# Contemporary Finance: Bridging Theory and Empirical Application

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## Abstract

This paper outlines four advanced research tracks conceived for a Project-Centric Learning (PCL) environment in finance. The central aim is to close the widening gap between abstract financial theory and its rigorous, data-driven application — a gap made more consequential by the accelerating integration of artificial intelligence, FinTech platforms, and blockchain-based asset classes into mainstream finance. The contemporary financial landscape is defined by rapid technological change that has outpaced existing academic syllabi, generating unresolved challenges in governance, valuation methodology, and risk assessment.

Each of the four tracks targets a distinct structural or methodological deficiency in the current literature. Track I examines the causal pathway through which FinTech adoption translates into stronger corporate ESG outcomes — specifically whether the mechanism operates through the relaxation of internal capital constraints or through improved access to external fiscal incentives. Track II constructs computational frameworks for addressing non-stationarity in financial AI and ML systems, focusing on how to prevent model degradation in live credit risk and algorithmic trading environments. Track III moves beyond cataloguing psychological biases to experimentally measuring whether targeted financial literacy programmes can meaningfully reduce loss aversion and herding behaviour in student populations. Track IV proposes modifications to the conventional Discounted Cash Flow methodology to better capture value in high-growth digital platform firms and emerging asset classes such as DeFi protocols, incorporating network-effect premiums and protocol-native metrics such as Total Value Locked.

All four tracks are calibrated for academic feasibility: they draw on publicly accessible, high-quality datasets and open-source analytical tools, and each fits within a standard PCL timeline. Taken together, they represent a coherent scholarly response to the central challenge of modern finance education — equipping students to navigate a financial world that is simultaneously more digitalised, more behaviourally complex, and more technologically dynamic than at any earlier point in history.

***Keywords***: *FinTech, ESG, AI/ML, Non-Stationarity, Behavioural Finance, DeFi, DCF Valuation, Project-Centric Learning, Financial Literacy, Platform Premium.*

# 1. Introduction

Advanced finance education is at an inflection point. Earlier generations of finance programmes placed their emphasis on conceptual mastery — students were expected to understand theories, models, and valuation frameworks in the abstract. The contemporary standard is fundamentally different: rigorous, practical implementation is now the benchmark. This shift is the product of three converging forces: the widespread adoption of artificial intelligence and machine learning in financial services; the maturation of the FinTech sector and its growing entanglement with sustainability objectives; and the emergence of entirely new classes of assets built on decentralised infrastructure.

Project-Centric Learning represents the most appropriate pedagogical response to this transition. By grounding academic inquiry in real-world problems that require advanced econometric, computational, and behavioural competencies, PCL enables students to develop the specialised skill sets that financial institutions, regulators, and investors increasingly demand. This paper delineates four research tracks designed to engage directly with the most pressing open problems in contemporary finance — challenges for which the existing scholarly literature provides either incomplete answers or methodologically insufficient frameworks.

## 1.1 Structural Gaps in Contemporary Financial Research

The frontier of financial research has largely shifted from discovery to governance and robust implementation. Four structural gaps warrant particular attention:

In financial AI, the primary challenge in moving models from the research environment to live deployment lies not in raw predictive performance but in handling market non-stationarity — the persistent drift in data distributions that erodes model accuracy over time — and in building systems that remain auditable and compliant with evolving regulatory requirements.

In corporate valuation, the standard Discounted Cash Flow model is ill-suited to two categories of entity that now constitute a growing share of total market capitalisation: platform companies, whose value is substantially driven by network effects and data assets that free cash flow projections cannot capture; and DeFi protocols, for which conventional cash flow proxies are structurally inapplicable.

In sustainable finance, the aggregate relationship between FinTech adoption and improved ESG performance is broadly accepted in the literature, but the precise micro-level causal mechanism remains empirically underspecified — a gap that prevents policymakers from designing well-targeted interventions.

In behavioural finance, the role of digital platforms and social media in amplifying cognitive biases is well documented, but the evidence base on scalable, effective educational interventions capable of reducing these biases remains thin.

## 1.2 Selection Criteria: Rigour and Feasibility

The four tracks satisfy two equally important criteria. The first is academic rigour: every project responds to an explicitly documented gap in the technical literature, whether the need to manage concept drift in production AI systems or the absence of definitive causal evidence linking FinTech to ESG improvement. The second is practical feasibility: all methodologies depend on accessible, high-quality data and open-source tools — including the CRSP US Stock Databases, the Finnhub API,

Scikit-learn, and public DeFi metrics from DefiLlama — ensuring that each track can be completed within a standard academic PCL timeline.

## 2. Literature Review

### 2.1 The FinTech–ESG Nexus and Causal Mechanisms

Sustainable finance, in broad terms, seeks to direct capital toward activities that generate positive environmental and social outcomes. FinTech is widely recognised as a significant accelerator of this transition; its adoption within banking and financial services is partly driven by social forces reinforced by ESG considerations. However, a critical gap persists: existing scholarship has not produced sufficient micro-empirical evidence to pinpoint the precise mechanism by which FinTech development leads to improved corporate ESG outcomes.

The prevailing theoretical account posits a dual-channel model. In the internal channel, FinTech alleviates financing constraints within firms, freeing up capital for ESG-oriented investments that would otherwise be crowded out. In the external channel, FinTech enhances a firm's access to outside resources — including government subsidies and tax incentives tied to sustainable activity — by improving information transparency and lowering the cost of compliance reporting. Estimating the relative magnitude of these two effects is a prerequisite for designing effective sustainability policy.

A further dimension that emerges from the literature is the moderating influence of organisational agility. Evidence suggests that the ESG benefits of FinTech adoption are more pronounced in firms whose chief executives do not come from a traditional banking background, implying that institutional inertia meaningfully constrains FinTech-driven sustainability improvements.

### 2.2 AI/ML Deployment Challenges: Non-Stationarity and Governance

Artificial intelligence and machine learning models have demonstrated strong predictive capabilities across a wide range of financial applications, including credit scoring, algorithmic trading, fraud detection, and portfolio optimisation. Despite this, their integration into mainstream production environments confronts persistent and often underappreciated obstacles. The most significant is market non-stationarity: the statistical properties of financial data evolve continuously as market regimes shift, macroeconomic conditions change, and participant behaviour adapts. A model trained on historical data will progressively suffer from concept drift — its predictive accuracy declines as the real-world environment diverges from the one on which it was trained.

This problem demands robust frameworks for continuous performance monitoring, transparent and auditable retraining procedures, and automated rollback mechanisms capable of restoring a system to a known stable state when drift is detected. Regulatory developments add a further layer of complexity: financial authorities increasingly require real-time reporting and automated compliance verification for algorithmic trading and credit systems, meaning that governance architecture must be embedded in the model design from the outset rather than added retroactively.

### 2.3 Behavioural Biases, Digital Platforms, and Mitigation

Behavioural finance has established that investor decisions are systematically distorted by psychological biases including anchoring, loss aversion, overconfidence, and herding. The growth of digital trading platforms and social media has

substantially intensified these effects, enabling herding behaviour to propagate across geographies in near real-time and creating feedback loops between sentiment and price movements that amplify volatility, particularly in speculative markets.

This problem is compounded by persistently low levels of financial literacy among young adults. Secondary and tertiary students are frequently ill-equipped to navigate complex financial decisions, and the interactive, emotionally engaging design of modern investment platforms may heighten rather than reduce vulnerability to cognitive biases. The gap in this domain is twofold: existing research concentrates on measuring and cataloguing biases rather than testing the effectiveness of targeted educational interventions; and the specific contribution of social media sentiment to herding frequency has not been systematically quantified.

### 2.4 Valuation Shortfalls in the Digital Economy

Mainstream corporate valuation is anchored in the Discounted Cash Flow model, which treats firm value as a function of the present value of anticipated future free cash flows. While this framework is theoretically coherent for asset-intensive or stable-growth businesses, it is structurally inadequate for two categories of entity that now represent a growing share of the digital economy.

Platform companies — commonly referred to as 'unicorns' — command a statistically significant valuation premium relative to conventional-sector peers, estimated at approximately 129 percent in North America, which is attributable to network effects, multi-sided business models, and data assets that standard cash flow projections cannot incorporate. Data, in particular, functions as what the literature describes as an "endless resource": unlike physical capital, it does not depreciate through use, yet it lacks a standardised market value, creating methodological difficulties for DCF modelling.

DeFi protocols constitute an entirely distinct asset category for which conventional cash flow proxies are inappropriate. Valuing these instruments requires protocol-native metrics — Total Value Locked, verifiable protocol revenue, token inflation schedules, and governance token distributions. The collapse of the Terra-Luna ecosystem in 2022 offered a stark illustration of the systemic risks embedded in this asset class and highlighted the importance of rigorous analysis of contagion and spillover between digital asset markets and traditional financial markets.

## 3. Research Methodology

This study adopts a multi-methodological approach, drawing on econometric, computational, and quasi-experimental research designs. Each track's methodology is tailored to the specific nature of its research question and the characteristics of the data available.

### 3.1 Track I: FinTech–ESG Causal Analysis — Panel Data with Mediation and Moderation

Track I employs a panel data regression framework that incorporates both mediation and moderation analysis. The core specification uses either firm-level fixed effects or a Generalised Method of Moments estimator to address endogeneity and unobserved firm heterogeneity — a critical consideration given that ESG performance and FinTech adoption are likely co-determined by firm-specific characteristics that simultaneously drive both outcomes.

The key analytical requirement is a path analysis or three-way interaction specification capable of isolating and quantifying the two hypothesised causal channels: (1) the relaxation of internal financing constraints, measured through the Kaplan-Zingales index or the cash-flow sensitivity of investment; and (2) the improvement in access to external fiscal incentives,

captured through firm-level data on government subsidies and tax rebates received. The dependent variable is the firm's ESG rating; the primary explanatory variable is a regional FinTech adoption index; and the CEO's professional background — presence or absence of prior experience in traditional banking and finance — is included as a moderating variable.

### 3.2 Track II: AI/ML Non-Stationarity Management — Computational Simulation

Track II is designed as a computational modelling and comparative simulation study, implemented in Python using the Scikit-learn library. The study proceeds in three stages. In the first stage, a baseline predictive model is constructed — either a Random Forest or Logistic Regression classifier applied to credit risk classification using the German Credit Dataset, or a regression model for stock price prediction using high-frequency data from the Finnhub API or CRSP.

In the second stage, artificial non-stationarity is introduced by engineering abrupt shifts in the relative importance of input features or in the distributional parameters of the data-generating process, thereby simulating market regime changes in a controlled and reproducible manner. This approach surpasses conventional static backtesting by directly testing the model's resilience to the type of distributional shift it will encounter in a live deployment environment.

In the third stage, an Adaptive Learning and Tracking System (ALATS) is developed around the baseline model. This system incorporates a drift detection mechanism — such as the Drift Detection Method (DDM) or Adaptive Windowing (ADWIN) — to monitor performance metrics continuously and automatically trigger a transparent, auditable retraining or safe model rollback procedure whenever drift is detected. Governance outputs, including the completeness and reliability of the audit logs, are treated as primary outcomes alongside standard predictive performance metrics.

### 3.3 Track III: Behavioural Intervention Efficacy — Quasi-Experimental Design

Track III combines a quasi-experimental design with two complementary data streams. The first involves empirical market analysis: high-frequency trading data from CRSP or Finnhub is used to compute a Herding Index for a selection of speculative securities, while social media sentiment data sourced from publicly available APIs is processed and correlated with herding frequency and market volatility, with the objective of estimating the digital amplification coefficient of behavioural biases.

The second stream involves a pre-post educational intervention study conducted with student cohorts. A targeted PCL educational module is designed to address a specific, well-defined bias — loss aversion in the context of portfolio construction and retirement planning — drawing on evidence-based approaches from the financial literacy education literature. Student performance is evaluated before and after the intervention using a standardised rubric that assesses conceptual understanding of money management, quality of financial goal-setting, and decision quality in a simulated investment environment. Demographic and socioeconomic controls sourced from U.S. Census Bureau and NASSGAP surveys allow for analysis of heterogeneous treatment effects across student subgroups.

### 3.4 Track IV: Advanced Valuation — Comparative Financial Modelling and Event Study

Track IV combines comparative financial modelling with an econometric event study. The valuation component develops a Data-Adjusted DCF (DA-DCF) framework as a direct extension of the standard DCF model. The conventional DCF foundation — projecting unlevered free cash flow, computing the Weighted Average Cost of Capital, and determining a terminal value — is retained, with two targeted adjustments. For platform companies, platform-specific valuation multipliers derived from documented regional network-effect premiums are incorporated into either the WACC or the terminal value.

For DeFi protocols, the free cash flow input is replaced with a function of TVL and verifiable protocol revenue, adjusted for the token's inflation factor.

Both the standard DCF and the DA-DCF are then applied to a case study set comprising unicorn platform firms and major DeFi protocols, and the resulting valuations are compared against observed market values to assess each framework's explanatory power. The systemic risk component consists of an econometric event study centred on the Terra-Luna collapse of May 2022, treated as a natural experiment, using time-series analysis of CRSP data to quantify conditional volatility spillover between major DeFi indices and the S&P 500.

## 4. Analysis and Findings (Anticipated Outcomes)

As this report constitutes a research proposal rather than a completed empirical investigation, the following section outlines the anticipated analytical process and the expected outcomes derived from the theoretical frameworks and empirical precedents reviewed in the literature. These projections serve as falsifiable hypotheses for the execution phase of each PCL track.

### 4.1 Anticipated Findings: Track I — FinTech–ESG

The panel data and GMM analysis is expected to produce statistically significant coefficients for both causal channels, with the internal financing constraint pathway anticipated to exhibit the larger effect magnitude — a result consistent with findings reported in the environmental finance literature (Cheng et al., 2022). The three-way interaction term incorporating FinTech development, ESG performance, and CEO professional background is expected to be statistically significant, indicating that the strongest ESG improvements occur in firms led by executives without a conventional banking background, thereby quantifying the organisational agility premium in FinTech-enabled sustainability transitions.

### 4.2 Anticipated Findings: Track II — AI/ML Non-Stationarity

The comparative simulation is expected to demonstrate that the ALATS framework substantially outperforms the static baseline model on operational safety metrics under conditions of simulated non-stationarity. Specifically, ALATS is projected to deliver a higher Sharpe ratio and a materially lower maximum drawdown during simulated regime change episodes. The system's governance outputs — drift detection timestamps, retraining triggers, and model rollback logs — are expected to confirm that the framework satisfies the transparency and auditability standards associated with real-time regulatory reporting requirements.

### 4.3 Anticipated Findings: Track III — Behavioural Intervention

The market analysis component is expected to reveal a positive and statistically significant association between elevated social media sentiment volatility and higher calculated herding indices, particularly in speculative technology and cryptocurrency-adjacent securities, providing an empirical estimate of the digital amplification of cognitive biases. The quasi-experimental study is expected to show that students who receive targeted financial literacy education — specifically addressing loss aversion — exhibit measurably better outcomes in simulated financial decision tasks, including higher portfolio diversification scores and less risk-averse retirement planning choices, relative to the control group.

### 4.4 Anticipated Findings: Track IV — Advanced Valuation

The standard free cash flow DCF is expected to systematically undervalue platform companies relative to their observed market prices, producing a statistically significant negative valuation residual. Incorporating platform-specific network-effect multipliers through the DA-DCF framework is expected to substantially reduce this residual, suggesting meaningfully improved explanatory power. For DeFi protocols, using TVL and protocol revenue as cash flow proxies is expected to yield more stable and interpretable valuation multiples than conventional financial metrics. The Terra-Luna event study is expected to reveal a statistically significant, if time-bounded, conditional volatility spillover from DeFi markets to the S&P 500, providing empirical grounding for ongoing systemic risk policy discussions.

## 5. Discussion

### 5.1 Governance Frameworks and Financial Decision-Making

The technical findings of the four tracks must be situated within a broader context of financial governance and regulatory oversight. Financial markets operate across multiple jurisdictions, and repeated episodes of market stress have underscored the inadequacy of purely domestic regulatory frameworks. Information gaps that emerge during periods of volatility complicate the work of regulators and can amplify systemic risk — a consideration that elevates the governance capabilities developed in Track II from a technical feature to a regulatory necessity.

In corporate finance, any rigorous treatment of capital structure and acquisition activity must account for the agency conflicts arising from concentrated ownership. The academic literature documents a negative relationship between a firm's largest shareholder's voting stake and both its propensity to take on debt and its likelihood of pursuing acquisitions. This aversion to external equity financing — particularly pronounced in intermediate ownership structures — represents a binding constraint on corporate strategy that must be incorporated into any PCL-level valuation or capital structure analysis.

### 5.2 Regulatory Context and Valuation Implications

Research tracks involving cross-border investment or globally operating entities — including Track IV's valuation of multinational platform firms and DeFi protocols — must explicitly incorporate national security and geopolitical risk considerations. Policy trends in recent years reflect an intensifying focus on limiting access to capital and strategic technology, including proposals to extend investment screening authority and tighten outbound investment restrictions across AI, quantum computing, and advanced semiconductor sectors.

These constraints carry material implications for the DA-DCF framework developed in Track IV. Compliance with complex regulatory regimes — export controls, sanctions, and investment restrictions — introduces costs and market access limitations that must be reflected in either the discount rate or the free cash flow projections used in the valuation model. A DA-DCF model that fails to incorporate geopolitical risk premiums will systematically overestimate the fair value of firms with significant exposure to restricted jurisdictions or technology export controls.

### 5.3 Synthesis: The Interconnections Across the Four Tracks

While the four research tracks are presented as distinct projects, they share a common underlying theme: the imperative to adapt financial theory, methodology, and practice to a world that is simultaneously more digitalised, more technologically volatile, and more susceptible to behavioural amplification than at any prior point in financial history.

The interconnections are substantive rather than merely thematic. The AI governance infrastructure developed in Track II provides the secure and compliant technological foundation on which FinTech-enabled ESG initiatives of the kind explored in Track I can be scaled with confidence. Accurate valuation of platform companies in Track IV requires explicit engagement with the same data-as-asset and network-effect dynamics that shape the information environment studied in Track III. And all four tracks demand fluency in advanced computational tools — Python, Scikit-learn, Pandas — that have become standard requirements for professional roles across financial analysis, risk management, and investment banking.

## 6. Conclusion and Recommendations

The four research tracks described in this paper collectively offer high-impact, rigorous opportunities for PCL students to engage with some of the most urgent open problems in contemporary finance. Each track responds to a documented gap in the empirical literature, is organised around a methodologically sound research protocol, and is constrained to data sources and tools accessible within a standard academic timeline. The thematic coherence across the four tracks — FinTech and sustainability, AI governance, behavioural finance in digital contexts, and digital asset valuation — reflects the integrated character of the challenges now confronting financial practitioners and regulators alike.

### 6.1 Assessment Criteria and Deliverables

Evaluation of research tracks of this complexity must extend well beyond the production of a written report. Methodological rigour and the quality of practical outputs must carry equal weight. Across all tracks, core deliverables should include a detailed and reproducible methodology section, a comprehensive data dictionary and citation log, and a thorough sensitivity analysis of the key assumptions underlying the models. For computational tracks such as Track II, the emphasis should be placed on demonstrating governance capabilities — specifically auditable records of continuous learning cycles, drift detection events, and model rollback actions — rather than on raw predictive accuracy alone. For valuation tracks such as Track IV, fully documented financial models that can be independently interrogated and verified are essential.

### 6.2 Implementation Recommendations

Based on the literature reviewed and the methodological analysis presented, the following recommendations are offered for the implementation phase of the PCL projects:

- Embed AI Governance from the Outset (Track II): All computational models should incorporate mandatory governance features as a core architectural element from the beginning, including A/B testing protocols, automated compliance checks, and real-time performance dashboards. These are not post-deployment enhancements but foundational design requirements.
- Contextualise Behavioural Interventions by Demographic Profile (Track III): Financial literacy modules should draw on documented socioeconomic heterogeneity — including gender-based differences in financial decision-making patterns among young adults — to maximise the precision and effectiveness of targeted bias-reduction interventions.
- Secure Institutional Data Access Early (Tracks II and IV): The longitudinal and high-frequency data requirements of Tracks II and IV necessitate institutional-level access to the CRSP US Stock Databases. This should be arranged at the outset of the project lifecycle to avoid downstream delays.
- Adopt Updated Valuation Paradigms Systematically (Track IV): The DA-DCF framework developed in this track should be positioned not as an ad hoc refinement of standard DCF methodology but as a systematic update to the finance curriculum, reflecting the growing proportion of total market capitalisation attributable to platform and digital asset companies.

## 7. Future Research Directions

Successful completion of the four PCL tracks will establish robust empirical and computational foundations for a second generation of research inquiries, several of which carry direct potential for publication in peer-reviewed finance and information systems journals.

The ALATS governance framework developed in Track II can serve as a springboard for investigating the deployment characteristics of large-scale multimodal Foundation Models in finance — models that integrate language and vision capabilities for financial analysis tasks and represent an emerging frontier in financial AI research. The governance challenges associated with these models are considerably more complex than those of conventional supervised learning systems, and ALATS provides a natural starting point for their systematic study.

The systemic risk analysis in Track IV can be extended beyond the Terra-Luna episode to construct a generalisable, policy-relevant risk framework for the broader digital asset ecosystem, identifying the threshold conditions under which DeFi-originated volatility poses a material threat to the stability of traditional financial markets — directly addressing the most significant unresolved empirical question in the DeFi literature.

The finding regarding the moderating role of CEO professional background in Track I opens a natural avenue for future corporate governance research: specifically, which organisational change strategies — leadership development programmes, board composition reforms, or institutional redesign — most effectively reduce the inertia that limits firms' ability to harness FinTech as a driver of sustainability improvement?

## Appendix A: Recommended Data Sources and Analytical Tools

| Data Category | Recommended Sources | Research Application | Track(s) |
|---|---|---|---|
| Historical Equity Data | CRSP US Stock Databases | Stock returns, long-run backtesting, corporate events | II, IV |
| Live Market / API Data | Finnhub API, Kaggle Datasets | Credit risk modelling, real-time price feeds, trading backtests | II |
| ESG & FinTech Indices | Frontiers, IDEAS/RePEc, Refinitiv Eikon | FinTech adoption scores, firm ESG ratings, Kaplan-Zingales financing index | I |
| Socioeconomic Data | U.S. Census Bureau, NASSGAP Surveys | Student demographics, income heterogeneity, financial literacy controls | III |
| Corporate Financials | SEC EDGAR, Bloomberg | DCF inputs, WACC computation, platform valuation | IV |
| DeFi & Platform Metrics | DefiLlama, CoinGecko, Unicorn Databases | TVL, protocol revenue, token inflation schedules, network-effect premiums | IV |
| Analytical Toolkits | Python (Scikit-learn, Pandas, Streamlit) | ML training, drift detection, statistical testing, interactive dashboards | II, III |

## Appendix B: PCL Assessment Rubric

| Assessment Area | Criteria for Excellent Performance |
|---|---|
| Money Management Proficiency | The student articulates a thorough grasp of core money management principles and clearly explains how each principle applies to a specified financial objective. |
| Financial Goal Setting | Goals are precisely worded, grammatically sound, and include at least one measurable near-term target and one measurable long-range objective. |
| Empirical Task Completion | All required empirical tasks (e.g., deploying an ML classifier on a public dataset; applying DA-DCF to a case company) are completed with thorough, accurate documentation. |
| Methodological Rigour | The methodology is fully reproducible; a complete data dictionary is provided; every assumption is stated explicitly and subjected to sensitivity analysis. |
| Model Governance (Track II) | The ALATS framework holds up under simulated stress conditions; audit logs document all drift detection events and reversion actions with timestamps; governance outputs meet stated regulatory criteria. |
| Valuation Accuracy (Track IV) | The DA-DCF model correctly integrates platform premiums and/or DeFi-native metrics; residual analysis is conducted; comparison with both the standard DCF and observed market valuations is rigorous. |

## References


- Cheng, M., Qu, Y., Jiang, H., & Qiu, C. (2022). Can FinTech improve corporate environmental, social, and governance performance? A study based on the dual path of internal financing constraints and external fiscal incentives. Frontiers in Environmental Science. https://doi.org/10.3389/fenvs.2022.1061454
- Chen, W., et al. (2024). A Survey of Financial AI: Architectures, Advances and Open Challenges. arXiv preprint arXiv:2411.12747.
- Jansen, S. (2020). Hands-On Machine Learning for Algorithmic Trading. Packt Publishing.
- Yilmaz, M. K., et al. (2022). Decentralized Finance (DeFi) Projects: A Study of Key Performance Indicators in Terms of DeFi Protocols' Valuations. International Journal of Financial Studies, 10(4), 108. https://doi.org/10.3390/ijfs10040108
- Martins, F., et al. (2024). Risks of Decentralized Finance and their potential negative effects on capital markets: the Terra-Luna case. Studies in Economics and Finance. https://doi.org/10.1108/SEF-02-2024-0075
- Kamar, A., et al. (2023). Is There a 'Platform Premium'? An Exploratory Study of Unicorn Business Models and Valuations. Platform Strategy Research Symposium, Boston University.
- Damodaran, A. (2023). DCF Model Training Free Guide. Corporate Finance Institute. https://corporatefinanceinstitute.com/resources/financial-modeling/dcf-model-training-free-guide/
- CRSP (2025). CRSP US Stock Databases. Center for Research in Security Prices. https://www.crsp.org/research/crsp-us-stock-databases/
- Federal Reserve Bank of Atlanta (2015). Project-Based Learning for the Personal Finance Classroom. Federal Reserve Bank of Atlanta Education Publications.
- Finnhub (2025). Finnhub Stock APIs. https://finnhub.io/
- Intuit (2025). Financial Literacy in High School: Survey and Statistics. Intuit Blog. https://www.intuit.com/blog/innovative-thinking/intuit-survey/

- IOSCO (2008). Principles Regarding Cross-Border Supervisory Cooperation. International Organisation of Securities Commissions.
- Morgan Lewis (2025). In the Know: Private Equity and Cross-Border Investment Challenges. https://www.morganlewis.com/pubs/2025/10/in-the-know-private-equity-and-cross-border-investment-challenges
- Personal Finance Lab (2025). Grading Rubrics. https://www.personalfinancelab.com/grading-rubrics/
- ProjectPro (2025). 15 Projects on Machine Learning Applications in Finance. https://www.projectpro.io/article/projects-on-machine-learning-applications-in-finance/510
- Raza, M., & Ali, T. (2024). Redefining Finance: The Influence of Artificial Intelligence (AI) and Machine Learning (ML). arXiv preprint arXiv:2410.15951.
- RCampus (2025). iRubric: Financial Plan-Project Rubric VA3C2B. https://www.rcampus.com/rubricshowc.cfm?sp=yes&code=VA3C2B