty mechanisms. The system can identify optimal balance transfer opportunities, refinancing possibilities, and payment timing strategies that minimise total debt service costs while maintaining financial stability [87].

Layer 3 optimisation addresses wealth maximisation and goal achievement once both stability and debt management objectives are met. This layer incorporates sophisticated goal-based financial planning including housing deposit accumulation, retirement planning and investment portfolio optimisation. Relevant economic aspects of wealth accumulation over time are examined thoroughly in [81],[88].

4.3 Personalisation and behavioural integration

Drawing from Sopra Steria's Research & Development work, smart personalised finance management synthesises clustering-driven persona construction with a hierarchical optimisation engine to tailor financial recommendations precisely.

Persona Construction

Clustering analysis has identified eight distinct customer segments (personas), revealing heterogeneous financial conditions and behaviours:

- **Emerging Professionals with Debt:** Young renters in professional roles, facing moderate incomes but significant debt burdens and arrears risks.

- **Disciplined Debt Navigators:** Financially responsible professionals adept at managing debt and sustaining healthy cash flows.
- **Established and Secure Homeowners:** Mature homeowners with stable incomes, robust savings and strong financial discipline.
- **Vulnerable and Delinquent Renters:** Low-income young renters burdened by high financial distress and poor payment behaviours.
- **Affluent and Prudent Investors:** High earners focused on wealth accumulation, investing strategically.
- **Struggling to Start:** Entry-level earners with low income and minimal savings, vulnerable to shocks despite good payment discipline.
- **Steady and Responsible Managers:** Balanced demographic with solid surplus and moderate liabilities; exemplary payment records.
- **Crisis-Prone and Underbanked:** Younger renters with persistent negative cash flow, low savings, and limited credit access.

Defining such personas enables contextualisation of recommendations and establishes communication frameworks aligned with customer needs and motivational factors.

Effective personalised financial management must account for individual behavioural patterns, risk preferences and life circumstances that influence financial decision-making effectiveness. This requires integration of behavioural finance principles with technical optimisation capabilities [89],[90]. For example, modelling the optimal illiquidity levels for retirement saving based on present bias [91]. This research shows the relationship with present bias impacts these levels via early pre-retirement withdrawal penalties from mandatory savings accounts, illustrating how a social planner would set up a simple socially optimal pension scheme. Their very simple mechanisms provide good welfare approximations to arbitrarily complex, optimal mechanisms.

Other sources investigate saving goals' effectiveness in increasing individuals' savings from a fintech app's data, finding that setting soft goals (whereby individuals face no penalties when deviating from their plan) causally increases individuals' savings rate [92]. Increased savings within the app are not at the cost of reduced savings outside the app, and soft goal setting is especially effective for those in the population at greater risk of under-saving. Soft goals could thus be deployed to help low-income individuals, who are arguably among those who could benefit from such fintech solutions the most, and are also more scalable and easier to administer compared to their counterpart hard goals, especially in real-life settings [92].

Other studies explore welfare consequences of retirement plan automatic enrolment policies, for example in [93]. At 43 to 48 months of tenure, their experimental policy raises cumulative contributions to such plans by 4.1% of first-year annualised salary. However, they find little evidence that auto-enrolment increases financial distress, which holds even among subpopulations very likely to have large auto-enrolment effects on plan contributions. Automatic enrolment has a precisely estimated zero effect on credit scores, no significant effect on debt excluding auto loans and first mortgages and no significant positive effects on a range of measures of adverse credit outcomes, with the exception of first-mortgage foreclosures.

Some researchers find that offering consumers the opportunity to adopt increased retirement saving behaviour immediately and then, only if they decline, inviting them to adopt it later (i.e. offering “sequential pre-commitment”) increases inferred urgency, predicting greater adoption [94],[95].

Lastly, various nudge interventions for increased retirement saving merit consideration. These alter people’s decisions without coercion or significant changes to economic incentives and include especially efficacious variations like fresh start nudging and semi-automated nudging. Moreover, they compare favourably with traditional interventions/policy tools such as tax incentives and other financial inducements, even without restricting the menu of options and without altering financial incentives [96],[97].

Customer segmentation insights derived from clustering analysis inform personalisation strategies that recognise different customer archetypes require different communication approaches, recommendation timing and motivational frameworks. "Disciplined Debt Navigators" respond well to detailed analytical information and long-term planning frameworks, while "Vulnerable and Delinquent Renters" require more immediate, practical guidance with simplified decision frameworks.

Behavioural consistency modelling recognises that financial improvement requires sustainable behaviour change rather than short-term sacrifice. The system incorporates understanding of customer spending patterns, seasonal variations and discretionary spending preferences to develop realistic improvement strategies that can be maintained over time [40].

Risk appetite integration ensures that investment and planning recommendations align with individual comfort levels and life circumstances. For instance, income-level considerations and personal risk tolerance assessments combine to generate investment allocations that balance growth potential with downside protection.

4.4 Continuous improvement and outcome tracking

Advanced personalised finance management systems incorporate comprehensive feedback mechanisms that enable continuous improvement in recommendation effectiveness and customer outcome optimisation. These systems must track customer financial health improvements, recommendation adoption rates, and long-term financial trajectory changes [40].

Performance monitoring is needed to track key metrics including emergency fund adequacy, debt service ratio improvements, investment goal progress and overall financial stress reduction. These metrics provide objective measures of system effectiveness and identify areas requiring refinement.

Customer satisfaction integration ensures that technical optimisation aligns with customer experience and perceived value [89]. Feedback mechanisms capture customer preferences, communication effectiveness, and recommendation relevance to guide system enhancement.

The integration of macroeconomic monitoring enables system adaptation to changing economic conditions and regulatory frameworks [98]. This ensures that recommendations remain relevant and effective across different economic scenarios.

Through a comprehensive framework, smart personalised finance management systems can deliver significant value to customers while maintaining operational efficiency and regulatory compliance, ultimately democratising access to sophisticated financial guidance previously available only to high-net-worth individuals.

5. Conclusion

The convergence of AI and Open Finance marks a fundamental shift in how financial health is understood, measured and supported. This whitepaper has demonstrated that moving beyond legacy, credit-score-centric systems is no longer simply an innovation opportunity, but a necessity. Recent economic shocks, widening inequalities and changing consumer expectations demand data-driven financial modelling that is inclusive and focused on long-term resilience.

Open Finance will provide the infrastructure to enable this transformation by facilitating secure, consent-driven access to a far broader range of financial data. Combined with advanced AI and machine learning techniques, such as predictive cashflow modelling, persona-based optimisation and explainable analytics – this data becomes the foundation for intelligent financial guidance. Rather than relying on retrospective assessments, financial institutions can offer proactive support: anticipating risk, identifying opportunity and tailoring interventions to individual circumstances.

However, technology alone is not sufficient. Ethical data stewardship, fairness, transparency and regulatory compliance must remain central. The FCA's Advice Guidance Boundary Review and Consumer Duty framework show that innovation and consumer protection are not mutually exclusive but mutually reinforcing. Responsible AI, anchored in explainability, bias mitigation and privacy safeguards, ensures these advances enhance trust rather than diminish it.

This transformation enables financial institutions to evolve from product providers to long-term financial partners – supporting everyday budgeting, responsible borrowing, future planning and improved financial wellbeing. Consumers, in turn, can gain access to personalised, non-product-specific guidance that empowers informed decision-making and strengthens resilience through life's uncertainties.

As Open Finance infrastructure matures in future, continued collaboration between policymakers, regulators, academia, industry and technology providers will be crucial. Those who act early – investing in data capabilities, ethical AI and human-centric design, will define a more inclusive and trustworthy financial ecosystem. Out of crisis arises opportunity: a pathway towards prosperity built on transparency, accountability and holistic financial health evaluation.

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