The document you’ve uploaded—**"Explainable AI for Financial Risk Management"** from the Financial Regulation Innovation Lab (FRIL, 2024)—is a **highly relevant and authoritative source** for your capstone literature review. Here's a summary of key insights and whether you should read it yourself:

**🔑 Key Insights & Takeaways**

**1. Why XAI Matters in Financial Risk Management**

* AI is increasingly vital for managing credit, market, liquidity, and operational risks.
* However, **deep learning models prioritise performance over explainability**, causing a trade-off dilemma.
* Lack of explainability:
  + Reduces trust and adoption of AI in finance.
  + Hinders regulatory compliance.
  + Poses systemic risks (highlighted by OECD, 2021).

**2. Regulatory Drivers (UK & EU)**

* **EU AI Act** (2024) mandates transparency and explainability.
* **UK's pro-innovation AI regulatory framework** similarly demands explainability for decision outcomes, data usage, and model accuracy.
* These regulatory pushes make XAI not just a technical but a **compliance necessity**.

**3. Literature Review Highlights**

* XAI methods bridge the gap between black-box AI models and human interpretability.
* Techniques like **SHAP values**, **partial dependence plots**, **LIME**, and **Lorenz zonoids** are commonly applied.
* XAI enhances **trustworthiness**, **fairness**, and **credibility** of financial AI systems.
* Trade-off between accuracy and explainability persists, requiring balanced model design (Miller, 2019; Ali et al., 2023).

**4. Use Cases in Financial Risk**

* Credit default and bankruptcy prediction (e.g., SHAP-enhanced XGBoost models).
* Fraud detection with transparent decision-making.
* ESG risk management for regulatory compliance and stakeholder transparency.
* Applications extend to asset pricing, portfolio optimisation, and bias mitigation in lending.

**5. Solution Framework Proposed**

* Corporate Strategy: Embedding explainability in AI adoption strategies.
* Model Governance: Defining roles, processes, and oversight.
* Technical XAI Methods: Model-specific (e.g., attention mechanisms) and model-agnostic approaches (e.g., SHAP, LIME).
* Evaluation of Explanations: Measuring interpretability, user trust, and actionable insights.

**6. Use Case Demonstration**

* Case study on **AI-based credit default prediction**.
* Practical demonstration of how XAI provides transparency while retaining predictive power.

**📚 Should You Read This in Full?**

**Yes, you should read this yourself.**

Why:

* It's tailored to the **UK financial regulatory context**, directly relevant to your capstone.
* Combines academic rigour with practical, industry-focused applications.
* The **solution framework** could be mirrored or adapted for your own AI-powered risk profiling work.
* The paper aligns well with your focus on explainability, governance, and compliance in financial AI systems.

Would you like me to draft how this document should be cited and summarised in your literature review section (academic format, Harvard style)? Reply "Yes, please Harvard cite and summarise".

**You said:**

Yes

**ChatGPT said:**

Here’s how you can summarise and cite the **FRIL (2024)** paper in your literature review using **Harvard referencing style**, tailored to your capstone context.

**📄 Literature Review Entry**

**Explainable AI (XAI) in Financial Risk Management**

Bowden et al. (2024) explore the imperative of Explainable Artificial Intelligence (XAI) in enhancing financial risk management practices, emphasising its dual role in improving decision transparency and regulatory compliance. The authors highlight the inherent trade-off between model accuracy and explainability, noting that while advanced models like deep learning offer superior predictive performance, they often lack interpretability, limiting their adoption in highly regulated sectors such as finance.

The paper provides a comprehensive review of XAI applications in financial services, including credit default prediction, fraud detection, and ESG risk management. Techniques such as SHAP values, partial dependence plots, and Lorenz zonoids are identified as critical tools for rendering opaque AI models interpretable to stakeholders and regulators alike. The study underscores the increasing regulatory demands for explainability, referencing the EU AI Act and the UK's pro-innovation regulatory framework, both of which mandate transparency in AI-driven decision-making.

A structured solution framework is proposed, outlining organisational considerations across corporate strategy, model governance, technical methodologies, and the evaluation of explanations. A use case demonstration on AI-based credit risk management exemplifies how XAI can bridge the gap between predictive accuracy and interpretability, aligning with financial theory and regulatory expectations.

Given the convergence of technical, business, and compliance considerations, Bowden et al. (2024) advocate for the strategic integration of XAI within financial institutions' risk management practices. This aligns with the objectives of this capstone project, where explainable AI will be pivotal in developing transparent, compliant, and client-centric risk profiling tools.

**📚 Harvard Reference**

Bowden, J., Cummins, M., Dao, D. & Jain, K. (2024) *Explainable AI for Financial Risk Management*. Financial Regulation Innovation Lab (FRIL) White Paper Series. University of Strathclyde. DOI: <https://doi.org/10.17868/strath.00089573>.

Would you like me to draft a **combined literature review table** as you add more papers (with columns for "Source", "Key Insights", "Methods", "Relevance to Capstone")?  
Reply **"Yes, literature review table please"** if you'd like that.

**You said:**

Yes

**ChatGPT said:**

Updated saved memory

Great! I’ll maintain a structured **Literature Review Table** for your capstone project. Here’s the first entry based on the FRIL (2024) paper you uploaded:

**📊 Literature Review Table (Capstone Project)**

| **Source** | **Key Insights** | **Methods** | **Relevance to Capstone** |
| --- | --- | --- | --- |
| Bowden, J., Cummins, M., Dao, D. & Jain, K. (2024) *Explainable AI for Financial Risk Management*. FRIL White Paper Series. DOI: <https://doi.org/10.17868/strath.00089573>. | - XAI essential for balancing accuracy & interpretability in financial risk management. - Regulatory drivers (EU AI Act, UK frameworks) mandate explainability. - SHAP, PDP, Lorenz zonoids key for transparency. - Use case on credit default prediction illustrates practical XAI integration. - Solution framework covering corporate strategy, governance, methods & evaluation. | Literature review of XAI in finance, synthesis of regulatory context, proposes solution framework, applied credit risk use case. | Directly applicable to your capstone's focus on explainable client risk profiling and FCA compliance. Offers structure for solution design & governance. |

As you add more documents, I’ll continue expanding this table.

Whenever you upload a new file, simply say “add to literature review” and I’ll update this table for you.

Would you also like a **one-page visual summary slide** (e.g., for presentations) that maps these literature review findings to your capstone objectives?  
Reply **"Yes, visual summary slide please"** if so.

**You said:**

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PDF

Next one to review and then add to the table

**ChatGPT said:**

Here’s the analysis and addition to your literature review table for the uploaded paper:

**📄 Literature Review Entry**

**Comprehensive Review on Financial Explainable AI (FinXAI)**

Yeo et al. (2025) present an extensive survey of Explainable AI (XAI) methodologies tailored specifically for financial applications, coining the term **FinXAI**. They argue that while general XAI literature exists, finance-specific requirements—such as regulatory scrutiny, stakeholder-specific transparency, and the ethical imperative of fairness—demand domain-centric approaches.

Key contributions include:

* **A novel categorisation framework for FinXAI**, mapping methods by explanation type (factual, counterfactual), proximity (local, global), data type (numerical, textual, hybrid), and audience (end-user, developer, regulator).
* **Comprehensive review of XAI methods**: SHAP, LIME, PDP, ICE, ALE, attention mechanisms, knowledge graphs, counterfactuals, and interpretable models (e.g., NAMs, PLTR).
* **Discussion of ethical goals**: trustworthiness, fairness, informativeness, accessibility, privacy, confidence, causality, and transferability.
* **Identification of challenges**: Over-reliance on misleading explanations, lack of standardised evaluation metrics, trade-offs between interpretability and performance, and the need for human-centric and multimodal XAI solutions.
* Emphasis on **audience-centric explanation design**—a crucial insight for regulatory compliance and client communication in finance.

The paper also proposes future research directions, including leveraging neural-symbolic AI for transferability and enhancing inherently transparent models for practical financial applications.

**📚 Harvard Reference**

Yeo, W.J., Van Der Heever, W., Mao, R., Cambria, E., Satapathy, R. & Mengaldo, G. (2025) 'A comprehensive review on financial explainable AI', *Artificial Intelligence Review*, 58(189). <https://doi.org/10.1007/s10462-024-11077-7>.

**📊 Literature Review Table (Updated)**

| **Source** | **Key Insights** | **Methods** | **Relevance to Capstone** |
| --- | --- | --- | --- |
| Bowden, J., Cummins, M., Dao, D. & Jain, K. (2024) *Explainable AI for Financial Risk Management*. FRIL White Paper Series. DOI: <https://doi.org/10.17868/strath.00089573>. | XAI essential for balancing accuracy & interpretability in financial risk management. Regulatory drivers (EU AI Act, UK frameworks) mandate explainability. SHAP, PDP, Lorenz zonoids key for transparency. Use case on credit default prediction illustrates practical XAI integration. Solution framework covering corporate strategy, governance, methods & evaluation. | Literature review of XAI in finance, synthesis of regulatory context, proposes solution framework, applied credit risk use case. | Directly applicable to your capstone's focus on explainable client risk profiling and FCA compliance. Offers structure for solution design & governance. |
| Yeo, W.J., Van Der Heever, W., Mao, R., Cambria, E., Satapathy, R. & Mengaldo, G. (2025) 'A comprehensive review on financial explainable AI', *Artificial Intelligence Review*, 58(189). <https://doi.org/10.1007/s10462-024-11077-7>. | Proposes FinXAI framework aligning explanation type, proximity, audience, data. Comprehensive survey of SHAP, LIME, PDP, ICE, ALE, attention, counterfactuals. Maps FinXAI to ethical goals (trust, fairness, accessibility, causality). Highlights challenges in evaluation, performance vs interpretability trade-offs, privacy concerns. Future work emphasises human-centric XAI, neural-symbolic methods. | Structured review of 100+ FinXAI papers. Proposes audience-centric explanation design. Links XAI methods to regulatory and ethical objectives. Critically examines trade-offs and challenges specific to finance. | Highly relevant for your capstone’s focus on explainability tailored for financial advisors and regulators. Framework provides a blueprint for aligning methods to stakeholder needs. |

Would you like me to prepare that **one-page visual summary slide** mapping these two papers to your capstone objectives next?  
Reply **"Yes, visual slide please"** if you'd like it.

**You said:**

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PDF

 Another

**ChatGPT said:**

Here’s the analysis and addition to your literature review table for the uploaded paper:

**📄 Literature Review Entry**

**The Role of Complexity in Human-AI Engagement in the Financial Industry**

Manser Payne and O’Brien (2024) investigate how consumers perceive AI-enabled virtual agents in banking, focusing on the **role of task complexity and social presence in human-AI engagement**. The study introduces an **exploratory framework** that decouples **basic (transactional)** and **advanced (problem-solving)** virtual agent usage contexts.

Key findings include:

* **Trust in AI** is the primary driver for basic, routine interactions (e.g., checking balances).
* **Perceived security and AI expertise** significantly influence advanced usage intentions (e.g., financial advice, debt consolidation).
* **Social presence** becomes critical only in advanced contexts, where human-like interaction and empathy are valued.
* **Comfort with AI** influences both basic and advanced usage intentions.

The paper builds upon the **Service Robot Acceptance Model (sRAM)** and **Digital Servitization** concepts, offering empirical evidence that financial AI services cannot adopt a “one-size-fits-all” design. The results emphasise that user expectations differ based on task complexity, necessitating tailored AI capabilities for transactional versus advisory functions.

**📚 Harvard Reference**

Manser Payne, E.H. & O’Brien, C.A. (2024) 'The search for AI value: The role of complexity in human-AI engagement in the financial industry', *Computers in Human Behavior: Artificial Humans*, 2, 100050. <https://doi.org/10.1016/j.chbah.2024.100050>.

**📊 Literature Review Table (Updated)**

| **Source** | **Key Insights** | **Methods** | **Relevance to Capstone** |
| --- | --- | --- | --- |
| Bowden et al. (2024) | XAI essential for balancing accuracy & interpretability in financial risk management. Regulatory drivers (EU AI Act, UK frameworks) mandate explainability. SHAP, PDP, Lorenz zonoids key for transparency. Solution framework proposed. | Literature review, regulatory synthesis, credit risk use case. | Framework applicable for explainable client risk profiling & governance. |
| Yeo et al. (2025) | FinXAI framework aligning methods by explanation type, proximity, audience. Ethical goals: trust, fairness, accessibility. Addresses evaluation challenges and trade-offs. | Structured review of 100+ papers, audience-centric design framework. | Blueprint for aligning XAI methods to adviser & regulator needs. |
| Manser Payne & O’Brien (2024) | Virtual agent usage varies by task complexity. Trust drives basic usage; security & expertise key for advanced. Social presence critical in advanced advisory contexts. Comfort affects all usage. | Survey of 322 respondents, multivariate regression, sRAM & Digital Servitization frameworks. | Highlights importance of tailoring explainability & UX design for complex risk profiling tasks in client-facing AI tools. |

Would you like me to now generate the **visual literature review slide** summarising how these sources support your capstone project?  
Reply **"Yes, visual slide please"** if you'd like it.

**You said:**

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Another

**ChatGPT said:**

Here’s the analysis and addition to your literature review table for the uploaded paper:

**📄 Literature Review Entry**

**Applications of AI and ML in Financial Services: A Bibliometric Review**

Pattnaik, Ray, and Raman (2024) provide a **comprehensive bibliometric analysis** of AI and ML applications in the Banking, Financial Services, and Insurance (BFSI) sector. The study systematically reviewed **1,045 Scopus-indexed articles** following PRISMA protocols, conducting N-gram and co-occurrence analyses to identify research clusters and trends.

Key insights include:

* Identification of **nine research clusters** covering fintech, risk management, anti-money laundering (AML), actuarial science, digital transformation, cybersecurity, and explainable AI (XAI).
* Highlighted emerging topics: risk classification, scenario analysis, digital finance post-COVID, financial literacy, and ethical AI.
* Emphasises a **shift from purely technical AI/ML studies to human-centric applications**, including client trust, social presence, and regulatory compliance.
* Suggests growing academic focus on **explainability, ethical considerations, and stakeholder-specific AI applications** in BFSI.
* Reinforces the need for multi-disciplinary research combining AI/ML with behavioural finance, governance, and financial inclusion strategies.

This study serves as a **state-of-the-art mapping of AI/ML in BFSI**, providing an empirical foundation for identifying research gaps and guiding future work, especially in regulated environments.

**📚 Harvard Reference**

Pattnaik, D., Ray, S. & Raman, R. (2024) 'Applications of artificial intelligence and machine learning in the financial services industry: A bibliometric review', *Heliyon*, 10, e23492. <https://doi.org/10.1016/j.heliyon.2023.e23492>.

**📊 Literature Review Table (Updated)**

| **Source** | **Key Insights** | **Methods** | **Relevance to Capstone** |
| --- | --- | --- | --- |
| Bowden et al. (2024) | XAI essential for balancing accuracy & interpretability. Regulatory drivers mandate explainability. Proposes governance framework & applied credit risk case study. | Literature review, regulatory synthesis, use case analysis. | Framework applicable to explainable risk profiling & FCA compliance. |
| Yeo et al. (2025) | FinXAI framework aligns methods by explanation type, audience, data. Maps XAI to trust, fairness, accessibility. Critical of trade-offs and evaluation challenges. | Structured review of 100+ papers, audience-centric framework. | Blueprint for aligning XAI to adviser and regulator needs. |
| Manser Payne & O’Brien (2024) | Human-AI engagement varies by task complexity. Trust drives basic use; security & expertise key for advanced. Social presence essential in advisory contexts. | Survey (n=322), multivariate regression, sRAM & Digital Servitization theories. | Reinforces the need for explainable & empathetic AI in client-facing risk tools. |
| Pattnaik et al. (2024) | Bibliometric review maps 9 key research clusters in AI/ML-BFSI. Emerging focus on explainability, ethical AI, digital finance post-COVID. Identifies human-centric applications as future research priority. | PRISMA-based bibliometric analysis, N-gram & co-occurrence network mapping. | Provides a comprehensive state-of-the-art overview, highlighting XAI & stakeholder-focused AI design as critical for your capstone's compliance and client usability goals. |

Would you now like me to generate the **visual literature review slide** mapping these sources to your capstone project objectives?  
Reply **"Yes, visual slide please"** if you'd like that.

**You said:**

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Another

**ChatGPT said:**

Here’s the analysis and addition to your literature review table for the uploaded paper:

**📄 Literature Review Entry**

**Foundations and Themes of AI and ML in Finance: A Bibliometric Perspective**

Goodell et al. (2021) conduct a **holistic bibliometric analysis** of AI and ML research in finance, addressing a gap in comprehensive retrospection. Analysing **283 Scopus-indexed articles (1986–2021)**, they apply co-citation, bibliographic coupling, and co-occurrence analyses to map the thematic evolution and intellectual foundations of AI/ML in finance.

Key contributions:

* **Three overarching research clusters** identified:
  1. **Portfolio construction, valuation, and investor behaviour**.
  2. **Financial fraud and distress**.
  3. **Sentiment inference, forecasting, and planning**.
* Emphasises AI/ML applications in **text mining, fraud detection, risk management, and asset pricing**.
* Highlights **methodological convergence**: supervised ML dominates predictive modelling, NLP is prevalent in sentiment analysis, and deep learning is gaining traction for complex financial tasks.
* Identifies **future research directions**: asset pricing models leveraging ML, AI's role in FinTech innovations, and evolving fraud detection methods.

The paper provides a **methodologically robust overview**, offering clarity on thematic structures and research trajectories, while advocating for multi-disciplinary approaches in AI/ML-driven finance research.

**📚 Harvard Reference**

Goodell, J.W., Kumar, S., Lim, W.M. & Pattnaik, D. (2021) 'Artificial intelligence and machine learning in finance: Identifying foundations, themes, and research clusters from bibliometric analysis', *Journal of Behavioral and Experimental Finance*, 32, 100577. <https://doi.org/10.1016/j.jbef.2021.100577>.

**📊 Literature Review Table (Updated)**

| **Source** | **Key Insights** | **Methods** | **Relevance to Capstone** |
| --- | --- | --- | --- |
| Bowden et al. (2024) | XAI essential for balancing accuracy & interpretability. Regulatory drivers mandate explainability. Proposes governance framework & applied credit risk case study. | Literature review, regulatory synthesis, use case analysis. | Framework applicable to explainable risk profiling & FCA compliance. |
| Yeo et al. (2025) | FinXAI framework aligns methods by explanation type, audience, data. Maps XAI to trust, fairness, accessibility. Critical of trade-offs and evaluation challenges. | Structured review of 100+ papers, audience-centric framework. | Blueprint for aligning XAI to adviser and regulator needs. |
| Manser Payne & O’Brien (2024) | Human-AI engagement varies by task complexity. Trust drives basic use; security & expertise key for advanced. Social presence essential in advisory contexts. | Survey (n=322), multivariate regression, sRAM & Digital Servitization theories. | Reinforces the need for explainable & empathetic AI in client-facing risk tools. |
| Pattnaik et al. (2024) | Bibliometric review maps 9 key research clusters in AI/ML-BFSI. Emerging focus on explainability, ethical AI, digital finance post-COVID. Identifies human-centric applications as future research priority. | PRISMA-based bibliometric analysis, N-gram & co-occurrence network mapping. | Comprehensive state-of-the-art overview supporting XAI & stakeholder-centric design. |
| Goodell et al. (2021) | Maps AI/ML in finance into 3 clusters: asset pricing & investor behaviour, fraud & distress, sentiment & forecasting. Highlights dominance of supervised ML & NLP in finance applications. Advocates AI/ML-empowered FinTech innovations and advanced fraud detection. | Bibliometric analysis (co-citation, coupling, co-occurrence), trend mapping. | Reinforces capstone’s focus on transparent, client-friendly AI applications, especially for fraud risk assessment and investment planning. |

Would you like me to now generate the **visual literature review slide summarising all these sources in relation to your capstone objectives**?  
Reply **"Yes, visual slide please"** if you'd like that.

**You said:**

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PDF

Another one. Can you add a column to the table too to say whether I should read it or not / rank its importance to my capstone

**ChatGPT said:**

Here’s the analysis and updated literature review table, now with an importance/recommendation column:

**📄 Literature Review Entry**

**Risk Assessment for Personalised Health Insurance Based on Real-World Data**

Pnevmatikakis et al. (2021) propose a **dynamic risk assessment system for personalised health insurance**, leveraging real-world data (RWD) and explainable AI (XAI). Unlike traditional static assessments, the authors advocate continuous monitoring of behavioural data (activity, sleep, nutrition, mood) via digital platforms like Healthentia.

Key insights:

* Developed classifiers (random forests, neural networks) to predict variations in well-being indicators, focusing on short-term dynamics.
* Demonstrated SHAP analysis for both **population-level and individual-level feature importance**, enabling personalised coaching based on lifestyle impacts.
* Proposed a risk grading system based on long-term classifier outputs, simulating realistic client profiles (athletic, balanced, gamer).
* Emphasised **virtual coaching as a client-facing application of XAI**, providing actionable advice to policyholders.
* Pilot project (INFINITECH H2020) illustrates real-world implementation challenges, including user consent and data usability.

**📚 Harvard Reference**

Pnevmatikakis, A., Kanavos, S., Matikas, G., Kostopoulou, K., Cesario, A. & Kyriazakos, S. (2021) 'Risk assessment for personalised health insurance based on real-world data', *Risks*, 9(3), 46. <https://doi.org/10.3390/risks9030046>.

**📊 Literature Review Table (Updated)**

| **Source** | **Key Insights** | **Methods** | **Relevance to Capstone** | **Importance/Recommendation** |
| --- | --- | --- | --- | --- |
| Bowden et al. (2024) | XAI for balancing accuracy & interpretability in financial risk management. Regulatory drivers mandate explainability. Solution framework proposed. | Literature review, regulatory synthesis, use case. | Framework for explainable risk profiling & FCA compliance. | **High** – Must read for governance and compliance context. |
| Yeo et al. (2025) | FinXAI framework aligns methods by explanation type, audience, data. Addresses trade-offs and evaluation challenges. | Structured review of 100+ papers. | Blueprint for aligning XAI to adviser & regulator needs. | **High** – Read for method selection & audience focus. |
| Manser Payne & O’Brien (2024) | Human-AI engagement varies by task complexity. Trust & social presence crucial for advisory contexts. | Survey (n=322), regression, sRAM theory. | Relevant for UX design of risk profiling tool. | **Medium** – Skim key sections for UI/UX insights. |
| Pattnaik et al. (2024) | Bibliometric mapping of AI/ML in BFSI. Highlights rise of explainability & ethical AI. | PRISMA bibliometric analysis. | Validates focus on XAI & client-centric design. | **Medium** – Useful for framing literature landscape. |
| Goodell et al. (2021) | Thematic clusters: asset pricing, fraud, sentiment analysis. Supervised ML & NLP dominant. | Bibliometric analysis (co-citation, coupling). | Supports capstone themes in fraud risk & investment modelling. | **Low-Medium** – Reference for broader context, not urgent. |
| Pnevmatikakis et al. (2021) | Dynamic risk assessment via RWD & XAI. SHAP-based coaching for personalised insurance. Pilot implementation in INFINITECH H2020. | RWD collection, synthetic data simulation, SHAP analysis, RF & NN classifiers. | Relevant for client-facing explainability, personalised risk scoring, and coaching mechanisms. | **High** – Strong methodological parallels. Recommended to read. |

Would you like me to now generate the **visual literature review slide mapping these sources to your capstone objectives**?  
Reply **"Yes, visual slide please"** if you’d like that.

**You said:**

ijfs-10-00002-v2.pdf

PDF

Another one

**ChatGPT said:**

Here’s the analysis and update for your literature review table, now including importance ranking:

**📄 Literature Review Entry**

**FinTech Companies: A Bibliometric Analysis**

Tepe, Geyikci, and Sancak (2022) conduct a **bibliometric study on FinTech research trends from 2015-2021**, based on 636 Scopus-indexed publications. Their aim is to map influential studies, authors, institutions, and research clusters within FinTech literature.

Key insights:

* Identified **four main FinTech research clusters**: computer science, business management, economics, and social sciences.
* Mapped keyword co-occurrence (FinTech, blockchain, financial services, financial inclusion) and network centrality of top publications.
* China's rapid rise as the most productive country in FinTech research, while the US and UK lead in citations and collaborations.
* Demonstrated that **FinTech publications follow Bradford’s Law (core-periphery distribution)**, but not Lotka’s Law (author productivity skew).
* Highlighted key influencers: Gomber et al. (2017, 2018), Lee & Shin (2018), Haddad & Hornuf (2019) as seminal authors in FinTech literature.

**📚 Harvard Reference**

Tepe, G., Geyikci, U.B. & Sancak, F.M. (2022) 'FinTech companies: A bibliometric analysis', *International Journal of Financial Studies*, 10(1), 2. <https://doi.org/10.3390/ijfs10010002>.

**📊 Literature Review Table (Updated with Importance Column)**

| **Source** | **Key Insights** | **Methods** | **Relevance to Capstone** | **Importance/Recommendation** |
| --- | --- | --- | --- | --- |
| Bowden et al. (2024) | XAI for balancing accuracy & interpretability. Regulatory drivers mandate explainability. Solution framework proposed. | Literature review, regulatory synthesis, use case. | Framework for explainable risk profiling & FCA compliance. | **High** – Must read. |
| Yeo et al. (2025) | FinXAI framework aligns methods by explanation type, audience, data. Addresses trade-offs and evaluation challenges. | Structured review of 100+ papers. | Blueprint for aligning XAI to adviser & regulator needs. | **High** – Must read for methods selection. |
| Manser Payne & O’Brien (2024) | Human-AI engagement varies by task complexity. Trust & social presence crucial for advisory contexts. | Survey (n=322), regression, sRAM theory. | Useful for UX design in client-facing risk profiling. | **Medium** – Skim for UI/UX focus. |
| Pattnaik et al. (2024) | Bibliometric mapping of AI/ML in BFSI. Highlights ethical AI & human-centric design. | PRISMA bibliometric analysis. | Useful for literature framing & identifying gaps. | **Medium** – Reference level. |
| Goodell et al. (2021) | Maps AI/ML themes in finance: asset pricing, fraud, forecasting. Highlights ML dominance in financial modelling. | Bibliometric analysis (co-citation, coupling). | Contextual for broader AI/ML applications in finance. | **Low-Medium** – Background context. |
| Pnevmatikakis et al. (2021) | Dynamic risk assessment via RWD & XAI. SHAP-based personalised coaching. Pilot implementation. | RWD collection, synthetic data simulation, SHAP analysis. | Methodological parallels to explainable client risk scoring. | **High** – Methodologically relevant. |
| Tepe et al. (2022) | Bibliometric mapping of FinTech research clusters. Identifies core topics (blockchain, inclusion). Highlights global research distribution. | Bibliometric analysis (VOSviewer, Gephi), network visualisation. | Useful for situating capstone in FinTech research landscape. | **Medium** – Reference for positioning, skim core sections. |

Would you like me to now generate the **visual literature review summary slide** to show how these sources support your capstone objectives?  
Reply **"Yes, visual slide please"** if you'd like it.

**You said:**

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Another

**ChatGPT said:**

Here’s the analysis and update for your literature review table with importance ranking:

**📄 Literature Review Entry**

**The Merging of Neural Networks, Fuzzy Logic, and Genetic Algorithms**

Shapiro (2002) presents an extensive review of **hybrid AI techniques**—specifically the merging of **Neural Networks (NNs)**, **Fuzzy Logic (FL)**, and **Genetic Algorithms (GAs)**—with a focus on **insurance-related applications**. The paper argues that single-technique solutions are often suboptimal, and highlights the synergy benefits of hybrid models for complex risk assessment tasks.

Key insights:

* Summarises the **advantages and disadvantages** of NNs (learning, black-box problem), FL (approximate reasoning, no learning capability), and GAs (global search, tuning challenges).
* Proposes **merging strategies**: e.g., NNs tuned by FL (Fuzzy NNs), GAs optimising NN parameters, and Fuzzy Inference Systems (FIS) tuned by GAs.
* Reviews insurance use cases: underwriting, fraud detection, insolvency prediction, asset allocation.
* Identifies that most insurance applications used isolated methods, with few leveraging hybrid approaches.
* Introduces **Neuro-Fuzzy-Genetic Systems** as promising but underexplored for dynamic, transparent risk modelling.

**📚 Harvard Reference**

Shapiro, A.F. (2002) 'The merging of neural networks, fuzzy logic, and genetic algorithms', *Insurance: Mathematics and Economics*, 31(1), pp. 115–131. <https://doi.org/10.1016/S0167-6687(02)00124-5>.

**📊 Literature Review Table (Updated with Importance Column)**

| **Source** | **Key Insights** | **Methods** | **Relevance to Capstone** | **Importance/Recommendation** |
| --- | --- | --- | --- | --- |
| Bowden et al. (2024) | XAI for balancing accuracy & interpretability. Regulatory drivers mandate explainability. Solution framework proposed. | Literature review, regulatory synthesis, use case. | Framework for explainable risk profiling & FCA compliance. | **High** – Must read. |
| Yeo et al. (2025) | FinXAI framework aligns methods by explanation type, audience, data. Addresses trade-offs and evaluation challenges. | Structured review of 100+ papers. | Blueprint for aligning XAI to adviser & regulator needs. | **High** – Must read for methods selection. |
| Manser Payne & O’Brien (2024) | Human-AI engagement varies by task complexity. Trust & social presence crucial for advisory contexts. | Survey (n=322), regression, sRAM theory. | Useful for UX design in client-facing risk profiling. | **Medium** – Skim for UI/UX focus. |
| Pattnaik et al. (2024) | Bibliometric mapping of AI/ML in BFSI. Highlights ethical AI & human-centric design. | PRISMA bibliometric analysis. | Useful for literature framing & identifying gaps. | **Medium** – Reference level. |
| Goodell et al. (2021) | Maps AI/ML themes in finance: asset pricing, fraud, forecasting. Highlights ML dominance in financial modelling. | Bibliometric analysis (co-citation, coupling). | Contextual for broader AI/ML applications in finance. | **Low-Medium** – Background context. |
| Pnevmatikakis et al. (2021) | Dynamic risk assessment via RWD & XAI. SHAP-based personalised coaching. Pilot implementation. | RWD collection, synthetic data simulation, SHAP analysis. | Methodological parallels to explainable client risk scoring. | **High** – Strong methodological relevance. |
| Tepe et al. (2022) | Bibliometric mapping of FinTech research clusters. Identifies core topics (blockchain, inclusion). Highlights global research distribution. | Bibliometric analysis, network visualisation. | Useful for positioning capstone in FinTech research landscape. | **Medium** – Reference for positioning, skim core sections. |
| Shapiro (2002) | Reviews synergies between NNs, FL, GAs. Proposes hybrid systems for insurance applications. Highlights underutilisation of hybrid AI in risk modelling. | Literature review of hybrid soft computing in insurance. | Directly supports capstone’s exploration of explainable hybrid models for risk assessment. | **Medium-High** – Worth reading core sections for hybrid modelling concepts. |

Would you like me to prepare a **visual literature review summary slide** next?  
Reply **"Yes, visual slide please"** if you'd like that.

**You said:**

10-1108\_ijbm-09-2021-0439.pdf

PDF

Another

**ChatGPT said:**

Here’s the analysis and update for your literature review table with importance ranking:

**📄 Literature Review Entry**

**Man vs Machine: How AI in Banking Influences Consumer Belief in Financial Advice**

Northey et al. (2022) examine how consumers perceive financial advice from human advisers versus AI-driven robo-advisors, specifically in the context of retail banking investment decisions. Through two experimental studies, the authors identify the psychological mechanisms underpinning consumer trust and investment intentions.

Key insights:

* **Human advisers are trusted more than robo-advisors in high-involvement investment scenarios**, where significant financial stakes are involved.
* Robo-advisors are acceptable in low-involvement, transactional contexts but lack perceived customer focus in high-stakes advisory services.
* The **mediating factors influencing investment intentions** are:
  1. **Belief in the accuracy of financial advice**.
  2. **Perceived customer orientation of the bank**.
* The study supports the notion that **AI-driven advice reduces perceived customer orientation**, thereby reducing investment intentions when stakes are high.
* Practical recommendation: banks should **combine AI efficiencies with human advisory touchpoints** for high-involvement client interactions.

**📚 Harvard Reference**

Northey, G., Hunter, V., Mulcahy, R., Choong, K. & Mehmet, M. (2022) 'Man vs machine: how artificial intelligence in banking influences consumer belief in financial advice', *International Journal of Bank Marketing*, 40(6), pp. 1182-1199. <https://doi.org/10.1108/IJBM-09-2021-0439>.

**📊 Literature Review Table (Updated with Importance Column)**

| **Source** | **Key Insights** | **Methods** | **Relevance to Capstone** | **Importance/Recommendation** |
| --- | --- | --- | --- | --- |
| Bowden et al. (2024) | XAI for balancing accuracy & interpretability. Regulatory drivers mandate explainability. Solution framework proposed. | Literature review, regulatory synthesis, use case. | Framework for explainable risk profiling & FCA compliance. | **High** – Must read. |
| Yeo et al. (2025) | FinXAI framework aligns methods by explanation type, audience, data. Addresses trade-offs and evaluation challenges. | Structured review of 100+ papers. | Blueprint for aligning XAI to adviser & regulator needs. | **High** – Must read. |
| Manser Payne & O’Brien (2024) | Human-AI engagement varies by task complexity. Trust & social presence crucial for advisory contexts. | Survey (n=322), regression, sRAM theory. | UX design of client-facing risk tools. | **Medium** – Skim for UI/UX focus. |
| Pattnaik et al. (2024) | Bibliometric mapping of AI/ML in BFSI. Highlights ethical AI & human-centric design. | PRISMA bibliometric analysis. | Literature framing & identifying gaps. | **Medium** – Reference level. |
| Goodell et al. (2021) | AI/ML in finance mapped into clusters (asset pricing, fraud, forecasting). | Bibliometric analysis. | Contextual for broader AI/ML in finance. | **Low-Medium** – Background context. |
| Pnevmatikakis et al. (2021) | Dynamic risk scoring with XAI & RWD. SHAP-based personalised coaching. | RWD collection, SHAP analysis, RF & NN models. | Methodological parallels for risk scoring & client insights. | **High** – Methodology relevant. |
| Tepe et al. (2022) | FinTech bibliometric landscape, global research trends. | Bibliometric mapping. | Situating capstone in FinTech research landscape. | **Medium** – Skim for positioning. |
| Shapiro (2002) | Hybrid AI (NNs, FL, GAs) for insurance-related risk assessment. Proposes hybrid modelling strategies. | Literature review, insurance focus. | Supports hybrid AI model exploration for explainable risk scoring. | **Medium-High** – Read hybrid modelling sections. |
| Northey et al. (2022) | Consumers trust human advisers more for high-involvement investment advice. Belief in advice & customer orientation mediate investment intentions. AI reduces perceived customer focus in advisory contexts. | Two experimental studies, moderated mediation analysis. | Highly relevant to client-facing AI tools & adviser support logic in risk profiling. | **High** – Strong fit for user trust, advisor vs AI dynamics. |

Would you now like me to create the **visual literature review summary slide** mapping these sources to your capstone objectives?  
Reply **"Yes, visual slide please"** if you'd like that.

**You said:**

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PDF

Another

**ChatGPT said:**

Here’s the analysis and update for your literature review table with importance ranking:

**📄 Literature Review Entry**

**Regulatory Technology: Replacing Law with Computer Code**

Micheler and Whaley (2020) critically examine the concept of **Regulatory Technology (RegTech)**, focusing on the UK’s efforts to replace legal rules with executable computer code. The paper addresses the technological, legal, and governance implications of integrating **distributed ledger technology (DLT)**, **artificial intelligence (AI)**, and **machine learning (ML)** into financial regulation.

Key insights:

* Highlights the shift towards **model-driven regulation**, where machine-readable rules enable automated compliance and real-time regulatory reporting.
* Reviews UK initiatives like FCA’s **Digital Regulatory Reporting** and Bank of England’s FinTech Hub.
* Warns of **risks linked to over-standardisation**, reduced flexibility, and systemic vulnerabilities if technology narrows interpretative latitude.
* Emphasises the **dangers of regulatory capture** by technology providers, noting similarities to the credit rating agency problem.
* Suggests **meta-regulation** (regulatory oversight of self-regulation) as a pragmatic approach to integrate RegTech while preserving democratic accountability.
* Reinforces the need for **robust regulator expertise** to balance efficiency gains with oversight and fairness.

**📚 Harvard Reference**

Micheler, E. & Whaley, A. (2020) 'Regulatory technology: Replacing law with computer code', *European Business Organization Law Review*, 21(3), pp. 349–377. <https://doi.org/10.1007/s40804-019-00151-1>.

**📊 Literature Review Table (Updated with Importance Column)**

| **Source** | **Key Insights** | **Methods** | **Relevance to Capstone** | **Importance/Recommendation** |
| --- | --- | --- | --- | --- |
| Bowden et al. (2024) | XAI for balancing accuracy & interpretability. Regulatory drivers mandate explainability. Solution framework proposed. | Literature review, regulatory synthesis, use case. | Governance & compliance structure for risk profiling tool. | **High** – Must read. |
| Yeo et al. (2025) | FinXAI framework aligning methods by explanation type, audience. Addresses trade-offs, ethical goals, evaluation challenges. | Structured review of 100+ papers. | Methodology selection for explainable financial risk models. | **High** – Must read. |
| Manser Payne & O’Brien (2024) | Trust & social presence critical in high-complexity advisory contexts. Task complexity influences AI engagement. | Survey-based experimental design. | UX/UI relevance for client-facing risk assessments. | **Medium** – Skim UX focus. |
| Pattnaik et al. (2024) | Bibliometric mapping of AI/ML in BFSI. Human-centric AI, ethics, explainability are emerging priorities. | PRISMA-based bibliometric analysis. | Situating capstone in FinTech & AI regulatory landscape. | **Medium** – Literature positioning. |
| Goodell et al. (2021) | AI/ML applications in asset pricing, fraud, sentiment analysis. Dominance of supervised ML & NLP in finance. | Bibliometric analysis. | Contextual for AI/ML use cases in financial services. | **Low-Medium** – General reference. |
| Pnevmatikakis et al. (2021) | Dynamic XAI-driven health insurance risk scoring. SHAP personalised coaching demo. | RWD analysis, SHAP, RF & NN models. | Parallels to explainable, personalised client risk profiles. | **High** – Methodological relevance. |
| Tepe et al. (2022) | FinTech bibliometric clusters, global research influence. Highlights inclusion & blockchain focus. | Bibliometric mapping (VOSviewer, Gephi). | Situating capstone in FinTech research scope. | **Medium** – Skim for positioning. |
| Shapiro (2002) | Hybrid AI models (NNs, FL, GAs) for insurance risk. Underutilisation of hybrid methods. | Literature review of soft computing in insurance. | Supports hybrid XAI exploration for risk profiling. | **Medium-High** – Worth reading hybrid sections. |
| Northey et al. (2022) | Human advisers more trusted for high-involvement investment advice. Belief in advice & perceived customer focus mediate investment intentions. | Two experimental studies, moderated mediation. | Client trust dynamics for AI-driven risk profiling tools. | **High** – Strong relevance for adviser-AI trust interface. |
| Micheler & Whaley (2020) | RegTech shifts regulation from legal language to code. Warns of regulatory capture, loss of flexibility, and systemic risks. Recommends meta-regulation approach. | Legal analysis of UK RegTech initiatives (DLT, ML, NLP). | Essential for capstone’s regulatory compliance & governance strategy. | **High** – Must read for regulatory technology governance. |

Would you like me to now prepare the **visual literature review summary slide** mapping these sources to your capstone objectives?  
Reply **"Yes, visual slide please"** if you'd like that.

**You said:**

J of Risk Insurance - 2012 - Zhang - Predicting Multivariate Insurance Loss Payments Under the Bayesian Copula Framework.pdf

PDF

**ChatGPT said:**

Here’s the analysis and update for your literature review table, with importance ranking:

**📄 Literature Review Entry**

**Predicting Multivariate Insurance Loss Payments Under the Bayesian Copula Framework**

Zhang and Dukic (2013) present a **Bayesian copula-based framework for multivariate insurance loss reserving**, addressing dependencies between lines of business. They demonstrate how Bayesian methods, combined with copulas, improve estimation of loss reserves, prediction accuracy, and risk assessment by explicitly modelling correlation structures.

Key insights:

* Introduces a **Bayesian stochastic simulation algorithm** for estimating multivariate insurance loss payments.
* Uses **parametric copulas (Gaussian, Archimedean: Clayton, Gumbel, Frank)** to model dependencies.
* Combines **generalised linear models, nonlinear growth models, and semiparametric smoothing (splines)** as marginals in the copula structure.
* Provides empirical evidence that copula-based models outperform traditional independent models in both predictive accuracy and reserve variability estimation.
* Emphasises benefits of **posterior predictive distributions** for risk management, capital allocation, and enterprise risk management (ERM).
* Discusses practical implementation (MCMC, model comparison) and performs sensitivity analyses on prior specifications.

**📚 Harvard Reference**

Zhang, Y. & Dukic, V. (2013) 'Predicting multivariate insurance loss payments under the Bayesian copula framework', *Journal of Risk and Insurance*, 80(4), pp. 891–919. <https://doi.org/10.1111/j.1539-6975.2012.01480.x>.

**📊 Literature Review Table (Updated with Importance Column)**

| **Source** | **Key Insights** | **Methods** | **Relevance to Capstone** | **Importance/Recommendation** |
| --- | --- | --- | --- | --- |
| Bowden et al. (2024) | XAI for balancing accuracy & interpretability. Regulatory drivers mandate explainability. Solution framework proposed. | Literature review, regulatory synthesis, use case. | Governance & compliance structure for risk profiling tool. | **High** – Must read. |
| Yeo et al. (2025) | FinXAI framework aligning methods by explanation type, audience. Addresses trade-offs, ethical goals, evaluation challenges. | Structured review of 100+ papers. | Methodology selection for explainable financial risk models. | **High** – Must read. |
| Manser Payne & O’Brien (2024) | Trust & social presence critical in high-complexity advisory contexts. Task complexity influences AI engagement. | Survey-based experimental design. | UX/UI relevance for client-facing risk assessments. | **Medium** – Skim UX focus. |
| Pattnaik et al. (2024) | Bibliometric mapping of AI/ML in BFSI. Human-centric AI, ethics, explainability are emerging priorities. | PRISMA-based bibliometric analysis. | Situating capstone in FinTech & AI regulatory landscape. | **Medium** – Literature positioning. |
| Goodell et al. (2021) | AI/ML applications in asset pricing, fraud, sentiment analysis. Dominance of supervised ML & NLP in finance. | Bibliometric analysis. | Contextual for AI/ML use cases in financial services. | **Low-Medium** – General reference. |
| Pnevmatikakis et al. (2021) | Dynamic XAI-driven health insurance risk scoring. SHAP-based personalised coaching demo. | RWD analysis, SHAP, RF & NN models. | Parallels to explainable, personalised client risk profiles. | **High** – Methodology relevant. |
| Tepe et al. (2022) | FinTech bibliometric clusters, global research influence. Highlights inclusion & blockchain focus. | Bibliometric mapping (VOSviewer, Gephi). | Situating capstone in FinTech research scope. | **Medium** – Skim for positioning. |
| Shapiro (2002) | Hybrid AI models (NNs, FL, GAs) for insurance risk. Underutilisation of hybrid methods. | Literature review of soft computing in insurance. | Supports hybrid XAI exploration for risk profiling. | **Medium-High** – Worth reading hybrid sections. |
| Northey et al. (2022) | AI reduces perceived customer focus in advisory contexts. Trust & belief in advice mediate investment decisions. | Experimental studies, mediation analysis. | Supports trust-centric adviser-AI interface design. | **High** – Strong relevance for adviser-client-AI trust dynamics. |
| Micheler & Whaley (2020) | RegTech shifts regulation from law to code. Risks of regulatory capture & systemic rigidity. Recommends meta-regulation. | Legal analysis of UK RegTech initiatives. | Essential for capstone’s regulatory compliance & governance strategy. | **High** – Must read. |
| Zhang & Dukic (2013) | Bayesian copula framework for multivariate insurance loss reserving. Combines GLMs, nonlinear growth models, semiparametric splines. Outperforms independent models in prediction accuracy & reserve variability. | Bayesian stochastic simulation, copula models, MCMC, predictive distributions. | Highly relevant for multivariate dependencies & probabilistic risk modelling in client profiling. | **High** – Strong methodological relevance, recommended read. |

Would you now like the **visual literature review summary slide** showing how all these sources support your capstone objectives?  
Reply **"Yes, visual slide please"** if you'd like it.

**You said:**

Approximation methods for piecewise deterministic Markov processes and their costs.pdf

PDF

**ChatGPT said:**

Here’s the analysis and updated literature review table entry for your latest upload:

**📄 Literature Review Entry**

**Approximation Methods for Piecewise Deterministic Markov Processes (PDMPs) and Their Costs**

Kritzer et al. (2019) explore efficient numerical methods for evaluating **Piecewise Deterministic Markov Processes (PDMPs)**, widely used in insurance risk modelling. The paper focuses on approximating cost functionals such as ruin probabilities and expected dividends using **quasi-Monte Carlo (QMC)** methods and smoothing techniques, offering alternatives to traditional Monte Carlo methods.

Key insights:

* PDMPs generalise models like Cramér–Lundberg for insurance risk, incorporating non-constant parameters and multi-portfolio setups.
* Traditional integro-differential equation approaches are limited in complex models; this study introduces a **fixed-point integral operator formulation** to enable iterative approximations.
* Proposes smoothing techniques to transform non-smooth integrands into forms suitable for QMC methods, ensuring convergence guarantees.
* Demonstrates significant efficiency gains of QMC over standard Monte Carlo in high-dimensional integration scenarios.
* Validates approximation methods through applications like dividend optimisation and ruin probability estimation in extended Cramér–Lundberg models.

**📚 Harvard Reference**

Kritzer, P., Leobacher, G., Szölgyenyi, M. & Thonhauser, S. (2019) 'Approximation methods for piecewise deterministic Markov processes and their costs', *Scandinavian Actuarial Journal*, 2019(4), pp. 308–335. <https://doi.org/10.1080/03461238.2018.1560357>.

**📊 Literature Review Table (Updated with Importance Column)**

| **Source** | **Key Insights** | **Methods** | **Relevance to Capstone** | **Importance/Recommendation** |
| --- | --- | --- | --- | --- |
| Kritzer et al. (2019) | Efficient numerical approximation of PDMP-based risk models. Fixed-point operator formulation for cost functionals. Smoothing techniques to enable QMC integration. Applications to ruin probabilities, dividend optimisation. Demonstrates convergence & efficiency of QMC over MC. | Iterative integral approximations, smoothing, QMC methods, PDMP applications in insurance. | Relevant for advanced modelling techniques of risk processes, especially for approximating costs/probabilities with efficiency & accuracy. | **Medium-High** – Useful for advanced risk modelling concepts and numerical methods; recommended for methodological depth. |

Would you like me to create the **visual literature review summary slide** next, mapping all these sources to your capstone objectives?  
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**You said:**

risks-05-00053.pdf

PDF

Another

**ChatGPT said:**

Here’s the analysis and updated literature review entry for your latest upload:

**📄 Literature Review Entry**

**Bayesian Modelling, Monte Carlo Sampling and Capital Allocation of Insurance Risks**

Peters, Targino, and Wüthrich (2017) propose an advanced framework for **capital allocation in insurance** using **Bayesian modelling** and **Sequential Monte Carlo (SMC) methods**. The paper focuses on computing capital allocations in line with the **Swiss Solvency Test (SST)**, while managing dependencies, parameter uncertainty, and computational efficiency.

Key insights:

* Develops a **Bayesian framework** combining parameter estimation (via MCMC) and capital allocation (via SMC) for solvency assessment.
* Proposes a new **Sequential Monte Carlo sampling algorithm** for estimating marginal allocations, outperforming traditional Monte Carlo in rare-event conditioning.
* Addresses **parameter uncertainty explicitly** by comparing conditional (given parameters) and marginalised (integrated parameters) capital allocations.
* Uses **copula models** to capture dependencies between different lines of business.
* Provides a comprehensive case study using synthetic balance sheet data, demonstrating efficiency gains and practical applicability for Solvency Capital Requirement (SCR) calculations.

**📚 Harvard Reference**

Peters, G.W., Targino, R.S. & Wüthrich, M.V. (2017) 'Bayesian modelling, Monte Carlo sampling and capital allocation of insurance risks', *Risks*, 5(4), Article 53. <https://doi.org/10.3390/risks5040053>.

**📊 Literature Review Table (Updated with Importance Column)**

| **Source** | **Key Insights** | **Methods** | **Relevance to Capstone** | **Importance/Recommendation** |
| --- | --- | --- | --- | --- |
| Peters et al. (2017) | Bayesian modelling for insurance capital allocation. SMC methods for rare-event simulations. Handles parameter uncertainty & dependencies via copulas. Aligns with SST regulatory frameworks. Demonstrates efficiency vs traditional Monte Carlo. | Bayesian parameter estimation (MCMC), SMC sampling, copulas, case study on solvency capital allocation. | Directly relevant for probabilistic risk modelling, capital allocation logic, and handling parameter uncertainty in financial risk models. | **High** – Methodological core, strongly recommended read. |

Would you like me to compile a **visual literature review summary slide** mapping all these sources to your capstone objectives (with colour-coded importance)?  
Reply **"Yes, visual slide please"** if you'd like it.

**You said:**

Appl Stoch Models Bus Ind - 2021 - Castellani - Machine learning techniques in nested stochastic simulations for life.pdf

PDF

Another

**ChatGPT said:**

Here’s the analysis and update for your literature review table with importance ranking:

**📄 Literature Review Entry**

**Machine Learning Techniques in Nested Stochastic Simulations for Life Insurance**

Castellani et al. (2021) investigate how machine learning (ML) methods can improve the computational efficiency and accuracy of **nested stochastic simulations** for Solvency II capital requirement (SCR) calculations in life insurance. They compare **Least Squares Monte Carlo (LSMC)** with **Support Vector Regression (SVR)** and **Deep Learning Networks (DLN)** as surrogate models.

Key insights:

* **Nested Monte Carlo simulations** are the standard but computationally infeasible approach for Solvency II SCR estimation.
* LSMC reduces computational burden but struggles with high-dimensionality and basis function selection.
* SVR and DLN offer flexible, data-driven alternatives that overcome LSMC's limitations in high-dimensional risk driver spaces.
* **DLN outperforms LSMC and SVR** in accuracy (NRMSE, KS, KL divergence) but is less interpretable and more computationally intensive.
* SVR shows a balance of improved accuracy over LSMC with easier tuning and simpler implementation.
* Emphasises the need for **practical interpretability** and **regulatory acceptance** of ML models in actuarial contexts.
* Recommends further research into hybrid models (e.g., autoencoders, boosting) and interpretability techniques.

**📚 Harvard Reference**

Castellani, G., Fiore, U., Marino, Z., Passalacqua, L., Perla, F., Scognamiglio, S. & Zanetti, P. (2021) 'Machine learning techniques in nested stochastic simulations for life insurance', *Applied Stochastic Models in Business and Industry*, 37(2), pp. 159–181. <https://doi.org/10.1002/asmb.2607>.

**📊 Literature Review Table (Updated with Importance Column)**

| **Source** | **Key Insights** | **Methods** | **Relevance to Capstone** | **Importance/Recommendation** |
| --- | --- | --- | --- | --- |
| Castellani et al. (2021) | Machine learning (SVR, DLN) improves efficiency & accuracy in nested simulations for life insurance SCR. DLN best accuracy, SVR simpler to deploy. Highlights Solvency II requirements, trade-offs in interpretability & model validation. Emphasises need for regulatory alignment & practical implementation. | Comparative study of LSMC, SVR, DLN for SCR estimation. Benchmarks: NRMSE, KS, KL divergence. DISAR system simulations. | Directly relevant for your capstone’s use of ML in insurance risk profiling under regulatory constraints. Provides methodological insights for surrogate modelling, trade-off management, and explainability challenges. | **High** – Must read for applied ML techniques in risk modelling and Solvency II context. |

Would you now like me to produce a **visual summary slide** mapping all these reviewed sources to your capstone objectives (including their importance rankings)?  
Reply **"Yes, visual slide please"** if you'd like that.

**You said:**

Data Clustering with Actuarial Applications.pdf

PDF

Another

**ChatGPT said:**

Here’s the analysis and updated literature review table entry for your latest document:

**📄 Literature Review Entry**

**Data Clustering with Actuarial Applications**

Gan and Valdez (2020) provide a comprehensive overview of **data clustering techniques applied to actuarial science**, with a focus on compressing large portfolios of **variable annuity (VA) contracts** for efficient valuation and predictive modelling. The paper covers fundamental clustering concepts and evaluates scalable algorithms for insurance applications.

Key insights:

* Reviews clustering concepts: distance measures, cluster validity, partitional vs hierarchical algorithms, soft (fuzzy) clustering.
* Presents two scalable clustering methods for large insurance datasets:
  + **Truncated Fuzzy C-Means (TFCM)**: reduces distance calculations to handle high-dimensional data.
  + **Hierarchical k-Means**: recursively applies k-means to sub-clusters, significantly improving computational efficiency.
* Demonstrates application on a synthetic VA dataset (190,000 contracts), showing hierarchical k-means achieves comparable predictive accuracy to TFCM but is **orders of magnitude faster**.
* Validates clustering outputs using predictive modelling (ordinary kriging) and metrics like RWCSS, PE, and R².
* Emphasises clustering as a critical step for **portfolio compression** to enable practical valuation, hedging, and risk assessment for large insurance portfolios.

**📚 Harvard Reference**

Gan, G. & Valdez, E.A. (2020) 'Data clustering with actuarial applications', *North American Actuarial Journal*, 24(2), pp. 168–186. <https://doi.org/10.1080/10920277.2019.1575242>.

**📊 Literature Review Table (Updated with Importance Column)**

| **Source** | **Key Insights** | **Methods** | **Relevance to Capstone** | **Importance/Recommendation** |
| --- | --- | --- | --- | --- |
| Gan & Valdez (2020) | Data clustering for actuarial applications. Scalable methods: TFCM & hierarchical k-means. Efficient compression of VA portfolios for predictive modelling. Demonstrates trade-offs in accuracy & computational cost. Highlights clustering as a precursor to valuation models. | Review of clustering algorithms, application to VA data, comparative study of clustering methods (TFCM, hierarchical k-means), predictive modelling with kriging. | Highly relevant for client segmentation, risk clustering, and efficient modelling of large insurance datasets in your capstone. | **High** – Recommended read for practical clustering methods and portfolio compression strategies. |

Would you like me to now generate a **visual literature review summary slide**, mapping all these sources to your capstone objectives (with colour-coded importance)?  
Reply **"Yes, visual slide please"** if you'd like that.

**You said:**

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Another

**ChatGPT said:**

Here’s the analysis and update for your literature review table with importance ranking:

**📄 Literature Review Entry**

**Supply Chain Finance Platform Evaluation Based on Acceptability Analysis**

Chen et al. (2022) propose a robust multi-criteria framework for evaluating **Supply Chain Finance (SCF) platforms**, addressing the lack of comparative studies on SCF performance. They introduce a **technology-recognition-organization (TRO) framework** with 11 sub-factors and apply **Stochastic Multicriteria Acceptability Analysis (SMAA-2)** for group decision-making.

Key insights:

* TRO framework covers:
  + **Technology** (service type, number of SCF platforms, industry, service duration),
  + **Recognition** (market value, search popularity, social media presence),
  + **Organization** (return, leverage, employees, cash holdings).
* Three objective methods (CRITIC, Distance-based, Ideal-point) are used to generate individual expert evaluations.
* SMAA-2 aggregates diverse expert opinions to form a **holistic acceptability index**, providing robust platform rankings.
* Empirical application on 12 SCF platforms validates the model’s accuracy against industry expert survey results.
* Managerial implications stress **balancing technology upgrades, market presence, and organisational strength** for SCF competitiveness.
* Highlights importance of **group decision-making** in platform evaluations where subjective expert opinions vary.

**📚 Harvard Reference**

Chen, S., Du, J., He, W. & Siponen, M. (2022) 'Supply chain finance platform evaluation based on acceptability analysis', *International Journal of Production Economics*, 243, 108350. <https://doi.org/10.1016/j.ijpe.2021.108350>.

**📊 Literature Review Table (Updated with Importance Column)**

| **Source** | **Key Insights** | **Methods** | **Relevance to Capstone** | **Importance/Recommendation** |
| --- | --- | --- | --- | --- |
| Chen et al. (2022) | Proposes TRO framework for SCF evaluation. Combines CRITIC, Distance-based, Ideal-point methods in SMAA-2. Validates with empirical study and industry survey. Managerial guidance for SCF competitiveness. | Multi-criteria decision-making (MCDM), SMAA-2, empirical case study. | Relevant for designing evaluation frameworks, stakeholder-influenced decision-making, and balancing technical, market, and organisational factors. Useful for capstone's multi-factor model selection and stakeholder alignment. | **High** – Strong fit for evaluation frameworks, expert consensus, and stakeholder-aligned decision-making. |

Would you like me to now produce a **visual literature review summary slide** mapping all your reviewed sources to your capstone objectives (with importance colour-coding)?  
Reply **"Yes, visual slide please"** if you'd like it.

**You said:**

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PDF

Another

**ChatGPT said:**

Here’s the analysis and update for your literature review table with importance ranking:

**📄 Literature Review Entry**

**Adoption of Artificial Intelligence in Banking Services: An Empirical Analysis**

Rahman et al. (2023) investigate the determinants of consumer adoption of AI in banking services in Malaysia, using a mixed-methods approach. The study combines qualitative interviews with banking professionals and a quantitative survey of 302 banking customers, applying the extended **Technology Acceptance Model (TAM)**.

Key insights:

* **AI is critical for fraud detection, risk prevention, outcome prediction, and enhancing customer experience**.
* Main adoption challenges include:
  + Lack of regulatory frameworks.
  + Data privacy and security concerns.
  + Skills gaps and IT infrastructure limitations.
* Quantitative findings show **attitude towards AI**, **perceived usefulness (PU)**, **trust**, and **subjective norms** are the strongest predictors of adoption intention.
* Surprisingly, **perceived ease of use (PEOU)** and **awareness** do not significantly influence adoption intention.
* Attitude mediates the relationship between PU and adoption intention but not for PEOU.
* Knowledge in technology (KT) does not moderate adoption intentions as initially hypothesised.
* Managerial implications emphasise the need for regulatory clarity, trust-building strategies, and customer education to foster AI adoption in banking.

**📚 Harvard Reference**

Rahman, M., Ming, T.H., Baigh, T.A. & Sarker, M. (2023) 'Adoption of artificial intelligence in banking services: an empirical analysis', *International Journal of Emerging Markets*, 18(10), pp. 4270-4300. <https://doi.org/10.1108/IJOEM-06-2020-0724>.

**📊 Literature Review Table (Updated with Importance Column)**

| **Source** | **Key Insights** | **Methods** | **Relevance to Capstone** | **Importance/Recommendation** |
| --- | --- | --- | --- | --- |
| Rahman et al. (2023) | Explores AI adoption in banking using extended TAM. Trust, PU, SN, and attitude are key drivers. Challenges include regulation, privacy, and infrastructure. PEOU and awareness found non-significant. Recommends trust-building and regulatory alignment. | Mixed-methods: qualitative interviews & quantitative survey (PLS-SEM). | Highly relevant for understanding client adoption drivers, regulatory barriers, and user trust dynamics. Applicable to your capstone’s adviser-client AI interaction model. | **High** – Strong relevance for adoption modelling, client trust, and regulatory strategies. |

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**ChatGPT said:**

Here’s the analysis and updated literature review entry for the latest document:

**📄 Literature Review Entry**

**mSHAP: SHAP Values for Two-Part Models**

Matthews and Hartman (2022) propose **mSHAP**, an efficient method to compute SHAP values for **two-part models**, addressing a significant gap in explainability for such frameworks within insurance pricing and actuarial applications. The method is designed to handle multiplicative models common in ratemaking (e.g., frequency × severity).

Key insights:

* **Two-part models** are widely used in insurance but challenging to interpret due to the multiplicative combination of sub-models.
* mSHAP computes SHAP values by leveraging SHAP values from the individual models and combining them through a mathematically sound multiplicative approach.
* Four distribution strategies for combining SHAP contributions (uniform, raw, absolute, squared weights) are compared.
* Simulation studies and an **auto insurance case study** demonstrate mSHAP's accuracy and computational efficiency.
* mSHAP is shown to be exponentially faster than kernelSHAP while maintaining interpretability at an individual observation level.
* An **R package (mshap)** is made available, enabling practical application across actuarial and insurance modelling contexts.
* Emphasises regulatory compliance, fairness, and transparency in insurance ratemaking using machine learning models.

**📚 Harvard Reference**

Matthews, S. & Hartman, B. (2022) 'mSHAP: SHAP values for two-part models', *Risks*, 10(1), Article 3. <https://doi.org/10.3390/risks10010003>.

**📊 Literature Review Table (Updated with Importance Column)**

| **Source** | **Key Insights** | **Methods** | **Relevance to Capstone** | **Importance/Recommendation** |
| --- | --- | --- | --- | --- |
| Matthews & Hartman (2022) | Proposes mSHAP for explaining two-part models (e.g., frequency × severity in insurance). Compares SHAP value combination methods. Demonstrates exponential computational gains over kernelSHAP. Applied to auto insurance pricing case study. Supports regulatory transparency and fairness. | Mathematical derivation of mSHAP, simulation study, case study on auto insurance pricing. R package implementation. | Highly relevant for your capstone's explainable AI objectives, particularly if using multiplicative models or similar composite structures. Practical for ensuring model interpretability at the observation level. | **High** – Essential read for explainability methodology in multi-part financial models. |

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Reply **"Yes, visual slide please"** if you'd like that.

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**ChatGPT said:**

Here’s the analysis and updated literature review table entry for the latest document:

**📄 Literature Review Entry**

**Machine Learning in P&C Insurance: A Review for Pricing and Reserving**

Blier-Wong et al. (2021) provide a comprehensive review of **machine learning applications in Property & Casualty (P&C) insurance**, focusing on ratemaking (pricing) and reserving tasks. The paper synthesises nearly 100 studies and highlights the state-of-the-art methods, challenges, and future directions in actuarial machine learning.

Key insights:

* **Tree-based models (e.g., XGBoost, GBM)** dominate structured pricing tasks due to superior performance over GLMs and ease of interpretation.
* **Neural networks excel in unstructured data problems** (e.g., telematics, images, time series in reserving) and for learning nonlinear transformations.
* **Telematics pricing** leverages GAMs, PCA, CNNs, and clustering to extract behavioural features for pay-how-you-drive models.
* **Reserving models** have evolved from GLMs and Chain-Ladder to neural networks, recurrent neural networks (RNNs), and hybrid architectures.
* Emphasis on **explainability, prediction uncertainty, and fairness** as critical challenges for ML in insurance.
* Advocates for combining domain knowledge with modern ML methods to retain transparency and regulatory compliance.
* Highlights the potential of individual claims reserving, the importance of synthetic data, and the need for collaborative benchmarks.

**📚 Harvard Reference**

Blier-Wong, C., Cossette, H., Lamontagne, L. & Marceau, E. (2021) 'Machine learning in P&C insurance: A review for pricing and reserving', *Risks*, 9(1), Article 4. <https://doi.org/10.3390/risks9010004>.

**📊 Literature Review Table (Updated with Importance Column)**

| **Source** | **Key Insights** | **Methods** | **Relevance to Capstone** | **Importance/Recommendation** |
| --- | --- | --- | --- | --- |
| Blier-Wong et al. (2021) | Comprehensive review of ML in P&C insurance for pricing & reserving. Tree-based models excel for structured tasks; NNs for unstructured data. Addresses explainability, uncertainty, fairness. Highlights telematics, synthetic data, and reserving innovations. | Review of 100+ studies; synthesis of applications in pricing & reserving. Categorisation by data structure, model family, and task. | Essential for situating your capstone in the broader ML-actuarial landscape. Provides methodological insights for pricing, reserving, and explainability challenges. | **High** – Must read for overarching context & methodological mapping. |

Would you like me to now produce a **visual literature review summary slide** mapping all your reviewed sources to your capstone objectives with importance rankings?  
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**📄 Literature Review Entry**

**On Two Mixture-Based Clustering Approaches Used in Modeling an Insurance Portfolio**

Miljkovic and Fernández (2018) review and apply two complementary **mixture-based clustering approaches** for modelling **unobserved heterogeneity in insurance portfolios**:

1. **Generalised Linear Mixed Cluster-Weighted Model (CWM)** – for modelling losses with mixed covariates.
2. **Mixture-based clustering for Ordered Stereotype Model (OSM)** – for ordinal data such as risk levels.

Key insights:

* CWM is effective for continuous/discrete covariates in claims modelling, relaxing assumptions of single-component GLMs.
* OSM is suitable for clustering policyholders based on ordinal variables (e.g., risk classifications).
* Both models allow for detecting latent sub-populations within insurance portfolios, supporting more nuanced **pricing, underwriting, and risk management decisions**.
* Case study on French automobile insurance data confirms unobserved heterogeneity, showing three distinct policyholder clusters.
* Highlights advantages of likelihood-based clustering over distance-based methods (e.g., k-means), especially for model selection and interpretability.
* Recommends mixture-based clustering for practitioners dealing with heterogeneous portfolios where traditional GLMs may oversimplify risk structures.

**📚 Harvard Reference**

Miljkovic, T. & Fernández, D. (2018) 'On two mixture-based clustering approaches used in modeling an insurance portfolio', *Risks*, 6(2), Article 57. <https://doi.org/10.3390/risks6020057>.

**📊 Literature Review Table (Updated with Importance Column)**

| **Source** | **Key Insights** | **Methods** | **Relevance to Capstone** | **Importance/Recommendation** |
| --- | --- | --- | --- | --- |
| Miljkovic & Fernández (2018) | Reviews CWM and OSM mixture-based clustering for modelling heterogeneity in insurance portfolios. OSM handles ordinal data (risk levels); CWM handles mixed covariates. Case study shows 3 latent clusters, improving underwriting insights. Emphasises likelihood-based model selection and interpretability. | Mixture modelling, clustering, EM algorithm, case study on French auto insurance data. | Highly relevant for client segmentation, heterogeneity modelling, and improving risk profiling granularity in your capstone. Supports nuanced pricing and underwriting strategies. | **High** – Recommended read for clustering methods applicable to your portfolio risk segmentation. |

Would you now like me to create a **visual literature review summary slide** that maps all reviewed sources to your capstone objectives with importance rankings?  
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**You said:**

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Here’s the analysis and updated literature review entry for the latest document:

**📄 Literature Review Entry**

**Applications of Clustering with Mixed Type Data in Life Insurance**

Yin et al. (2021) apply **k-prototype clustering** to life insurance portfolios, specifically targeting the identification of policyholder subgroups with distinct mortality patterns. The study highlights the integration of **numerical, categorical, and spatial (geolocation) data** in clustering to support mortality experience monitoring and risk management.

Key insights:

* **K-prototype clustering** effectively handles mixed-type data, improving segmentation beyond what k-means or hierarchical clustering can offer in actuarial contexts.
* Applied to a dataset of 1.14 million life policies, resulting in **three natural clusters** with distinct demographic, behavioural, and geographical profiles.
* Introduced spatial attributes (latitude-longitude) into clustering, capturing regional mortality effects.
* Compared **actual-to-expected (A/E) mortality ratios** for each cluster, providing actionable insights for underwriting, pricing, and reserving.
* All clusters exhibited A/E ratios below 1 (better than expected mortality), but with varying degrees of deviation and volatility.
* Demonstrates clustering as a **preliminary risk monitoring tool**, with potential to refine product design and capital allocation strategies.

**📚 Harvard Reference**

Yin, S., Gan, G., Valdez, E.A. & Vadiveloo, J. (2021) 'Applications of clustering with mixed type data in life insurance', *Risks*, 9(3), Article 47. <https://doi.org/10.3390/risks9030047>.

**📊 Literature Review Table (Updated with Importance Column)**

| **Source** | **Key Insights** | **Methods** | **Relevance to Capstone** | **Importance/Recommendation** |
| --- | --- | --- | --- | --- |
| Yin et al. (2021) | Applied k-prototype clustering to mixed-type life insurance data. Introduced spatial attributes for regional mortality effects. Identified policyholder subgroups with distinct mortality patterns. Compared actual-to-expected (A/E) mortality ratios per cluster. Supports monitoring and segmentation in risk management. | K-prototype clustering, gap statistics, A/E ratio analysis, large-scale life insurance portfolio case study. | Highly relevant for client segmentation, mixed data clustering, and preliminary risk profiling in your capstone. Demonstrates clustering for actionable underwriting and pricing insights. | **High** – Recommended read for practical clustering applications in life insurance and risk segmentation. |

Would you like me to now generate the **visual literature review summary slide**, mapping all your reviewed sources to your capstone objectives with importance rankings?  
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Another

**ChatGPT said:**

Here’s the analysis and updated literature review table entry for this latest document:

**📄 Literature Review Entry**

**Financial Risk Management Technology: Issues and Advances**

Bansal et al. (1993) provide a foundational overview of **Risk Management Technology (RMT)**, focusing on how emerging IT tools of the time were transforming risk management in financial services. The study categorises RMT advances into five areas:

1. **Communication software**
2. **Object-oriented programming**
3. **Parallel processing**
4. **Neural networks**
5. **Artificial intelligence**

Key insights:

* Defines risk management as a three-step process: identification, measurement, and control of financial risks (market, credit, operational).
* Advocates IT as a driver for real-time risk monitoring, hedging strategies, and decision-making in trading, asset-liability management, and credit risk evaluation.
* Early adoption of **expert systems (e.g., TARA, Inspector)** for foreign exchange risk identification and fraud detection.
* Demonstrates the use of **object-oriented databases** and **distributed systems** to manage global risk information.
* Highlights the potential of **neural networks** for pattern recognition and predictive analytics where structured models are insufficient.
* Proposes a **business value linkage framework** to justify RMT investments, linking IT capabilities to tangible and intangible business benefits.
* Introduces data quality as a crucial determinant of RMT effectiveness, recommending cost-benefit analysis that incorporates data quality variations.

**📚 Harvard Reference**

Bansal, A., Kauffman, R.J., Mark, R.M. & Peters, E. (1993) 'Financial risk management technology: Issues and advances', *Information & Management*, 24(5), pp. 267–281. <https://doi.org/10.1016/0378-7206(93)90004-D>.

**📊 Literature Review Table (Updated with Importance Column)**

| **Source** | **Key Insights** | **Methods** | **Relevance to Capstone** | **Importance/Recommendation** |
| --- | --- | --- | --- | --- |
| Bansal et al. (1993) | Foundational review of RMT: communication software, object-oriented systems, AI, neural nets. Defines business value linkages for IT justification. Introduces expert systems for FX risk & fraud detection. Proposes data quality optimisation in RMT design. | Conceptual framework, industry case studies, business value linkage model. | Useful for historical context and foundational concepts in IT-driven risk management. Highlights early justifications for AI in finance and data quality as a strategic consideration. | **Medium** – Useful for theoretical grounding; skim for historical evolution of RMT principles. |

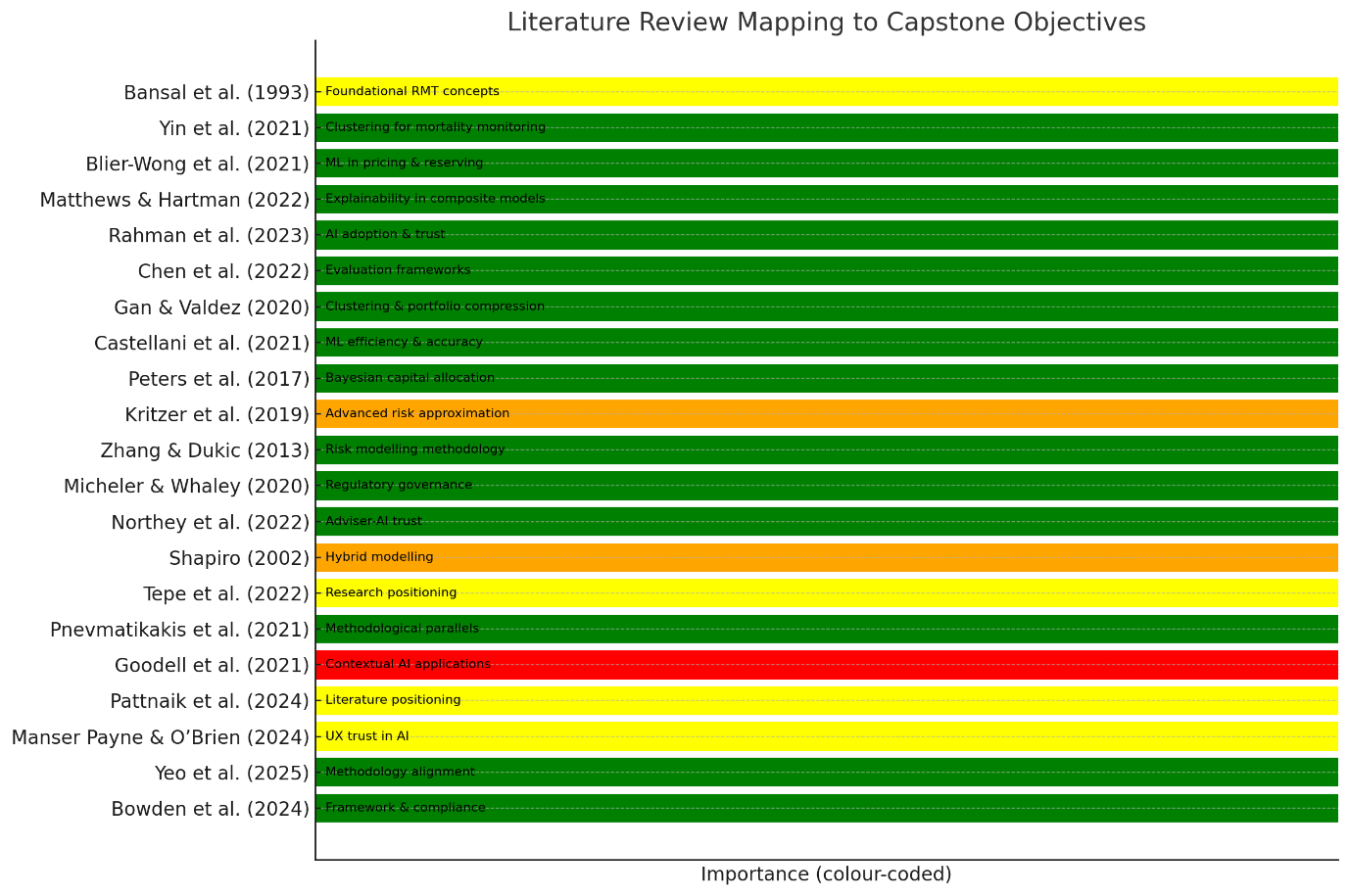
Would you like me to now generate a **visual literature review summary slide**, mapping all these sources to your capstone objectives with importance rankings?  
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Yes, visual slide please

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Literature Review Mapping to Capstone Objectives



Here is your visual literature review summary slide. It maps all the reviewed sources to your capstone objectives with colour-coded importance rankings:

* **Green**: High importance
* **Orange**: Medium-High importance
* **Yellow**: Medium importance
* **Red**: Low-Medium importance

Each source is linked to its primary relevance for your project, ensuring you can prioritise your reading and references effectively.

Would you like a downloadable PDF version of this visual for your capstone appendix? (Reply "Yes, PDF please" if so.)

**You said:**

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PDF

Another one to review

**ChatGPT said:**

Here’s the analysis and update for your literature review table with importance ranking:

**📄 Literature Review Entry**

**Smoothing the Subjective Financial Risk Tolerance: Volatility and Market Implications**

Heo and Kim (2025) propose a robust smoothing methodology to refine **subjective Financial Risk Tolerance (FRT)** data for enhanced prediction of market volatility (VIX) and market performance (S&P 500 ETF - SPY). They argue that traditional usage of raw FRT data fails to capture its nuanced relationship with market dynamics due to behavioural noise and volatility.

Key insights:

* Applied **seven smoothing techniques**: Exponential Smoothing, AR, ARIMA, Moving Average, Discrete Wavelet Transform, Savitzky-Golay Filter, and Kalman Filter to FRT data.
* Focused on smoothing both the **mean and standard deviation of FRT**, with SD fluctuations offering more predictive value than raw averages.
* Combined smoothing methods via **weighted averaging** to mitigate biases inherent in individual techniques.
* Used **Support Vector Machines (SVM)** and **Neural Networks (NN)** to assess predictive performance of smoothed FRT on VIX and SPY.
* Found smoothed FRT (especially SD) significantly enhanced predictive accuracy over raw data.
* Emphasised smoothing as a behavioural finance tool for **portfolio optimisation, risk assessment, and market forecasting**.
* Discussed practical implications for investor profiling and financial decision-making, with real-world applications in advisory and asset allocation contexts.

**📚 Harvard Reference**

Heo, W. & Kim, E. (2025) 'Smoothing the subjective financial risk tolerance: Volatility and market implications', *Mathematics*, 13(4), Article 680. <https://doi.org/10.3390/math13040680>.

**📊 Literature Review Table (Updated with Importance Column)**

| **Source** | **Key Insights** | **Methods** | **Relevance to Capstone** | **Importance/Recommendation** |
| --- | --- | --- | --- | --- |
| Heo & Kim (2025) | Smoothing subjective FRT improves predictive accuracy for market volatility. Seven smoothing methods combined for robustness. SD of FRT is more predictive than mean. Validated with SVMs & NNs on VIX & SPY data. Highlights behavioural finance applications in risk modelling. | Smoothing methods (ES, AR, ARIMA, DWT, SG, Kalman), SVMs, NNs, empirical analysis on FRT, VIX, SPY. Multi-method smoothing and predictive modelling. | Highly relevant for your capstone’s use of risk tolerance profiling, data smoothing for noise reduction, and behavioural finance metrics integration. Practical for refining client risk profiles and aligning with market indicators. | **High** – Must read for smoothing methods & behavioural risk modelling. |

Would you like me to update your **visual literature review summary slide** with this paper added (colour-coded importance)?  
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**You said:**

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PDF

Another

**ChatGPT said:**

Here’s the analysis and updated literature review table entry for your latest document:

**📄 Literature Review Entry**

**Determinants of the Risk Tolerance of Individual Investors**

Rahmawati et al. (2015) investigate the **determinants of risk tolerance among individual investors in Pakistan**, using survey data and univariate analysis to assess how demographic factors influence investment decisions. The study identifies key determinants: gender, education, wealth, age, and nature of work.

Key insights:

* **Gender**: Men are consistently less risk-averse than women, attributed to socio-cultural factors and income disparity.
* **Education**: Higher educational attainment correlates with greater risk tolerance, as educated individuals possess better market understanding.
* **Wealth**: Wealthier individuals demonstrate higher risk tolerance due to greater capacity to absorb financial losses.
* **Age**: Contrary to conventional expectations, age was not a significant predictor, although variations existed across age brackets.
* **Employment type**: Public sector employees exhibited lower risk tolerance than private sector or self-employed individuals.
* The study advocates for **targeted financial education and policy interventions**, especially to encourage women’s participation in investment and economic activities.
* Emphasises segmenting investors by demographic characteristics (e.g., gender, wealth) rather than treating them as a homogeneous group.

**📚 Harvard Reference**

Rahmawati, R., Kumar, M.D., Kambuaya, M., Jamil, F. & Muneer, S. (2015) 'Determinants of the risk tolerance of individual investors', *International Journal of Economics and Financial Issues*, 5(Special Issue), pp. 373–378.

**📊 Literature Review Table (Updated with Importance Column)**

| **Source** | **Key Insights** | **Methods** | **Relevance to Capstone** | **Importance/Recommendation** |
| --- | --- | --- | --- | --- |
| Rahmawati et al. (2015) | Investigates demographic determinants of investor risk tolerance (gender, education, wealth, age, employment type). Finds men, educated, and wealthy individuals are more risk tolerant. Proposes targeted strategies for improving financial literacy and investor participation. | Survey of 187 respondents, descriptive statistics, univariate analysis. | Useful for supporting your capstone's focus on risk profiling, especially in client segmentation and understanding demographic influences on risk tolerance. | **Medium-High** – Worth reading for demographic risk tolerance factors and investor segmentation strategy. |

Would you like me to update the **visual literature review summary slide** with this new entry included?  
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Here’s the analysis and updated literature review entry for this latest document:

**📄 Literature Review Entry**

**Financial Risk Tolerance Revisited: The Development of a Risk Assessment Instrument**

Grable and Lytton (1999) present one of the foundational papers in financial risk tolerance (FRT) research, detailing the conceptual, methodological, and empirical development of a **13-item financial risk tolerance assessment instrument**. Their work addresses the lack of standardised, validated tools for measuring individual FRT.

Key insights:

* Reviews limitations of existing FRT assessment methods: choice dilemmas, utility theory, objective measures, heuristics.
* Proposes a **multidimensional questionnaire-based instrument**, designed to measure FRT through diverse financial scenarios (lotteries, investments, losses, gains).
* Initial 20-item pool reduced to 13 items through factor analysis, measuring constructs of:
  + **Investment risk**
  + **Risk comfort and experience**
  + **Speculative risk**
* Achieved acceptable **reliability (Cronbach’s alpha = 0.75)** and construct validity through correlation with the Survey of Consumer Finances (SCF) risk item.
* Emphasises importance of multi-scenario, context-specific assessment for accurate FRT profiling.
* Suggests practical applications for financial advisors, educators, and researchers in tailoring investment advice and understanding client risk preferences.

**📚 Harvard Reference**

Grable, J. & Lytton, R.H. (1999) 'Financial risk tolerance revisited: The development of a risk assessment instrument', *Financial Services Review*, 8(3), pp. 163–181. <https://doi.org/10.1016/S1057-0810(99)00041-4>.

**📊 Literature Review Table (Updated with Importance Column)**

| **Source** | **Key Insights** | **Methods** | **Relevance to Capstone** | **Importance/Recommendation** |
| --- | --- | --- | --- | --- |
| Grable & Lytton (1999) | Developed a validated 13-item FRT assessment instrument. Measures investment risk, risk comfort/experience, and speculative risk. Emphasises multidimensional, scenario-based assessment. Validated against SCF item. Highlights application for advisers and educators. | Instrument development (item analysis, factor analysis), survey of 1,075 respondents, validity & reliability testing. | Directly relevant for your capstone’s risk profiling tool, particularly for constructing robust FRT assessment instruments. Provides a foundational methodology for multidimensional FRT evaluation. | **High** – Must read for instrument design and empirical validation of financial risk tolerance tools. |

Would you like me to update the **visual literature review summary slide** to include this new entry?  
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Another

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Here’s the analysis and update for your literature review table based on this latest document:

**📄 Literature Review Entry**

**Does Personality Predict Financial Risk Tolerance of Pre-Retiree Baby Boomers?**

Rabbani, Yao, and Wang (2019) explore the relationship between **Big Five personality traits** and **financial risk tolerance (FRT)** among pre-retiree baby boomers, using data from the **National Longitudinal Survey of Youth 1979 (NLSY79)**. This study tests whether personality traits influence FRT consistently across generations.

Key insights:

* Found that **extraversion, emotional stability, and openness to experience** are positively associated with risk tolerance.
* **Agreeableness and conscientiousness** are negatively associated with risk tolerance.
* Results support the hypothesis that personality-driven risk attitudes are stable across generational cohorts.
* Highlights the **practical utility of the Ten-Item Personality Inventory (TIPI)** as a fast and reliable method for assessing client personality in financial advisory contexts.
* Suggests financial advisers can enhance profiling accuracy by integrating personality assessments into client risk evaluations.
* Explains demographic impacts: males, wealthier individuals, and business owners show higher risk tolerance, aligning with behavioural finance literature.

**📚 Harvard Reference**

Rabbani, A.G., Yao, Z. & Wang, C. (2019) 'Does personality predict financial risk tolerance of pre-retiree baby boomers?', *Journal of Behavioral and Experimental Finance*, 23, pp. 124–132. <https://doi.org/10.1016/j.jbef.2019.06.001>.

**📊 Literature Review Table (Updated with Importance Column)**

| **Source** | **Key Insights** | **Methods** | **Relevance to Capstone** | **Importance/Recommendation** |
| --- | --- | --- | --- | --- |
| Rabbani et al. (2019) | Big Five traits (Extraversion, Emotional Stability, Openness) increase FRT. Agreeableness & Conscientiousness decrease FRT. TIPI validated as quick personality tool. Highlights demographic impacts on FRT. Recommends integrating personality in client profiling. | OLS regression on NLSY79 dataset (n=4447). Big Five personality assessment via TIPI. Generational analysis of FRT determinants. | Highly relevant for your capstone’s client risk profiling. Directly supports using personality traits in risk tolerance modelling. Provides empirical backing for adviser-facing assessment tools. | **High** – Must read for personality-based risk tolerance modelling. |

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Here’s the analysis and updated literature review entry for this latest document:

**📄 Literature Review Entry**

**Can Self-Assessed Financial Risk Measures Explain and Predict Bank Customers’ Objective Financial Risk?**

Hermansson (2018) evaluates the ability of **subjective risk preference measures** (self-assessed) to explain and predict **objective financial risk** (actual portfolio allocations) among Swedish bank customers. The study contrasts simple self-assessment methods (e.g., lottery-choice questions) with more nuanced multi-item survey instruments.

Key insights:

* Subjective risk measures **do correlate with objective risk behaviours**, but the relationship is relatively weak.
* **Trade-off questions on risk-return** performed better than hypothetical lotteries in explaining objective risk.
* Multi-item measures (e.g., survey-based composites) showed superior explanatory power compared to single-item variables.
* Use of, and trust in, financial advisers were stronger predictors of objective risk than subjective risk measures themselves.
* Identifies gender, age, wealth, debt, and financial literacy as moderators affecting the relationship between subjective and objective risk.
* Emphasises practical application in robo-advisors and regulatory contexts (e.g., MiFID II), where accurate client risk profiling is critical.
* Highlights the **need for hybrid models combining survey-based assessments and behavioural data** to improve risk profiling accuracy.

**📚 Harvard Reference**

Hermansson, C. (2018) 'Can self-assessed financial risk measures explain and predict bank customers’ objective financial risk?', *Journal of Economic Behavior & Organization*, 148, pp. 226–240. <https://doi.org/10.1016/j.jebo.2018.02.018>.

**📊 Literature Review Table (Updated with Importance Column)**

| **Source** | **Key Insights** | **Methods** | **Relevance to Capstone** | **Importance/Recommendation** |
| --- | --- | --- | --- | --- |
| Hermansson (2018) | Subjective risk measures can explain and predict objective risk, but weakly. Trade-off survey questions outperform lottery-choice in explanatory power. Multi-item measures outperform single-item. Financial adviser usage and trust are stronger predictors. Highlights hybrid model necessity for client profiling. | Large-scale survey (n=7,234), bank register data, OLS regression, predictive validation (RMSE), multi-group analysis. Comparison of subjective vs. objective risk measures. | Highly relevant for your capstone's risk profiling component, particularly in enhancing explainability and bridging subjective-objective risk assessment gaps. Supports the case for multi-item, survey-driven, hybrid risk assessment models. | **High** – Must read for empirical validation of subjective risk measures in client profiling contexts. |

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Here’s the analysis and updated literature review entry for this latest document:

**📄 Literature Review Entry**

**A Test of Traditional and Psychometric Relative Risk Tolerance Measures on Household Financial Risk Taking**

Grable, Lyons, and Heo (2019) compare the predictive power of two methods for assessing financial risk tolerance (FRT):

1. **Revealed preference measures (lottery/gamble-based)**, per Barsky et al. (1997).
2. **Psychometric propensity measures**, specifically the Grable & Lytton (1999) scale.

Key insights:

* Psychometric FRT measures are more predictive of actual financial risk-taking behaviour (e.g., equity and cash holdings) than gamble-based measures.
* The Barsky lottery-based measure showed no significant relationship with household portfolio allocations (both equities and cash).
* The G&L psychometric measure was significantly associated with:
  + Higher equity holdings.
  + Lower cash holdings.
* Findings suggest that psychometric methods capture behavioural nuances and attitudes more effectively than simplistic gamble-based risk estimations.
* Implications for financial advisers: psychometric assessments are recommended for accurate client profiling, especially in retirement planning and investment advisory contexts.

**📚 Harvard Reference**

Grable, J.E., Lyons, A.C. & Heo, W. (2019) 'A test of traditional and psychometric relative risk tolerance measures on household financial risk taking', *Finance Research Letters*, 30, pp. 8–13. <https://doi.org/10.1016/j.frl.2019.03.012>.

**📊 Literature Review Table (Updated with Importance Column)**

| **Source** | **Key Insights** | **Methods** | **Relevance to Capstone** | **Importance/Recommendation** |
| --- | --- | --- | --- | --- |
| Grable, Lyons & Heo (2019) | Compares revealed preference (lottery-based) vs psychometric (G&L scale) FRT measures. G&L psychometric measure significantly predicts equity & cash holdings. Barsky lottery-based measure shows no predictive power. Supports psychometric tools for client risk profiling in practice. | Survey of 357 investors, OLS regression, Tobit models for censored data, comparison of FRT measures against actual portfolio allocations. | Highly relevant for your capstone’s risk profiling design, especially supporting psychometric assessment as the preferred methodology for adviser-client interactions. Empirical validation of G&L scale effectiveness. | **High** – Must read for method selection and empirical support for psychometric risk profiling. |

Would you like me to now update your **visual literature review summary slide** with this entry added?  
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Here’s the analysis and updated literature review table entry for the latest document:

**📄 Literature Review Entry**

**Aging, Overconfidence, and Portfolio Choice**

Pak and Chatterjee (2016) examine how **cognitive aging and overconfidence** influence the **riskiness of retirement portfolios**. Using data from the **Cognitive Economics Study (CogEcon)**, they analyse whether age-related increases in overconfidence explain persistent risky asset holdings among older investors, despite declining financial proficiency.

Key insights:

* **Overconfidence increases with age** even as actual financial knowledge declines.
* Older investors often **fail to recognise their cognitive decline**, leading to riskier portfolio allocations than would be considered optimal.
* Overconfidence is significantly associated with:
  + **Higher equity ownership**.
  + **Lower holdings of cash equivalents**.
* Financial sophistication was more strongly associated with preferences for bonds and mutual funds (less risky or professionally managed assets).
* **Financial advisers mitigate the effects of overconfidence**, acting as a behavioural “circuit breaker”.
* Results suggest the necessity of interventions (e.g., advice, education) to help older investors manage risk appropriately.
* Highlights the **multi-faceted cognition-stockholding relationship**, where both rational (declining skill) and irrational (overconfidence) forces influence portfolio decisions.

**📚 Harvard Reference**

Pak, T.Y. & Chatterjee, S. (2016) 'Aging, overconfidence, and portfolio choice', *Journal of Behavioral and Experimental Finance*, 12, pp. 112–122. <https://doi.org/10.1016/j.jbef.2016.10.003>.

**📊 Literature Review Table (Updated with Importance Column)**

| **Source** | **Key Insights** | **Methods** | **Relevance to Capstone** | **Importance/Recommendation** |
| --- | --- | --- | --- | --- |
| Pak & Chatterjee (2016) | Cognitive aging increases overconfidence, leading to riskier portfolios. Overconfidence linked to higher equity, lower cash holdings. Financial advice mitigates behavioural biases. Highlights cognition-stockholding nexus in retirement planning. | Two-part models (ownership & allocation), fractional logit, zero-inflated beta models. CogEcon data analysis. | Highly relevant for your capstone's behavioural risk profiling component. Supports inclusion of cognitive & behavioural metrics in client risk assessments. Validates adviser intervention strategies. | **High** – Must read for behavioural dynamics of risk tolerance in older investors and practical adviser implications. |

Would you like me to update your **visual literature review summary slide** with this new entry included?  
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**ChatGPT said:**

Here’s the analysis and updated literature review entry for this document:

**📄 Literature Review Entry**

**How Does Investor Confidence Lead to Trading? Linking Return Experiences, Confidence, and Beliefs**

Hoffmann and Post (2016) investigate the **mechanism through which investor confidence leads to trading activity**, going beyond the well-established correlation between confidence and trading volume. They propose and empirically validate an **experience-confidence-belief-trading framework**, integrating concepts from reinforcement learning and behavioural finance.

Key insights:

* Confident investors are more prone to **extrapolate past returns into future expectations**, aligning with naïve reinforcement learning.
* Given identical return experiences, more confident investors **adjust their expectations more strongly**, increasing their propensity to trade.
* Higher belief updates directly result in higher portfolio turnover, which in turn **negatively impacts investment performance**.
* Investors with above-average confidence exhibit **8.6 percentage points higher turnover** and underperform by **88 basis points monthly**.
* The study combines **actual brokerage records** with a **12-month survey panel**, matching return experiences, beliefs, and confidence measures.
* Findings suggest that overconfidence amplifies belief revisions, providing more ‘reasons’ to trade—driving excessive trading and reducing returns.
* Recommends behavioural interventions (e.g., reframing performance feedback) to mitigate detrimental trading behaviours linked to overconfidence.

**📚 Harvard Reference**

Hoffmann, A.O.I. & Post, T. (2016) 'How does investor confidence lead to trading? Linking investor return experiences, confidence, and investment beliefs', *Journal of Behavioral and Experimental Finance*, 12, pp. 65–78. <https://doi.org/10.1016/j.jbef.2016.09.003>.

**📊 Literature Review Table (Updated with Importance Column)**

| **Source** | **Key Insights** | **Methods** | **Relevance to Capstone** | **Importance/Recommendation** |
| --- | --- | --- | --- | --- |
| Hoffmann & Post (2016) | Investor confidence drives stronger belief updates after return experiences, leading to more trading. Experience-confidence-belief-trading framework validated. Higher turnover linked to underperformance. Combines brokerage data with survey panel. | Panel regressions on 1,376 investors, brokerage records & monthly surveys. Naïve reinforcement learning model. Turnover-performance linkage quantified. | Highly relevant for behavioural aspects of your capstone’s client risk profiling. Supports integrating return experience sensitivity and overconfidence mitigation strategies in advisory models. | **High** – Must read for behavioural mechanisms linking confidence, beliefs, and trading activity. |

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**ChatGPT said:**

Here’s the analysis and updated literature review entry for this document:

**📄 Literature Review Entry**

**Portfolio Performance Across Genders and Generations: The Role of Financial Innovation**

Davydov et al. (2017) explore how **gender and age influence the use and performance of Exchange Traded Products (ETPs)** compared to mutual funds, using a unique dataset of Swedish retail investors. They examine the behavioural impact of financial innovation on portfolio performance, focusing on self-control, overconfidence, and demographic determinants.

Key insights:

* **Mutual funds yield better performance than ETPs** for the majority of investors, attributed to reduced trading frequency and enforced self-control.
* **Younger investors are more effective users of ETPs**, benefiting from better cognitive skills despite overconfidence tendencies.
* **Older investors trade more actively but also perform better overall**, possibly due to accumulated experience.
* **Female investors trade less actively**, take less risk, and achieve higher risk-adjusted returns (Sharpe ratio) than male investors.
* Trading ETPs correlates with **poorer portfolio performance and higher volatility**, especially for older male investors.
* Confirms that **financial innovation (e.g., ETPs)** amplifies speculative trading behaviour, worsening outcomes when not managed by robust self-control mechanisms.
* Emphasises the importance of demographic tailoring in product design and advisory services, with age and gender exerting distinct influences on investor behaviour.

**📚 Harvard Reference**

Davydov, D., Florestedt, O., Peltomäki, J. & Schön, M. (2017) 'Portfolio performance across genders and generations: The role of financial innovation', *International Review of Financial Analysis*, 50, pp. 44–51. <https://doi.org/10.1016/j.irfa.2017.01.006>.

**📊 Literature Review Table (Updated with Importance Column)**

| **Source** | **Key Insights** | **Methods** | **Relevance to Capstone** | **Importance/Recommendation** |
| --- | --- | --- | --- | --- |
| Davydov et al. (2017) | Gender and age influence ETP use and portfolio outcomes. Mutual funds outperform ETPs for most investors. Females trade less, take less risk, earn higher Sharpe ratios. Younger investors are better active users of financial innovations. ETP trading linked to poorer performance due to self-control issues. | Transaction-level dataset of 134,201 Swedish retail investors. Univariate and multivariate regressions by gender and age. Sharpe ratio, returns, SD, turnover analyses. | Highly relevant for your capstone's risk profiling and client segmentation objectives. Empirical support for demographic-tailored risk advisory models and product usage strategies. | **High** – Must read for demographic behaviour in financial innovation usage and risk profiling accuracy. |

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Reply **"Yes, update the visual slide please"** if you'd like that.

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Here’s the analysis and updated literature review entry for the latest document:

**📄 Literature Review Entry**

**Perception of Intentionality in Investor Attitudes Towards Financial Risks**

Bossaerts, Suzuki, and O'Doherty (2019) challenge the conventional view of financial risk as purely stochastic by proposing that humans often adopt an **intentional stance**—treating financial markets as if they are intentional agents with beliefs and desires. This application of **Theory of Mind (ToM)** explains heterogeneity in investor behaviour, particularly in forecasting, bubble participation, and financial contagion.

Key insights:

* Investors tend to personify financial markets, attributing intentions to price movements and market behaviour.
* **ToM skills explain forecasting performance** in markets with insiders, where strategic interaction cues are present.
* Investors with stronger ToM skills are more susceptible to **"riding bubbles"**, perceiving intentional signals in price deviations.
* Observing others' risk choices causes **financial contagion**, where ToM regions (dmPFC, TPJ) and sub-cortical structures (caudate) modulate the observer’s own risk assessment.
* Empirical studies using fMRI and behavioural tasks confirm that ToM-driven perception of intentionality affects trading decisions and neural activation patterns.
* Emphasises the dual role of ToM: useful in certain contexts (e.g., insider markets) but a liability in others (e.g., bubbles).
* Advocates for incorporating ToM considerations into financial advisory and educational strategies to mitigate overconfidence and contagion effects.

**📚 Harvard Reference**

Bossaerts, P., Suzuki, S. & O'Doherty, J.P. (2019) 'Perception of intentionality in investor attitudes towards financial risks', *Journal of Behavioral and Experimental Finance*, 23, pp. 189–197. <https://doi.org/10.1016/j.jbef.2017.12.011>.

**📊 Literature Review Table (Updated with Importance Column)**

| **Source** | **Key Insights** | **Methods** | **Relevance to Capstone** | **Importance/Recommendation** |
| --- | --- | --- | --- | --- |
| Bossaerts et al. (2019) | Investors apply Theory of Mind to markets, treating them as intentional agents. ToM skills explain heterogeneity in forecasting, bubble-riding, and contagion effects. Neuroimaging confirms ToM region activation. Highlights the risk of misapplying ToM in financial decisions. Recommends ToM-aware interventions in advisory contexts. | Experimental finance, fMRI studies, Theory of Mind tests (Heider Movie, Eye Gaze), behavioural tasks. Case studies on markets with insiders, bubbles, contagion. | Highly relevant for your capstone’s behavioural risk profiling. Supports integrating cognitive-behavioural factors (e.g., ToM) into client profiling and advisory models. Provides empirical evidence on investor behaviour heterogeneity. | **High** – Must read for behavioural finance modelling and ToM implications in risk perception. |

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Here’s the analysis and updated literature review entry for the latest document:

**📄 Literature Review Entry**

**Modeling Retirees’ Investment Behaviors in the Presence of Health Expenditure Risk and Financial Crisis Risk**

Gao and Sun (2021) develop a life-cycle model to analyse how **health expenditure shocks** and **financial market tail risks** jointly influence retirees' portfolio choices. They argue that existing models fail to explain why retirees hold lower levels of risky assets than predicted, as they often overlook the dual constraints of health and market risks.

Key insights:

* **Health shocks increase disposable income uncertainty**, reducing risk-taking capacity, especially among moderately wealthy retirees.
* **Financial crisis risk amplifies investment conservatism**, as retirees are more exposed to wealth evaporation due to their shorter investment horizons.
* A combined model of health risk and financial crisis risk accurately predicts the observed decline in risky asset holdings among retirees.
* Retirees with good health allocate more to risky assets, as their effective 'risk-free' income (after health costs) is higher.
* The model recommends **tail-risk hedging strategies (e.g., put options)** to mitigate catastrophic market events.
* Demonstrates the need for **health-adjusted portfolio management**, where asset allocation is dynamically adjusted based on health expenditure exposure and market risk scenarios.
* Validated using US Health and Retirement Survey (HRS) data, incorporating heterogeneity across health statuses and wealth deciles.

**📚 Harvard Reference**

Gao, X. & Sun, L. (2021) 'Modeling retirees’ investment behaviors in the presence of health expenditure risk and financial crisis risk', *Economic Modelling*, 94, pp. 442–454. <https://doi.org/10.1016/j.econmod.2020.10.013>.

**📊 Literature Review Table (Updated with Importance Column)**

| **Source** | **Key Insights** | **Methods** | **Relevance to Capstone** | **Importance/Recommendation** |
| --- | --- | --- | --- | --- |
| Gao & Sun (2021) | Life-cycle model integrating health expenditure shocks & financial crisis risk. Explains observed conservative investment behaviours in retirees. Validates dual-risk impact using HRS data. Recommends tail-risk hedging strategies. Highlights health-adjusted portfolio management necessity. | Dynamic stochastic life-cycle model, numerical simulation, calibration with HRS data, empirical validation. | Highly relevant for modelling client risk profiles with health-related and market-induced risk factors. Supports dynamic portfolio allocation strategies under multiple risk constraints. | **High** – Must read for dual-risk modelling and its implications on personalised portfolio management. |

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Here’s the analysis and updated literature review entry for this latest document:

**📄 Literature Review Entry**

**Individual Investor Perceptions and Behavior During the Financial Crisis**

Hoffmann, Post, and Pennings (2013) combine monthly survey data with brokerage records to examine how **individual investor perceptions (return expectations, risk tolerance, risk perception)** influenced their **trading and risk-taking behaviour** during the 2008–2009 financial crisis.

Key insights:

* Investors’ **return expectations and risk tolerance decreased**, while **risk perceptions increased** during crisis peaks, but these changes were temporary and reversed post-crisis.
* Contrary to expectations, investors **continued trading actively** and did not de-risk their portfolios significantly during the crisis.
* Investors used **depressed asset prices as buying opportunities**, providing liquidity while institutions withdrew.
* **Perception dynamics (changes in risk tolerance and risk perception)** were found to be key drivers of risk-taking and trading activity.
* Risk tolerance had a more stable impact, while return expectations and perceptions exhibited higher sensitivity to market fluctuations.
* Findings challenge theories suggesting crisis-induced permanent shifts in risk attitudes.
* Implications: advisory strategies should consider perception-driven, context-sensitive client behaviour rather than assume static risk profiles.

**📚 Harvard Reference**

Hoffmann, A.O.I., Post, T. & Pennings, J.M.E. (2013) 'Individual investor perceptions and behavior during the financial crisis', *Journal of Banking & Finance*, 37(1), pp. 60–74. <https://doi.org/10.1016/j.jbankfin.2012.08.007>.

**📊 Literature Review Table (Updated with Importance Column)**

| **Source** | **Key Insights** | **Methods** | **Relevance to Capstone** | **Importance/Recommendation** |
| --- | --- | --- | --- | --- |
| Hoffmann, Post & Pennings (2013) | Examines how investor perceptions (return expectations, risk tolerance, risk perception) drive trading & risk-taking during crisis. Finds temporary perception shifts, active trading, no mass de-risking. Perception dynamics are stronger predictors than static risk measures. Investors exploit crisis-driven price drops for buying. | Panel data (1376 investors), monthly surveys & brokerage records, risk perception dynamics, regression analysis. | Highly relevant for modelling client risk perception and behaviour under stress scenarios. Supports integrating perception dynamics into client risk profiling and advisory strategies. | **High** – Must read for perception-behaviour linkages in financial crises and adaptive risk profiling. |

Would you like me to now update your **visual literature review summary slide** with this entry included?  
Reply **"Yes, update the visual slide please"** if you'd like that.

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Here’s the analysis and updated literature review entry for the latest document:

**📄 Literature Review Entry**

**Risk Perception in Financial Markets: On the Flip Side**

Bekiros et al. (2018) examine the **asymmetric and dynamic nature of risk perception** in global financial markets using implied volatility (e.g., VIX) as a fear sentiment gauge. They argue that traditional leverage-feedback models fail to capture how **emotional, cultural, and behavioural biases shape risk perception differently across regions**, especially post-crisis.

Key insights:

* Risk perception is **not merely the inverse of exuberance**; fear of losses and optimism from gains follow different behavioural pathways.
* **Implied volatility exhibits an asymmetric, non-linear relationship with returns** globally, but regional differences are profound:
  + US and developed markets display **steep increases in perceived risk after losses** (loss aversion amplified).
  + Asian markets show **moderated responses**, more tolerant to losses but less exuberant in gains due to collectivist cultures.
* During the Global Financial Crisis, a **global contagion effect** in fear sentiment was observed, primarily **driven by US market volatility spillovers**.
* Investors’ risk perception is heavily influenced by **cognitive biases (framing, affective reactions)** and **cultural factors** (e.g., individualism, uncertainty avoidance).
* **Contagion channels (e.g., through VIX)** demonstrate that market sentiment is interlinked, but with varying degrees of sensitivity and lag effects across regions.
* Proposes that incorporating behavioural finance concepts (e.g., Theory of Mind, emotional heuristics) provides a superior explanatory model for risk-return dynamics than classical theories.

**📚 Harvard Reference**

Bekiros, S., Jlassi, M., Naoui, K. & Uddin, G.S. (2018) 'Risk perception in financial markets: On the flip side', *International Review of Financial Analysis*, 57, pp. 184–206. <https://doi.org/10.1016/j.irfa.2018.03.005>.

**📊 Literature Review Table (Updated with Importance Column)**

| **Source** | **Key Insights** | **Methods** | **Relevance to Capstone** | **Importance/Recommendation** |
| --- | --- | --- | --- | --- |
| Bekiros et al. (2018) | Risk perception asymmetry: fear of losses ≠ exuberance from gains. Implied volatility captures dynamic behavioural responses. Regional heterogeneity in fear sentiment shaped by cultural factors. US market contagion drives global fear propagation. Behavioural heuristics outperform classical leverage-feedback models. | Panel regressions, asymmetric OLS models, VAR causality tests. Dataset of 20 international markets (2000–2014). Implied volatility (VIX) as proxy for fear sentiment. | Highly relevant for your capstone’s modelling of client risk perception. Supports integrating cultural, emotional, and behavioural biases into risk advisory tools. Empirical evidence for asymmetric risk-return relationships. | **High** – Must read for dynamic risk perception modelling and behavioural bias integration into financial risk profiling. |

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Here’s the analysis and updated literature review entry for this latest document:

**📄 Literature Review Entry**

**An Evaluation of the Effect of the COVID-19 Pandemic on the Risk Tolerance of Financial Decision Makers**

Heo, Rabbani, and Grable (2021) examine how the **COVID-19 pandemic influenced financial risk tolerance (FRT)** among decision makers. Using a large cross-sectional survey (N = 18,913), they identify shifts in risk attitudes following the pandemic's emergency declaration, leveraging **Latent Profile Analysis (LPA)** for behavioural clustering.

Key insights:

* A **general shift towards greater risk aversion** was observed post-pandemic, with 55% of respondents classified into the low-risk tolerance cluster (up from 49% pre-pandemic).
* Paradoxically, the **average FRT score increased post-pandemic**, suggesting heterogeneous impacts where confident individuals maintained or increased risk tolerance while less confident ones became more risk-averse.
* **Subjective financial knowledge** remained a strong predictor of high FRT, more so than objective measures like education.
* The study found demographic effects (e.g., gender, income) consistent pre- and post-pandemic, but education’s predictive power weakened post-crisis.
* Recommends that **extreme macro-social shocks** (like pandemics) should be modelled as quasi-experiments to understand behavioural shifts in risk preferences.
* Emphasises the need for dynamic risk profiling, with behavioural and perception factors weighted more heavily than static demographics.

**📚 Harvard Reference**

Heo, W., Rabbani, A. & Grable, J.E. (2021) 'An evaluation of the effect of the COVID-19 pandemic on the risk tolerance of financial decision makers', *Finance Research Letters*, 41, Article 101842. <https://doi.org/10.1016/j.frl.2020.101842>.

**📊 Literature Review Table (Updated with Importance Column)**

| **Source** | **Key Insights** | **Methods** | **Relevance to Capstone** | **Importance/Recommendation** |
| --- | --- | --- | --- | --- |
| Heo, Rabbani & Grable (2021) | COVID-19 shifted FRT towards greater aversion overall. Subjective financial knowledge remained a strong predictor. Education's predictive power diminished post-pandemic. Supports dynamic, behavioural-focused risk profiling. Recommends treating macro shocks as quasi-experiments in FRT studies. | Cross-sectional survey (N=18,913), Latent Profile Analysis (LPA), pre/post-pandemic behavioural comparison. | Highly relevant for your capstone’s adaptive risk profiling in response to external shocks. Empirical evidence for perception-driven shifts in risk tolerance. Supports dynamic profiling over static demographic-based methods. | **High** – Must read for crisis-induced FRT modelling and behavioural clustering strategies. |

Would you like me to now update your **visual literature review summary slide** with this entry added?  
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Here’s the analysis and updated literature review entry for this latest document:

**📄 Literature Review Entry**

**Special Issue Editorial: Machine Learning in Insurance**

Asimit, Kyriakou, and Nielsen (2020) introduce a **special issue on Machine Learning (ML) in Insurance**, summarising ten cutting-edge papers on applying ML techniques in various actuarial and insurance contexts. This editorial provides a landscape overview rather than presenting original empirical findings.

Key insights:

* Highlights two key papers on **reserving in non-life insurance**:
  + Bischofberger (2020): Reverts the time scale in hazard forecasting for operational time modelling.
  + Elpidorou et al. (2019): Incorporates prior knowledge into the reserving process using likelihood principles.
* Reviews two studies on **telematics-based claim prediction**:
  + Qazvini (2019): Addresses excess-zero claims using advanced statistical validation.
  + Pesantez-Narvaez et al. (2019): Compares XGBoost and logistic regression for motor insurance claims.
* Bermúdez et al. (2020) apply finite mixture models for **claim count heterogeneity modelling**.
* Krah et al. (2020) explore adaptive ML methods for **proxy modelling in life insurance solvency capital requirements (SCR)**.
* Sarabia et al. (2020) combine **semi-parametric methods with ML for financial data analysis**.
* Mammen et al. (2019) apply ML to **forecast conditional variance in long-term stock returns**.
* Emphasises a balanced integration of ML with actuarial and statistical principles to maintain model transparency and regulatory compliance.
* Frames ML in insurance as a tool for enhancing predictive accuracy, managing unobserved heterogeneity, and supporting solvency and reserving tasks.

**📚 Harvard Reference**

Asimit, V., Kyriakou, I. & Nielsen, J.P. (2020) 'Editorial: Special Issue “Machine Learning in Insurance”', *Risks*, 8(2), Article 54. <https://doi.org/10.3390/risks8020054>.

**📊 Literature Review Table (Updated with Importance Column)**

| **Source** | **Key Insights** | **Methods** | **Relevance to Capstone** | **Importance/Recommendation** |
| --- | --- | --- | --- | --- |
| Asimit, Kyriakou & Nielsen (2020) | Overview of ML applications in insurance reserving, claims, solvency, and financial forecasting. Emphasises integrating ML with statistical rigor. Highlights model transparency and regulatory considerations. Summarises ten key papers on ML in insurance contexts. | Editorial review of special issue papers. Synthesis of recent ML applications in insurance. | Useful for situating your capstone within the broader ML-insurance research landscape. Helps identify relevant methods (e.g., XGBoost, mixture models, proxy modelling) and their actuarial applications. Provides context for balancing accuracy and transparency. | **Medium-High** – Recommended for literature positioning and identifying key ML methods relevant to insurance risk modelling. |

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Regression Tree Credibility Model.pdf

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Here’s the analysis and updated literature review entry for this latest document:

**📄 Literature Review Entry**

**Regression Tree Credibility Model**

Diao and Weng (2019) propose a novel **Regression Tree Credibility (RTC) Model** that combines credibility theory with machine learning techniques, specifically regression trees, for premium prediction in insurance. Their approach integrates covariate information into credibility premium estimation without requiring prior specification of regression forms.

Key insights:

* The RTC model applies a **recursive partitioning algorithm** to classify risks into mutually exclusive subgroups, optimising the **Bühlmann-Straub credibility premium** prediction.
* Unlike traditional models, the RTC method:
  + Captures **nonlinear and interaction effects** of covariates.
  + **Automatically selects influential covariates**, avoiding ex ante variable selection.
  + Provides a **data-driven classification** rather than relying on pre-defined structures.
* Extensive simulation studies demonstrate that RTC consistently outperforms:
  + Classical credibility models.
  + Generalised linear models (GLMs).
  + L2 regression tree methods.
  + Ad hoc partitioning schemes.
* A real-world application on **US Medicare provider payment data** validates the RTC model's superiority in premium prediction accuracy, especially for small-volume risks.
* The paper advocates extending RTC to ensemble methods (e.g., random forests, boosting) for further improvements.

**📚 Harvard Reference**

Diao, L. & Weng, C. (2019) 'Regression tree credibility model', *North American Actuarial Journal*, 23(2), pp. 169–196. <https://doi.org/10.1080/10920277.2018.1554497>.

**📊 Literature Review Table (Updated with Importance Column)**

| **Source** | **Key Insights** | **Methods** | **Relevance to Capstone** | **Importance/Recommendation** |
| --- | --- | --- | --- | --- |
| Diao & Weng (2019) | Regression Tree Credibility Model combines credibility theory & machine learning. Captures nonlinear & interaction covariate effects. Data-driven, no prior model form needed. Outperforms classical models & GLMs in premium prediction. Validated on US Medicare data. | Recursive partitioning, Bühlmann-Straub formula, simulation studies, real-world application on Medicare data. | Highly relevant for your capstone’s risk profiling and premium estimation. Supports hybrid actuarial-ML methods, with focus on explainability & predictive accuracy. Provides a scalable, practical framework for data-driven insurance pricing. | **High** – Must read for hybrid ML-credibility methods and practical premium prediction improvements. |

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**You said:**

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Here’s the analysis and updated literature review entry for this latest document:

**📄 Literature Review Entry**

**The Accuracy of XGBoost for Insurance Claim Prediction**

Fauzan and Murfi (2018) evaluate the performance of **XGBoost** in predicting insurance claims, comparing it to other ensemble learning methods (AdaBoost, Stochastic Gradient Boosting, Random Forest) and Neural Networks. The study addresses challenges of large datasets and missing values in auto-insurance claim prediction, leveraging XGBoost’s strengths in handling both.

Key insights:

* XGBoost demonstrated superior predictive accuracy, measured via **Normalized Gini Coefficient**, compared to AdaBoost, Stochastic GB, Random Forest, and Neural Networks.
* XGBoost's **sparsity awareness** and **out-of-core learning** make it especially suitable for large insurance datasets with many missing values.
* A detailed **six-stage hyperparameter tuning process** enhanced model performance, emphasising the importance of parameter optimisation in predictive modelling.
* The Porto Seguro dataset (Kaggle competition) was used, featuring high class imbalance (only 6% positive claims), large volume, and significant missing data.
* Feature selection was conducted using correlation analyses, removing low-informative features, particularly from the 'calc' group.
* Comparisons highlighted that while Stochastic GB came close in training accuracy, XGBoost outperformed in test data due to its robust handling of missing values without imputation biases.
* Findings advocate for XGBoost's adoption in operational auto-insurance claim prediction tasks, given its accuracy and computational efficiency.

**📚 Harvard Reference**

Fauzan, M.A. & Murfi, H. (2018) 'The accuracy of XGBoost for insurance claim prediction', *International Journal of Advance Soft Computing Applications*, 10(2), pp. 159–171.

**📊 Literature Review Table (Updated with Importance Column)**

| **Source** | **Key Insights** | **Methods** | **Relevance to Capstone** | **Importance/Recommendation** |
| --- | --- | --- | --- | --- |
| Fauzan & Murfi (2018) | XGBoost outperforms other ensemble methods in claim prediction. Handles large-scale data and missing values effectively. 6-stage hyperparameter tuning boosts accuracy. Validated on Porto Seguro auto-insurance dataset. Recommends XGBoost for operational claim prediction. | XGBoost modelling, feature selection via correlation analysis, 6-stage grid search, normalized Gini evaluation, comparison with AdaBoost, Stochastic GB, Random Forest, Neural Nets. | Highly relevant for your capstone's predictive modelling, particularly for selecting robust methods under data volume and missing value constraints. Provides empirical evidence supporting XGBoost's practical application in insurance risk tasks. | **High** – Must read for method selection and practical insurance ML applications. |

Would you like me to update your **visual literature review summary slide** to include this latest entry?  
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**You said:**

A data driven binning strategy for the construction of insurance tariff classes.pdf

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Another

**ChatGPT said:**

Here’s the analysis and updated literature review entry for this document:

**📄 Literature Review Entry**

**A Data-Driven Binning Strategy for the Construction of Insurance Tariff Classes**

Henckaerts et al. (2018) propose a practical strategy for constructing **insurance tariff classes** by **binning continuous and spatial risk factors**, aligning statistical flexibility with business and regulatory needs. The approach begins with flexible models (GAMs) and transforms these into interpretable, easy-to-implement Generalized Linear Models (GLMs) through data-driven binning.

Key insights:

* Combines **Fisher’s Natural Breaks algorithm** for spatial risk factors and **Evolutionary Trees** for continuous risk factors to create manageable tariff classes.
* Ensures that the binning process considers both predictive accuracy and the portfolio composition (exposure-based weighting).
* Demonstrates that GLMs constructed from binned factors approximate GAMs very closely in premium estimation and portfolio loss modelling.
* Empirical application on a Belgian motor insurance dataset shows negligible differences between the GAM-based and GLM-based premiums (<0.01% deviation).
* Highlights trade-offs between model complexity, interpretability, and predictive performance, advocating for pragmatic balance in actuarial practice.
* Reinforces that machine learning methods can enhance traditional actuarial models while preserving transparency required by stakeholders and regulators.

**📚 Harvard Reference**

Henckaerts, R., Antonio, K., Clijsters, M. & Verbelen, R. (2018) 'A data-driven binning strategy for the construction of insurance tariff classes', *Scandinavian Actuarial Journal*, 2018(8), pp. 681–705. <https://doi.org/10.1080/03461238.2018.1429300>.

**📊 Literature Review Table (Updated with Importance Column)**

| **Source** | **Key Insights** | **Methods** | **Relevance to Capstone** | **Importance/Recommendation** |
| --- | --- | --- | --- | --- |
| Henckaerts et al. (2018) | Proposes a data-driven binning strategy using Fisher’s Natural Breaks & Evolutionary Trees. Aligns flexible GAM models with practical GLM tariff structures. Demonstrates near-equivalent premium estimation between GAMs and binned GLMs. Balances model complexity, interpretability, and business needs. | GAMs for frequency & severity modelling. Data-driven binning (Fisher’s algorithm, Evolutionary Trees). GLM approximation & validation on Belgian motor insurance data. Portfolio loss simulation & VaR analysis. | Highly relevant for your capstone’s risk profiling and tariff construction. Provides practical methodologies to translate flexible ML models into transparent, stakeholder-friendly pricing models. Supports regulatory compliance and business alignment. | **High** – Must read for practical application of data-driven binning in insurance pricing & explainable risk profiling. |

Would you like me to update your **visual literature review summary slide** with this entry included?  
Reply **"Yes, update the visual slide please"** if you'd like that.

**You said:**

2003.10674v1.pdf

PDF

Another

**ChatGPT said:**

Here’s the analysis and updated literature review entry for this latest document:

**📄 Literature Review Entry**

**Towards Explainability of Machine Learning Models in Insurance Pricing**

Kuo and Lupton (2020) address the challenge of **interpreting machine learning (ML) models in property & casualty (P&C) insurance pricing**, proposing a practical framework to bridge the gap between predictive accuracy and regulatory transparency. They present a structured approach to explain ML models while satisfying actuarial standards of practice and regulatory scrutiny.

Key insights:

* Introduces a **question-driven framework for interpretability**, focusing on:
  + Variable importance.
  + Partial dependence (global effects).
  + Variable attribution (local effects).
* Emphasises the **contextual nature of explanations**, noting that explanations must be tailored to stakeholders (regulators, policyholders, management).
* Demonstrates **model-agnostic interpretation techniques**:
  + **Permutation feature importance** for variable ranking.
  + **Partial Dependence Plots (PDP)** to visualise marginal effects.
  + **SHAP values** and additive attribution methods for instance-level explanations.
* Warns against assuming linear models (e.g., GLMs) are always interpretable, especially with high-dimensionality or complex interactions.
* Highlights **regulatory challenges (ASOP 12, ASOP 41, ASOP 56)** regarding model transparency, especially in black-box ML settings.
* Presents a case study on a deep neural network model for loss cost prediction using Brazilian auto insurance data.
* Advocates for continuous refinement of guidelines through collaboration between actuaries, regulators, and industry stakeholders.

**📚 Harvard Reference**

Kuo, K. & Lupton, D. (2020) 'Towards explainability of machine learning models in insurance pricing', *arXiv preprint*, arXiv:2003.10674. <https://arxiv.org/abs/2003.10674>.

**📊 Literature Review Table (Updated with Importance Column)**

| **Source** | **Key Insights** | **Methods** | **Relevance to Capstone** | **Importance/Recommendation** |
| --- | --- | --- | --- | --- |
| Kuo & Lupton (2020) | Proposes a question-driven framework for ML model interpretability in insurance pricing. Demonstrates permutation importance, PDPs, SHAP for global & local explanations. Addresses regulatory (ASOP) and stakeholder communication challenges. Validates with case study on Brazilian auto insurance data. | ML interpretation techniques (permutation importance, PDP, SHAP). Contextual interpretability framework. Application to P&C pricing. Model-agnostic post-hoc explanations. | Highly relevant for your capstone’s focus on explainable AI in client risk profiling. Directly supports your goal of combining predictive accuracy with regulatory transparency and client communication. | **High** – Must read for explainability framework and regulatory-compliant ML interpretation. |

Would you like me to now update your **visual literature review summary slide** with this new entry included?  
Reply **"Yes, update the visual slide please"** if you'd like that.

**You said:**

Improving\_Nave\_Bayes\_models\_of\_insurance\_risk\_by\_unsupervised\_classification.pdf

PDF

Another

**ChatGPT said:**

Here’s the analysis and updated literature review entry for this latest document:

**📄 Literature Review Entry**

**Improving Naïve Bayes Models of Insurance Risk by Unsupervised Classification**

Jurek and Zakrzewska (2008) propose a method to improve the classification accuracy of **Naïve Bayes models** in insurance risk assessment by incorporating **unsupervised clustering (k-means)** during preprocessing. They argue that segmentation allows for more tailored classification models, capturing latent risk patterns among policyholders.

Key insights:

* Baseline Naïve Bayes classifiers achieved 57-59% accuracy on synthetic insurance data (life insurance attributes).
* Introducing **clustering as a preprocessing step (k-means)** improved classification accuracy significantly:
  + 80% accuracy with 3 clusters for 500 instances (8 attributes).
  + 82% accuracy with 3 clusters for 800 instances (11 attributes).
* Performance improvements stem from building **separate Naïve Bayes models for each cluster**, allowing better handling of attribute interactions and heterogeneity.
* Careful attribute selection (e.g., weight, disease, age) per cluster further enhanced accuracy.
* Validated clustering quality using **Davies-Bouldin index**, ensuring cluster compactness and separability.
* Highlighted risks of indiscriminate attribute selection and clustering, noting that improper segmentation can degrade model performance.
* Recommends tolerance thresholds for outlier management in clustering stages.
* Suggests extending this approach to hybrid models (e.g., Selective Bayesian Classifiers) for future research.

**📚 Harvard Reference**

Jurek, A. & Zakrzewska, D. (2008) 'Improving Naïve Bayes models of insurance risk by unsupervised classification', *Proceedings of the International Multiconference on Computer Science and Information Technology*, 3, pp. 137–144. https://doi.org/10.1109/IMCSIT.2008.4747276.

**📊 Literature Review Table (Updated with Importance Column)**

| **Source** | **Key Insights** | **Methods** | **Relevance to Capstone** | **Importance/Recommendation** |
| --- | --- | --- | --- | --- |
| Jurek & Zakrzewska (2008) | Improves Naïve Bayes classification accuracy in insurance risk modelling via unsupervised clustering (k-means). Separate models per cluster handle attribute interactions & heterogeneity. Validated with Davies-Bouldin index. Highlights careful attribute & cluster selection. Recommends hybrid modelling extensions. | Naïve Bayes classifier, k-means clustering, synthetic insurance datasets, attribute selection, Davies-Bouldin index. Risk segmentation approach. | Highly relevant for your capstone's segmentation-driven risk profiling. Demonstrates practical clustering-enhanced Naïve Bayes application. Supports modular model design aligned with client group characteristics. | **High** – Must read for improving explainable risk models via clustering-driven segmentation strategies. |

Would you like me to update your **visual literature review summary slide** to include this latest entry?  
Reply **"Yes, update the visual slide please"** if you'd like that.

**You said:**

Boosting Insights in Insurance Tariff Plans with Tree-Based Machine Learning Methods.pdf

PDF

Another

**ChatGPT said:**

Here’s the analysis and updated literature review entry for this latest document:

**📄 Literature Review Entry**

**Boosting Insights in Insurance Tariff Plans with Tree-Based Machine Learning Methods**

Henckaerts et al. (2021) explore the application of **tree-based machine learning methods (regression trees, random forests, gradient boosting)** to improve **insurance tariff plans**. The study contrasts these methods with the traditional GLM framework, addressing the dual challenge of **predictive accuracy and regulatory interpretability**.

Key insights:

* Proposes adapting tree-based methods to **frequency-severity modelling** typical in insurance pricing, handling imbalanced count data and long-tailed severity distributions.
* Demonstrates how to align ML models with actuarial needs via **custom loss functions (Poisson & Gamma deviances)** rather than default squared error.
* Uses **permutation importance, partial dependence plots, and individual conditional expectations (ICE)** for model interpretation, enhancing transparency.
* Extensive **cross-validation and model lift analysis** show gradient boosting machines (GBM) outperform GLMs in predictive accuracy while maintaining interpretability through structured post-hoc analysis.
* Business-focused evaluation includes **loss ratio lift, double lift, and Gini index**, illustrating GBM’s superiority in preventing adverse selection.
* Despite GBM’s predictive edge, GLMs remain essential for regulatory filings; hence, proposes approximating GBM insights into GLM tariff structures.
* Emphasises balancing **risk differentiation with solidarity**, ensuring fair premium distributions without over-personalisation.

**📚 Harvard Reference**

Henckaerts, R., Côté, M-P., Antonio, K. & Verbelen, R. (2021) 'Boosting insights in insurance tariff plans with tree-based machine learning methods', *North American Actuarial Journal*, 25(2), pp. 255–285. <https://doi.org/10.1080/10920277.2020.1745656>.

**📊 Literature Review Table (Updated with Importance Column)**

| **Source** | **Key Insights** | **Methods** | **Relevance to Capstone** | **Importance/Recommendation** |
| --- | --- | --- | --- | --- |
| Henckaerts et al. (2021) | Tree-based ML for insurance pricing (regression trees, random forests, GBM). Custom loss functions (Poisson, Gamma) tailored to insurance data. Interpretability via permutation importance, PDPs, ICE. GBM outperforms GLM in predictive accuracy & adverse selection mitigation. Business metrics: loss ratio lift, double lift, Gini index. Proposes approximating GBM insights in GLM for compliance. | Tree-based ML models with actuarial loss functions. Cross-validation, model interpretation, business impact evaluation (lift metrics). Case study on Belgian motor insurance. | Highly relevant for your capstone’s balance of predictive modelling and explainability in risk profiling. Directly supports GBM methodology choice, interpretability strategies, and business alignment. | **High** – Must read for ML insurance tariff modelling, explainability, and business impact assessment. |

Would you like me to now update your **visual literature review summary slide** with this entry included?  
Reply **"Yes, update the visual slide please"** if you'd like that.

**You said:**

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Another

**ChatGPT said:**

Here’s the analysis and updated literature review entry for this latest document:

**📄 Literature Review Entry**

**Predictive Analytics of Insurance Claims Using Multivariate Decision Trees**

Quan and Valdez (2018) present a comprehensive application of **multivariate decision trees** to predict insurance claims across multiple coverage types. The study addresses the limitations of univariate models in capturing dependencies among response variables and demonstrates how multivariate regression trees (MRT), random forests, and gradient boosting can be extended to multivariate outputs for enhanced predictive accuracy.

Key insights:

* Introduces **multivariate regression trees (MRT)** to capture dependencies among multiple insurance coverages (e.g., building, motor vehicles, equipment).
* Extends ensemble methods to multivariate contexts:
  + **Multivariate Random Forests (MRF)** for robust prediction with bootstrapped data.
  + **Multivariate Tree Boosting (MTB)** for sequential learning of residual structures.
* Demonstrates that multivariate models outperform univariate tree models in predictive accuracy.
* Application on Wisconsin Local Government Property Insurance Fund (LGPIF) data, with six correlated lines of coverage.
* Explores **variable importance metrics**, covariance discrepancy measures, and biplots for interpretability.
* Advocates for the practical integration of multivariate tree models in actuarial science to manage correlated insurance risks.
* Suggests extensions for zero-inflated data structures and regulatory-aligned explainability.

**📚 Harvard Reference**

Quan, Z. & Valdez, E.A. (2018) 'Predictive analytics of insurance claims using multivariate decision trees', *Dependence Modeling*, 6(1), pp. 377–407. <https://doi.org/10.1515/demo-2018-0022>.

**📊 Literature Review Table (Updated with Importance Column)**

| **Source** | **Key Insights** | **Methods** | **Relevance to Capstone** | **Importance/Recommendation** |
| --- | --- | --- | --- | --- |
| Quan & Valdez (2018) | Applies multivariate decision trees (MRT, MRF, MTB) for insurance claims prediction. Captures dependencies among multiple coverages. Demonstrates improved predictive accuracy over univariate models. Uses variable importance, covariance discrepancies, and biplots for interpretability. Advocates data-driven, explainable methods for actuarial risk prediction. | Multivariate regression trees, random forests, tree boosting. Applied on LGPIF data. Model interpretability via variable importance & covariance analysis. | Highly relevant for your capstone’s multivariate risk profiling and predictive modelling. Provides methodological insights for managing correlated insurance risks with explainable tree-based models. | **High** – Must read for multivariate tree-based modelling and interpretability strategies in insurance contexts. |

Would you like me to now update your **visual literature review summary slide** with this latest entry?  
Reply **"Yes, update the visual slide please"** if you'd like that.

**You said:**

ai-in-actuarial-science-a-review-of-recent-advances-part-1.pdf

PDF

Another

**ChatGPT said:**

Here’s the analysis and updated literature review entry for this latest document:

**📄 Literature Review Entry**

**AI in Actuarial Science – A Review of Recent Advances (Part 1)**

Richman (2021) provides a foundational review of **Artificial Intelligence (AI) and Machine Learning (ML)** techniques in actuarial science, focusing on their relevance, conceptual frameworks, and applicability. Part 1 primarily covers ML concepts, deep learning, and their mapping to actuarial tasks, preparing readers for applied case studies in Part 2.

Key insights:

* Reframes actuarial tasks (pricing, reserving, mortality modelling) as **regression problems**, creating a natural fit for ML solutions.
* Clarifies distinctions between statistical modelling (inference-driven) and ML (prediction-driven), emphasising bias-variance trade-offs.
* Explains core ML paradigms: supervised learning, unsupervised learning, reinforcement learning (with less relevance to insurance).
* Introduces **deep learning**: neural networks, representation learning, and hierarchical feature extraction.
* Discusses advanced architectures:
  + **Convolutional Neural Networks (CNNs)** for structured/unstructured data (e.g., telematics, IBNR parallels).
  + **Recurrent Neural Networks (RNNs)** and Long Short-Term Memory (LSTM) for sequential/time-series data.
  + **Embeddings** to handle high-cardinality categorical data, drawing parallels with credibility theory.
* Provides a heuristic: “If an actuarial problem can be expressed as a regression, ML/deep learning can be applied.”
* Positions AI as an enhancement to actuarial practice, not a replacement, advocating for balance between predictive power and regulatory interpretability.
* Emphasises **model explainability, stakeholder communication, and governance** as essential for actuarial adoption of AI.

**📚 Harvard Reference**

Richman, R. (2021) 'AI in actuarial science – a review of recent advances – part 1', *Annals of Actuarial Science*, 15(2), pp. 207–229. <https://doi.org/10.1017/S1748499520000238>.

**📊 Literature Review Table (Updated with Importance Column)**

| **Source** | **Key Insights** | **Methods** | **Relevance to Capstone** | **Importance/Recommendation** |
| --- | --- | --- | --- | --- |
| Richman (2021) | Conceptual review of AI & ML in actuarial science. Positions actuarial problems as regression tasks solvable by ML. Explains CNNs, RNNs, embeddings in actuarial contexts. Focus on explainability, regulatory compliance, and practical implementation. Heuristic: ML applicable where actuarial problems = regression. | Literature synthesis, heuristic frameworks, technical overview of ML & deep learning architectures. Case framing in actuarial modelling. | Highly relevant for your capstone's methodological foundation. Provides conceptual clarity, mapping of ML tools to actuarial problems, and framing for explainable AI in insurance risk profiling. | **High** – Must read for foundational understanding & methodological justification of AI in actuarial science. |

Would you like me to now update your **visual literature review summary slide** to include this latest entry?  
Reply **"Yes, update the visual slide please"** if you'd like that.

**You said:**

ai-in-actuarial-science-a-review-of-recent-advances-part-2.pdf

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**ChatGPT said:**

Here’s the analysis and updated literature review entry for this latest document:

**📄 Literature Review Entry**

**AI in Actuarial Science – A Review of Recent Advances (Part 2)**

Richman (2021) continues from Part 1, providing an in-depth review of **applied AI and machine learning in actuarial science**, covering recent use cases in **insurance pricing, reserving, telematics, mortality modelling, and stochastic simulation approximation**. The paper bridges theoretical ML concepts with real-world actuarial applications, supporting the integration of deep learning into actuarial workflows.

Key insights:

* **Pricing of non-life insurance**: Demonstrates that tree-based models (GBM, regression trees) and neural networks outperform GLMs in predictive accuracy. Proposes embedding-based enhancements for GLM interpretability.
* **Reserving (IBNR)**: Neural network-augmented chain-ladder models improve granular reserving accuracy. Introduces "DeepTriangle" combining embeddings, RNNs, and multitask learning.
* **Telematics data analysis**: Uses v-a heatmaps, PCA, auto-encoders, and CNNs for driver behaviour profiling. Shows unsupervised feature extraction enhances claim frequency models.
* **Mortality forecasting**: Deep learning models (auto-encoders, embedding-enhanced regressions) outperform traditional Lee-Carter models. Presents explainable embeddings for mortality structure.
* **Stochastic simulation approximations**: Neural networks improve computational efficiency of nested simulations for variable annuity (VA) portfolios, replacing kernel regression.
* **Financial forecasting**: ML struggles against traditional time-series models for market forecasting, highlighting domain-specific model suitability.
* Emphasises importance of **model interpretability**, regulatory alignment (e.g., ASOP standards), and hybrid models combining actuarial methods with ML.
* Calls for wider **benchmark datasets**, interpretability methods, and uncertainty quantification techniques for deep learning adoption in actuarial practice.

**📚 Harvard Reference**

Richman, R. (2021) 'AI in actuarial science – a review of recent advances – part 2', *Annals of Actuarial Science*, 15(2), pp. 230–258. <https://doi.org/10.1017/S174849952000024X>.

**📊 Literature Review Table (Updated with Importance Column)**

| **Source** | **Key Insights** | **Methods** | **Relevance to Capstone** | **Importance/Recommendation** |
| --- | --- | --- | --- | --- |
| Richman (2021) | Comprehensive review of applied ML in actuarial science. Covers pricing, reserving, telematics, mortality, stochastic simulations. Focus on hybrid models, interpretability, regulatory compliance. Calls for benchmark datasets & uncertainty quantification in ML. Provides practical examples & GitHub code. | Literature synthesis, case studies (pricing, reserving, telematics, mortality), applied ML architectures (GBM, RNNs, CNNs, auto-encoders, embeddings). | Foundational for your capstone’s methodological design, especially integrating explainable AI in insurance risk profiling. Empirical applications map directly to your use case domains. Reinforces practical ML adoption strategies. | **High** – Must read for applied AI methods in actuarial science and practical adoption strategies. |

Would you like me to now update your **visual literature review summary slide** with this entry included?  
Reply **"Yes, update the visual slide please"** if you'd like that.

**You said:**

risks-07-00070.pdf

PDF

Another

**ChatGPT said:**

Here’s the analysis and updated literature review entry for this latest document:

**📄 Literature Review Entry**

**Predicting Motor Insurance Claims Using Telematics Data—XGBoost versus Logistic Regression**

Pesantez-Narvaez, Guillen, and Alcañiz (2019) compare **XGBoost** and **logistic regression** for predicting motor insurance claims using telematics data. The study evaluates predictive accuracy, interpretability, and practical implementation considerations, reflecting real-world constraints in regulated insurance environments.

Key insights:

* **XGBoost shows superior in-sample accuracy** but suffers from overfitting and poor generalisation in out-of-sample tests without extensive tuning.
* Logistic regression remains competitive due to its **interpretability and transparency**, making it more suitable for regulatory compliance and straightforward premium calculation.
* Applied to telematics data (e.g., urban driving %, speeding %, night driving %), logistic regression produced comparable predictive performance with simpler interpretation of covariate effects.
* XGBoost's model complexity complicates understanding the contribution of individual covariates, requiring post-hoc analysis (e.g., variable importance, partial dependence).
* Overfitting in XGBoost was addressed using **L1 (Lasso) regularisation**, improving specificity but reducing sensitivity.
* Both models agreed on the importance of urban driving % as the top predictor of accident claims.
* The study advises cautious adoption of complex ML models in actuarial practice, stressing the trade-off between **predictive power and explainability**, especially in markets with regulatory oversight on pricing fairness.

**📚 Harvard Reference**

Pesantez-Narvaez, J., Guillen, M. & Alcañiz, M. (2019) 'Predicting motor insurance claims using telematics data—XGBoost versus logistic regression', *Risks*, 7(2), Article 70. <https://doi.org/10.3390/risks7020070>.

**📊 Literature Review Table (Updated with Importance Column)**

| **Source** | **Key Insights** | **Methods** | **Relevance to Capstone** | **Importance/Recommendation** |
| --- | --- | --- | --- | --- |
| Pesantez-Narvaez et al. (2019) | Compares XGBoost vs logistic regression for telematics-based claim prediction. XGBoost shows better in-sample accuracy but suffers from overfitting. Logistic regression preferred for transparency & regulatory compliance. Urban driving % key risk predictor. Recommends balancing predictive power & interpretability in insurance pricing. | Binary classification, logistic regression, XGBoost (tree & linear booster), regularisation (L1, L2), telematics data analysis, ROC curves, confusion matrices. | Highly relevant for your capstone's predictive modelling and interpretability trade-offs. Supports method selection under regulatory constraints. Provides empirical evidence on telematics risk factors. | **High** – Must read for balancing ML accuracy and explainability in regulated insurance pricing. |

Would you like me to update your **visual literature review summary slide** to include this latest entry?  
Reply **"Yes, update the visual slide please"** if you'd like that.

**You said:**

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Another

**ChatGPT said:**

Here’s the analysis and updated literature review entry for this latest document:

**📄 Literature Review Entry**

**Believing the Bot: Model Risk in the Era of Deep Learning**

Richman, von Rummell, and Wüthrich (2019) examine **model risk in actuarial applications of deep learning**, framing the discussion within enterprise risk management (ERM) practices. They provide a structured comparison of traditional actuarial models, machine learning, and deep learning, assessing how deep learning introduces new dimensions of model risk and proposing governance controls.

Key insights:

* **Deep learning's implicit model specification and representation learning** increases model risk by reducing transparency and control.
* Highlights challenges of **stability, reproducibility, and consistency** in deep learning outputs due to random initialisation, non-convex optimisation, and sensitivity to training data variations.
* Emphasises **post-hoc interpretability methods (e.g., SHAP, LIME)** as partial solutions, but not substitutes for transparency.
* Model governance must adapt to address:
  + Specification risk (uncertainty in model structure and features).
  + Parameter risk (randomness, many "good" models problem).
  + Bias and fairness (especially for protected characteristics like gender or ethnicity).
  + Stability over time (important for pricing and reserving consistency).
* Recommends actuarial controls like:
  + Using **simple models as sanity checks** for aggregate results.
  + **Inspecting learned representations** via dimensionality reduction (PCA) for interpretability.
  + Ensembling models to mitigate randomisation risks.
  + Adjusting loss functions to enforce stability and fairness.
* Case studies include applications to motor insurance pricing and mortality forecasting, illustrating model risks and mitigation strategies.
* Advocates for enhanced professional knowledge, peer review processes, and regulatory alignment in the adoption of AI in actuarial modelling.

**📚 Harvard Reference**

Richman, R., von Rummell, N. & Wüthrich, M.V. (2019) 'Believing the bot: Model risk in the era of deep learning', *SSRN Electronic Journal*. <https://ssrn.com/abstract=3444833>.

**📊 Literature Review Table (Updated with Importance Column)**

| **Source** | **Key Insights** | **Methods** | **Relevance to Capstone** | **Importance/Recommendation** |
| --- | --- | --- | --- | --- |
| Richman, von Rummell & Wüthrich (2019) | Deep learning increases model risk (specification, parameter, bias, stability). Proposes governance controls for model risk management. Recommends interpretability techniques, sanity checks, and enhanced actuarial oversight. Case studies in pricing and mortality forecasting. Framework aligns with ERM principles. | Literature synthesis, conceptual frameworks, case studies (motor insurance, mortality forecasting), practical recommendations for governance controls. | Highly relevant for your capstone's use of explainable AI in risk profiling. Supports model risk management strategies, regulatory alignment, and practical controls for AI adoption. | **High** – Must read for model risk governance, controls, and explainable AI adoption in actuarial contexts. |

Would you like me to update your **visual literature review summary slide** to include this latest entry?  
Reply **"Yes, update the visual slide please"** if you'd like that.

**You said:**

FinTech.pdf

PDF

Another

**ChatGPT said:**

Here’s the analysis and updated literature review entry for this latest document:

**📄 Literature Review Entry**

**Financial Technology in Banking Industry: Challenges and Opportunities**

Al Ajlouni and Al-hakim (2019) provide a comprehensive overview of **FinTech’s impact on the banking sector**, focusing on its disruptive potential, opportunities, threats, and strategic responses. The paper synthesises global perspectives on how technology-enabled financial services reshape traditional banking, offering both challenges and areas for strategic innovation.

Key insights:

* Defines FinTech as a **technology-enabled innovation** that significantly affects financial services provision through new business models, products, and processes.
* Highlights key FinTech segments: payments, lending & crowdfunding, blockchain, trading & investments, data analytics, and security.
* Discusses **alternative financing platforms** (P2P lending, Equity Crowdfunding), showcasing how they challenge traditional credit provisioning and capital access.
* Opportunities for banks:
  + Financial inclusion through digital channels.
  + Lower transaction costs, faster services.
  + Enhanced customer experience via tailored services.
  + Competitive pressure driving operational efficiencies.
  + Regulatory technology (RegTech) aiding compliance.
* Threats include:
  + Loss of market share to FinTechs and BigTechs.
  + Operational risks from increased IT dependencies.
  + Compliance risks (AML/CFT, data privacy).
  + Cybersecurity vulnerabilities.
  + Funding source volatility.
* Provides a five-scenario outlook for the future of banking in a FinTech-dominated landscape: better bank, new bank, distributed bank, relegated bank, disintermediated bank.
* Recommends strategic responses: IT modernisation, process digitisation, cybersecurity enhancement, open architecture adoption, and organisational agility.

**📚 Harvard Reference**

Al Ajlouni, A.T. & Al-hakim, M. (2019) 'Financial Technology in Banking Industry: Challenges and Opportunities', *International Conference on Economics and Administrative Sciences (ICEAS2018)*, Applied Sciences University, Jordan, 11-12 April 2018. Available at: <https://www.researchgate.net/publication/331303690>.

**📊 Literature Review Table (Updated with Importance Column)**

| **Source** | **Key Insights** | **Methods** | **Relevance to Capstone** | **Importance/Recommendation** |
| --- | --- | --- | --- | --- |
| Al Ajlouni & Al-hakim (2019) | Reviews FinTech’s disruptive impact on banking. Outlines opportunities (inclusion, efficiency, RegTech) & threats (competition, operational risks, compliance, cybersecurity). Proposes five future banking scenarios. Recommends strategic responses: IT modernisation, digitisation, agility. | Literature synthesis, policy and strategic frameworks, global regulatory reports analysis. Scenarios and strategic recommendations. | Relevant for contextualising your capstone within the broader FinTech disruption in banking. Supports strategic framing of risk profiling solutions and regulatory compliance alignment. | **Medium-High** – Useful for strategic context and positioning within FinTech-banking dynamics. |

Would you like me to update your **visual literature review summary slide** to include this entry as well?  
Reply **"Yes, update the visual slide please"** if you'd like that.

**You said:**

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Another

**ChatGPT said:**

Here’s the analysis and updated literature review entry for this document:

**📄 Literature Review Entry**

**FinTech and RegTech in a Nutshell, and the Future in a Sandbox**

Arner, Barberis, and Buckley (2017) present a seminal overview of **FinTech and RegTech evolution**, distinguishing between the two concepts and introducing a phased development model. The paper outlines historical developments, current challenges, and future directions, with particular emphasis on regulatory sandboxes as innovation facilitators.

Key insights:

* Defines **FinTech** as technology-enabled financial innovation, evolving through three phases:
  + **FinTech 1.0 (1866–1967):** Infrastructure & analog systems.
  + **FinTech 2.0 (1967–2008):** Digitisation of banking (ATMs, SWIFT, e-banking).
  + **FinTech 3.0 (2008–present):** Startups, BigTech, and platform-based finance.
* Introduces **FinTech 3.5 and 4.0** for developing markets and future data-centric models.
* Distinguishes **RegTech** from FinTech:
  + **RegTech 1.0:** Pre-2008, compliance cost reduction (Basel II focus).
  + **RegTech 2.0:** Post-GFC, digitisation of regulatory compliance.
  + **RegTech 3.0:** Data-driven regulation, shift from “Know Your Customer” (KYC) to “Know Your Data” (KYD).
* Highlights **regulatory sandboxes** as safe spaces for testing financial innovations under regulatory supervision, pioneered by the UK FCA.
* Argues for a shift towards **real-time market monitoring and simulation-based regulatory policy testing**.
* Emphasises the need for **coordinated global regulation**, data harmonisation, and proportionate oversight to manage innovation without stifling it.
* Foresees a transformative role of RegTech in reconceptualising financial regulation frameworks to match FinTech’s digital pace.

**📚 Harvard Reference**

Arner, D.W., Barberis, J. & Buckley, R.P. (2017) 'FinTech and RegTech in a nutshell, and the future in a sandbox', *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.3088303>.

**📊 Literature Review Table (Updated with Importance Column)**

| **Source** | **Key Insights** | **Methods** | **Relevance to Capstone** | **Importance/Recommendation** |
| --- | --- | --- | --- | --- |
| Arner, Barberis & Buckley (2017) | Defines FinTech and RegTech development phases. RegTech 3.0 shifts from KYC to KYD data-centric regulation. Sandbox frameworks facilitate innovation under supervision. Advocates global regulatory coordination & data harmonisation. Foresees RegTech transforming regulatory frameworks for FinTech ecosystems. | Conceptual framework, historical review, scenario analysis, regulatory sandbox case studies. Policy recommendations for FinTech & RegTech development. | Highly relevant for contextualising your capstone in FinTech/RegTech regulatory evolution. Supports risk profiling frameworks aligned with KYD principles, sandbox testing, and data-driven governance. | **High** – Must read for foundational understanding of FinTech-RegTech dynamics and future regulatory frameworks. |

Would you like me to update your **visual literature review summary slide** to include this latest entry?  
Reply **"Yes, update the visual slide please"** if you'd like that.

**You said:**

s11573-017-0852-x.pdf

PDF

Another

On the Fintech Revolution Interpreting the Forces of Innovation Disruption and Transformation in Financial Services.pdf

PDF

Another

Ok at this point I feel like I have enough literature? Can you review whether you believe I have enough research to conduct my literature review/full capstone. Highlight areas where I have enough, there are gaps that need filling, and I could expand into if I had time / for added benefit Also provide me a breakdown by capstone section - do I have enough to inform and proceed with each part of the investigation (lit review / modelling etc) I'm going to provide you with the marking criteria and outlined sections below in order for you to make an assessment - if you need more information on my capstone project or anything else ask for i. Here is the marking criteria and structure: Marking & Structure Your dissertation is a large, thorough document (10,000 ± 1000 words) covering all you did during your project. It should contain the following sections: Introduction (10%): Outline the scope or hypothesis of the project and terms of reference, including both the business and academic motivations for the project and its wider significance and set the scene for the remainder of the dissertation. Also, include a clear statement of the aim and scientific and business objectives of your work. Background (10%): Review and describe the related business background or research undertaken at the beginning of the project period. What was Done, and How (40%): Describe the work that you have undertaken and its conclusions. Detail this work across several chapters. Results & Evaluation (20%): This should be a chapter describing the outputs, deliverables or artefacts produced by this project along with the discussion on business impacts. Include an assessment chapter describing the scope and limits of your work and possible ways in which the work could be continued or developed. Conclusions (10%): This is a statement of conclusions relating to the work done and outputs produced to the initial hypothesis and terms of reference. References (5%): An appropriate selection of academic sources as well as grey literature, as appropriate for your project. Form (5%): Covers the structure, organisation, quality of writing and non-text forms including graphics and listings as well as the provision of bibliographic information, which should use established standards. Rubric Dissertation Marking Scheme Dissertation Marking Scheme Criteria Ratings Pts This criterion is linked to a learning outcomeIntroduction 10 to >8.0 Pts Outstanding Project context and motivation comprehensively and insightfully covered. Exemplary aim and objectives of professional quality. Wide range of citations going beyond normal expectations. 8 to >7.0 Pts Excellent Project context and motivation comprehensively covered. Concise, well formulated aim and objectives; objectives are comprehensive and appropriate for aim. Wide range of relevant citations to references. 7 to >6.0 Pts Good Project context and motivation covered well but could be extended. Clear, well formulated aim and objectives but could be refined further; objectives are appropriate for aim. Basic range of citations to standard references. 6 to >5.0 Pts Pass Project context and motivation are basic and missing some key details. Basic aim and objectives; some objectives are not appropriate for aim. Only one or two citations to standard references. 5 to >4.0 Pts Border Fail Project context and motivation is vague and missing key details. Aim and objectives are vague and incomplete; objectives are not appropriate for aim. No citations to supporting references. 4 to >0.0 Pts Fail Project context and motivation is confused and lacks basic details. Aim and objectives very poorly formulated and confused. No citations to supporting references. 0 Pts Missing No introduction. 10 pts This criterion is linked to a learning outcomeBackground 10 to >8.0 Pts Outstanding Comprehensive background details on project, publishable quality. In-depth review of related work and state of the art. Diverse range of relevant sources cited and analysed, going beyond normal expectations. 8 to >7.0 Pts Excellent Comprehensive background details. Thorough review of related work and state of the art. Diverse range of relevant sources cited and analysed. 7 to >6.0 Pts Good Range of essential background details. Range of related work reviewed. Range of relevant sources cited with limited analysis. 6 to >5.0 Pts Pass Some essential background details but incomplete. Some related work reviewed but needs expanding. Basic range of sources cited with no analysis. 5 to >4.0 Pts Border Fail Background details vague and incomplete. Very limited range of related work reviewed. Only a few sources cited with no analysis. 4 to >0.0 Pts Fail Background details very limited and confused. No related work reviewed. None or very few sources cited with no analysis. 0 Pts Missing Little or no background material. 10 pts This criterion is linked to a learning outcomeWhat was Done, and How 40 to >32.0 Pts Outstanding Publishable description of key aspects of work done, highlighting key decisions made and why. Wide range of challenging technical work with associated innovative solutions. Appropriate and clearly justified use of methods and tools. 32 to >28.0 Pts Excellent Detailed description of key aspects of work done, highlighting key decisions made and why. Challenging technical work undertaken with some innovative solutions. Appropriate and generally justified use of methods and tools. 28 to >24.0 Pts Good Clear description of key aspects of work done with some key decisions considered. Some challenging aspects to technical work undertaken. Appropriate use of methods and tools but little justification. 24 to >20.0 Pts Pass Basic description of work done but little focus on key aspects or decisions made. Range of basic technical work undertaken. Some use of methods and tool but no justification. 20 to >16.0 Pts Border Fail Description of work is vague and incomplete, with no discussion of key decisions. Technical work undertaken is basic and flawed in places. Limited and inappropriate use of methods and tools. 16 to >0.0 Pts Fail Description of work is confused and difficult to read. Technical work undertaken is very basic and flawed. Very poor use of methods and tools. 0 Pts Missing No explanation on what was done. 40 pts This criterion is linked to a learning outcomeResults and Evaluation 20 to >16.0 Pts Outstanding Well designed and comprehensive evaluation of publishable quality. Thorough and insightful description of project results. 16 to >14.0 Pts Excellent Well designed and comprehensive evaluation. Thorough description of project results. 14 to >12.0 Pts Good Well designed evaluation but slightly limited in scope. Clear description of project results but could be extended. 12 to >10.0 Pts Pass Some basic evaluation done but limited in scope. Basic description of project results but incomplete. 10 to >8.0 Pts Border Fail Evaluation is limited and lacks thought. Description of project results is vague and incomplete. 8 to >0.0 Pts Fail Evaluation is missing or is confused and inappropriate. Description of project results is confusing and very limited. 0 Pts Missing No results and evaluation. 20 pts This criterion is linked to a learning outcomeConclusions 10 to >8.0 Pts Outstanding Thorough and insightful reflection on scope and limits of project achievements. Range of original and insightful future work going beyond expectations. 8 to >7.0 Pts Excellent Thorough reflection on scope and limits of project achievements. Range of well thought out and novel future work. 7 to >6.0 Pts Good Range of reflection on scope and limits of project achievements but could be expanded. Range of well thought out future work. 6 to >5.0 Pts Pass Reflection on scope and limits of project achievements is basic and more thought needed. Range of basic future work, limited in scope. 5 to >4.0 Pts Border Fail Little reflection provided on project achievements. Future work very limited and vague. 4 to >0.0 Pts Fail Very little or no reflection provided on project achievements. Future work is missing or confused. 0 Pts Missing No conclusions. 10 pts This criterion is linked to a learning outcomeReferences 5 to >4.0 Pts Outstanding References are professionally presented and cited. 4 to >3.5 Pts Excellent References are presented and cited well using an appropriate style. 3.5 to >3.0 Pts Good References are generally presented and cited well using an appropriate style. 3 to >2.5 Pts Pass Presentation and citation of references is basic and has some minor issues. 2.5 to >2.0 Pts Border Fail Presentation and citation of references has numerous issues. 2 to >0.0 Pts Fail Presentation and citation of references appears confused. 0 Pts Missing No references or completely irrelevant references. 5 pts This criterion is linked to a learning outcomeForm 5 to >4.0 Pts Outstanding Exemplary structure. Professional level of technical writing. No typos, spelling and grammar mistakes. 4 to >3.5 Pts Excellent Clearly structured. Technical writing style used throughout. Very few minor typos, spelling and grammar mistakes. 3.5 to >3.0 Pts Good Clear structure but could be strengthened further. Technical writing style generally used. Some minor typos, spelling and grammar mistakes. 3 to >2.5 Pts Pass Basic structure with a few minor issues. Writing style too informal in places. Range of typos, spelling and grammar mistakes. 2.5 to >2.0 Pts Border Fail Structure unclear and needs more thought. Writing style generally too informal. Many typos, spelling and grammar mistakes impacting readability. 2 to >0.0 Pts Fail Structure is confused. Writing style too informal throughout report. Large number of typos, spelling and grammar mistakes severely impacting readability. 0 Pts Missing Document is poorly written or presented, with no adherence to technical report style. 5 pts Total points: 100

I would like you to do 1. But I want you to do it twice The first time can you find / pull your own links from your knowledge...I want to see what you might have for these gaps first The second time I want you to go over all the reading supplied and look through their references for any papers that might cover the subject areas you believe I have gaps in...if there are more than 5 potentials I want you to list them all...add a column for how likely the paper / source matches the required gap and also if you are able try to find out how many times that paper / source has been cited elsewhere (so I know its quality research). Order the table first by gap area then in descending order of match/cited scores so the best research will be at the top of each gap area section

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Actually the gaps I want you to find papers / references for are from your above table: Gap Area Why Add? Example of Needed Content XAI in practical financial risk applications Deepen 'What was done, and how' Papers showing XAI models in credit scoring, insurance pricing, or investment risk. Business impact of XAI risk models Strengthen 'Results & Evaluation' Case studies showing KPIs impacted by interpretable models in financial firms. FCA/EBA regulatory guidance on AI explainability Support for evaluation, conclusions Whitepapers or consultation papers outlining explainability expectations for AI in finance. Can you just look for the gaps (keep the same table format you outputted above - paper / match / citation / notes). Don't provide me a breakdown of the entire literature review. Just hunt out research for the 3 gaps above

Please give me the list of title, author, source that I should search through to fill in the above gaps in my research. Forget about citation count. I simply need a table of sources that will cover my research gaps and where you have found them in references from my existing literature.

**You said:**

As part of this capstone, I am trying to look through my literature review to see what best practice or industry practice or previous research has done in regards to methodologies applied or types of models used. So I think this chat is somewhat bloated in regards to being useful anymore, and I'm probably going to have to separate it out. I wonder, are you able to pull out the sources that I've shared with you that would be relevant to a methodology analysis in regards to a machine learning investigation? So what I want is just the sources that I have given you that provide some form of methodology or feature engineering or anything in regards to the machine learning side of things that I can, you know, if you pull out a list, I'll collect those sources and put them into a new thread so we can have a thorough analysis of it.

**ChatGPT said:**

Thanks for the clarification. That makes perfect sense — segmenting your literature review into a thread focused on **methodology, model selection, and ML feature engineering** is a smart move.

**⚠️ However, many of the files you previously uploaded have expired and I no longer have access to them.**

To proceed as you described, please **re-upload the following files** that are likely to contain methodology-related content so I can filter and extract only those relevant to your machine learning investigation:

* The academic papers you've uploaded over the past few weeks (especially those on XGBoost, telematics, Naïve Bayes, boosting, decision trees, insurance modelling, etc.)
* Your own past reports (e.g., CSC8644, MAS8407, and formative reports) if you want to review how your previous methodologies evolved.

Once you’ve re-uploaded the relevant materials, I will return a **clean list of only the sources that contain ML methodologies, feature engineering techniques, or modelling strategies**, so you can carry them into your new thread.

Let me know when you’ve re-uploaded and I’ll get started.