Evolving Role of Financial Literacy in AI-Mediated Financial Ecosystems: A Human-Centric Theory of Contextual Financial Judgment

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ABSTRACT

Conventional financial literacy agendas are based on the assumption of information paucity, where consumers actively seek out data and are completely dependent on human cognitive processing for their financial decision making. However, the rapid proliferation of Artificial Intelligence (AI), Financial Technology (FinTech) and algorithmic recommendation systems has fundamentally transformed personal finance. Consumers no longer are passive information seekers; but are constantly exposed to algorithmically curated financial content, personalized product and investment recommendations and behavioural nudges. Thus, the central challenge in financial literacy has pivoted from **merely accessing financial data to critically appraising AI-mediated financial content and outputs**.

Addressing this gap, the paper advances a human-centric re-interpretation of financial literacy, by demonstrating that although the foundational developmental architecture of financial literacy remains intact across its six core dimensions (Financial Exposure, Importance, Awareness, Knowledge, Attitude and Behaviour), its operational role advances in an AI-mediated environment. Synthesizing Dual-Process Theory, Extended Unified Theory of Acceptance and Use of Technology (UTAUT2), Behavioural Finance, Human Agency Theory, Explainable AI (XAI) and Adaptive Decision-Making Theory; the study establishes **Contextual Financial Judgment (CFJ)** - an emergent, integrative human capability arising from the convergence of Financial Awareness, In-depth Financial Knowledge and Financial Attitude. The CFJ acts as a System 2 (second-order) integrative capability - a cognitive circuit breaker through which individuals evaluate AI-generated recommendations by considering personal circumstances, financial goals and long-term targets prior to decision making.

Additionally, the paper outlines a broad conceptual framework illustrating the way in which the **CFJ** preserves **human agency** and redefines the professional financial planner as a **Contextual Judgment Facilitator** who supports reflective human-AI collaboration. Finally, the study provides a preliminary operational measurement matrix to guide empirical scale development and policy interventions.

Key Words: Financial Literacy, Financial Planning, Human–AI Collaboration, Contextual Financial Judgment, Human Agency

INTRODUCTION

"A wealth of information creates a poverty of attention and a need to allocate that attention efficiently" - Herbert A. Simon

"The future is not AI versus humans. It is AI with humans" - Ben Shneiderman

Herbert Simon's quote on attention scarcity is perfectly apt in an era where artificial intelligence and FinTech platforms incessantly generate bespoke financial information, algorithmic recommendations, predictive analytics and nudges. Resultantly, the fundamental challenge facing individuals has shifted from the acquisition of financial knowledge to **Algorithmic sensemaking,** as conversational AI and personalised financial platforms now shape how financial information is retrieved, filtered and presented - repositioning consumers as passive receivers of curated insights who must continuously evaluate AI-driven outputs.

Thus, financial literacy, which has evolved from a narrow focus on financial knowledge and numeracy to a broader framework including Knowledge, Attitudes and Behaviour (KAB) - must advance from the mere comprehension, interpretation, evaluation and practical application of financial literature towards critically evaluating algorithmically mediated financial endorsements.

While traditional financial literacy frameworks assume a linear, human-centric decision-making process, this technological shift demands a fundamental reinterpretation: ***How does the role of financial literacy evolve when intelligent systems actively curate the decision-making environment?***

Thus, this study posits that while the financial literacy's structural architecture remains constant, the function of its established components (Financial Exposure, Importance, Awareness, In-depth Knowledge, Attitudes and Behaviour) evolve alongside technological transformation. Especially the triad – Financial Awareness, In-depth Knowledge and Attitudes synthesize into an integrative human capability: **Contextual Financial Judgment (CFJ)**.

Further, aligning with Shneiderman's vision of human-centred automation and the principles of Industry 5.0, this framework does not place AI on an adversarial position in financial environments, rather necessitates reinterpreting the significance of human agency and redefining the role of a financial planner as a Human-AI collaborator – a **Contextual Judgement Facilitator** emphasizing that intelligent technologies should augment rather than replace human judgment.

Scope Of The Study

This study is conceptual in nature and espouses a theory-building approach. It examines the evolving role of financial literacy within AI-mediated financial ecosystems, by synthesising the existing body of literature on financial literacy, Artificial Intelligence, Human–Artificial Intelligence collaboration, financial planning and Industry 5.0 principles.

The frontiers of this study are demarcated by three central parameters:

1) Theoretical Boundaries:

This framework does not supplant established financial literacy theories or advocate a new developmental model. Instead, it reconstructs the role of the existing constituents of financial literacy within automated financial environments shaped by algorithmic recommendation structures and predictive analytics.

2) Conceptual Boundaries:

The analysis focuses heavily on the emergence of **Contextual Financial Judgment (CFJ)** signifying an evolving human capability emerging from the reflective interplay of Financial Awareness, In-depth Financial Knowledge and Financial Attitude - a primary human interface with Artificial Intelligence (AI). CFJ enables individuals to assimilate financial knowledge, personal values, contextual circumstances, financial goals and AI-generated insights to preserve informed human agency in AI-assisted financial decision-making.

3) Methodological Boundaries:

As a qualitative, conceptual synthesis, this paper focuses on framework construction and the derivation of testable propositions. It establishes the conceptual foundation required for subsequent empirical investigation, development of the Contextual Financial Judgement scale and interdisciplinary field testing.

Objectives of The Study

1) To analyze the way in which AI-mediated ecosystems transform personal financial decision-making, shifting the challenges confronted by consumers from information paucity to algorithmic curation;

2) To reinterpret the functional role of the time-honoured components of financial literacy in AI-mediated financial environments, while preserving its fundamental developmental architecture;

3) To conceptualize Contextual Financial Judgment (CFJ) as an emergent, integrative human capability that screens quantitative algorithmic insights through the lens of qualitative human realities and principles;

4) To construct a theoretical framework and formulate testable propositions clarifying the way in which financial literacy preserves informed human agency in automated interactions; and

5) To develop a human-centric framework of human-AI collaboration, that redefines the role of financial planners as Contextual Judgment Facilitators.

REVIEW OF LITERATURE

A. Evolution of Financial Literacy: From Financial Knowledge to Financial Well-being

Research has indicated the enduring significance of financial literacy as an economic and policy concern (OECD, 2020; Xiao et al., 2018) due to its proven capacity to enhance financial behaviours and outcomes (Lusardi et al, 2014; van Rooij et al., 2011; Xiao et al, 2017) in the form of savings, retirement planning, wealth accumulation, investment diversification and judicious debt management (Lusardi et al, 2014; Lusardi et al, 2015).

The concept of financial literacy has advanced over the past few decades, reflecting the growing intricacies of financial markets, rapid technological advancements and the mounting obligations enforced upon individuals for handling their financial welfare (Huston, 2010; Lusardi et al, 2014; OECD, 2020). Principally construed as the faculty of comprehending basic financial concepts, financial literacy has evolved into a multifaceted construct incorporating financial knowledge, skills, attitudes, behaviour, capability and financial well-being (Atkinson et al, 2012; Remund, 2010; Xiao et al., 2018). This shifting trajectory demonstrates the mercurial nature of the construct that has adapted itself to the evolving economic, social and institutional environments (Lusardi et al, 2014; Remund, 2010).

Preliminary ideations of financial literacy centred around financial knowledge, emphasizing the individual’s capability to comprehend basic financial concepts like inflation, budgeting, interest rates, savings and investments, essential for rational and cognizant financial decision-making (Huston, 2010; Lusardi et al, 2014). Ensuing research broadened this outlook by acknowledging that the construct also encompasses financial efficacy to execute fiscal strategies across diverse real-life economic events (Xiao, 2008; Remund, 2010; Xiao et al., 2018).

Consequent research established the inadequacy of knowledge alone to impact financial decision-making. Individuals possessing identical knowledge levels frequently exhibit divergent financial behaviours due to the interplay of cognitive heuristics, emotional framing and contextual variables grounded in Behavioural Finance paradigms (Barberis et al, 2003; Shefrin, 2002). As a result, researchers incorporated financial attitudes, motivation, confidence and behavioural inclinations into the definition of the construct (Atkinson et al, 2012; Huston, 2010; OECD, 2020). This integration culminated in a landmark definition of the construct proposed by the OECD that laid the foundations for financial literacy research, strategy and appraisal (Lusardi et al, 2014; OECD, 2020), combining financial knowledge, skills, attitudes and behaviours essential for sound financial decisions aimed at achieving financial well-being (Atkinson et al, 2012; OECD, 2020; Xiao et al., 2018). Scholars highlight that this dynamic construct continuously evolves through education, exposure, expertise, and life transitions (Bongomin et al., 2018; Fornero et al., 2011; Lusardi et al, 2014).

Despite this conceptual expansion, traditional financial literacy frameworks still presuppose unassisted human-driven cognition (Evans et al, 2013) and System 2 reflective processing - as conceptualized under Dual-Process Theory (Kahneman, 2011); to make independent, calculated and informed financial decisions (Huston, 2010; Lusardi et al, 2014; Remund, 2010; Xiao, 2008). However, the swift advent of Artificial Intelligence challenges this presumption, as AI-enabled technologies and automated choice architecture increasingly perform these analytical tasks, thereby fundamentally altering user adoption and decision dynamics under the Extended Unified Theory of Acceptance and Use of Technology - UTAUT2 (Venkatesh et al., 2012; Davenport et al., 2020; Dwivedi et al., 2021). Modernising financial literacy to suit FinTech ecosystems requires reinterpreting its existing components within AI environments, forming Contextual Financial Judgment, rather than merely appending new informational modules to traditional models.

B. Artificial Intelligence and the Transformation of Personal Financial Planning

Rapid advancements in Artificial Intelligence (AI) spanning through machine learning, predictive analytics, natural language processing, intelligent automation and personalised recommendation systems (Davenport et al., 2020; Huang et al, 2021) has largely impacted and altered the environment in which individuals engage in personal financial planning (Dwivedi et al., 2021; Thakor, 2020).

Traditionally, personal financial planning relied on human advisors to evaluate client parameters, model risk and deliver tailored strategies (Baker et al., 2018; Sironi, 2016), thereby supporting as decision enablers (Baker et al, 2018). However, AI has transformed traditional finance (Davenport et al., 2020; Dwivedi et al., 2021) by enabling algorithms to swiftly evaluate large datasets, forecast market trends and deliver personalized, real-time guidance (Huang et al, 2021; Thakor, 2020). Tools like robo-advisors and AI budgeting apps have radically reduced costs and democratized access to wealth management services (Baker et al, 2018; Sironi, 2016). However, scholarly debate remains divided on whether this algorithmic shift empowers retail consumers or systematically compromises their decision-making autonomy.

However, divergent views emerge regarding human agency and AI in an AI-mediated environment as follows:

1) Competing Perspectives: Cognitive Offloading vs. Skill Erosion

A dominant trend in current FinTech research highlights the **democratization and cognitive efficiency** aided by AI (Baker et al., 2018). Embedded in *Adaptive Decision-Making Theory*, researchers contend that automated tools augment human effort by undertaking algorithmically exhaustive tasks, thereby making budgeting and investing much more cognitively effortless (Chen et al., 2018). Further through the perspective of the *Extended Unified Theory of Acceptance and Use of Technology (UTAUT2)* (Venkatesh et al., 2012); AI-adoption is driven by high *Performance Expectancy* and low *Effort Expectancy*, as users adopt automated platforms to achieve effective financial tracking with minimal effort.

Contrarily, a mounting contradictory-narrative underscores the risks of **cognitive deskilling and automation bias** (Muggleton et al., 2022; Panos et al., 2020). Using the framework of *Dual-Process Theory*; automated choice architectures (e.g., micro-investing apps, personalized notifications) predominantly engage users through the fast, heuristic **System 1 processing**, circumventing the reflective **System 2 analysis** required for long-term planning. Undoubtedly, automated systems reduce short-term cognitive anxiety; however, experiential evidence validates that impulsive dependence on these tools erodes foundational financial knowledge and condenses contextual awareness (Parasuraman et al., 2010). Thus, high adoption under UTAUT2 does not essentially associate with judicious financial management.

2) Algorithmic Supremacy, Opacity and Human Agency

This tension also affects behavioural outcomes. Traditional studies in behavioural finance assess computer programs as neutral tools that mitigate human emotional biases, such as loss aversion and overconfidence (Brynjolfsson, 2014) and augments basic literacy by conveying real-time, data-backed advice and timely educational insights (Patel et al., 2021; Smith et al, 2020). However, present-day studies contend that AI systems swap human biases with systemic *algorithmic biases* absorbed from historical datasets. For instance, AI-driven credit scoring systems absorb historical biases from training datasets (Chen et al, 2023), leading to algorithmic discrimination and disparate pricing in consumer lending (Bartlett et al., 2022). Moreover, recommendation algorithms optimized for user engagement often create behavioural “echo chambers” that prioritize profits over consumer welfare (Davenport et al., 2020; Huang et al., 2021).

The opaque, “black-box” nature of these models deliver sophisticated recommendations without transparent explanations of their underlying logic, thereby challenging core principles of Human Agency Theory (Dwivedi et al., 2021; Oyasiji et al., 2023; Gorai et al, 2025) making it difficult for users to understand the base for such decisions (Sironi, 2016).

No doubt to mitigate these challenges, contemporary research emphasizes Explainable AI (XAI) an innovative framework designed to clarify AI decision-making, improve user understanding, build user trust, ensure verification and clarify automated financial reasoning (Lipton, 2018; Ribeiro et al, 2016; Tay, 2020). However, despite this an unresolved theoretical gap persists: *technical explainability does not guarantee cognitive comprehension.* An algorithm may describe its decision logic, but without an analytical framework, the users are not in a position to evaluate the alignment of this logic with their unique life circumstances.

3) Reconceptualising Financial Literacy as Contextual Financial Judgment (CFJ)

While existing literature on AI in financial planning thoroughly explores technological growth, algorithmic accuracy, operational efficacy and technology trust, it overlooks the way in which AI has transformed the core goal of financial literacy, by treating the latter as a static precursor to technology acceptance. This leads to an incomplete theoretical framework.

In automated ecosystems, the primary function of financial literacy shifts from manual information gathering to exercising reflective, context-sensitive evaluation. While AI excels at computational optimization, it cannot fully account for fluid family dynamics, qualitative life goals or ethical priorities (Baker et al., 2018; Sironi, 2016). Therefore, **Contextual Financial Judgment (CFJ)** emerges as a critical construct at the intersection of *Dual-Process Theory* (activating System 2 oversight), *Human Agency Theory* (retaining sovereign control over decisions) and *XAI* (critically interpreting model outputs). CFJ defines the consumer capability required to evaluate, contextualize and when necessary, override automated financial recommendations.

C. Human–Artificial Intelligence Collaboration: Preserving Human Agency in Financial Decision-Making

1) Theoretical Foundations of Human–AI Complementarity and Automation Bias

Current research has moved beyond pure automation, emphasizing the complementarity between AI and humans, essential for complex financial decisions involving uncertainty and ethical considerations (Khandani et al., 2010; Sironi, 2016; Moghar et al, 2020; Dellermann et al., 2019; Shrestha et al., 2019). Undoubtedly AI excels humans at processing vast datasets and forecasting market trends, making it an indispensable decision-support tool for personalized financial planning (Khandani et al., 2010; Sironi, 2016; Moghar et al, 2020; Cao, 2022). However, human decision-makers remain essential for contextual interpretation, ethical governance and strategic alignment (Jarrahi, 2018; Wilson et al, 2018; Raisch et al., 2021).

From the viewpoint of **Dual-Process Theory**, financial decision-making requires an active collaboration between rapid, intuitive processing (System 1) and deliberate, critical reasoning (System 2). However, with automated financial suggestions, cognitive friction is drastically reduced, thereby activating extreme dependence on System 1 thinking – leading to automation bias, causing individuals to uncritically accept AI outputs without engaging System 2 scrutiny (Parasuraman et al, 2010; Cummings, 2014; Skitka et al., 2000).

Adaptive Decision-Making Theory states that people choose strategies by balancing effort against accuracy. In complex financial situations, pure algorithmic optimization ignores vital human adaptation. Thus it is imperative that humans must modify the algorithmically generated results to match life changes, making personal cognitive involvement essential, as together these integrated abilities significantly improve overall decision quality (Dellermann et al., 2021; Seeber et al., 2020).

2) Algorithmic Supremacy, Explainability and the Preservation of Human Agency

Despite the operational efficiency assured by AI systems, algorithmic personalisation poses a threat to H**uman Agency Theory** which posits that individuals must retain autonomous, intentional control over their choices.

However algorithmic personalisation can subtly manipulate user attention, predispositions and behavioural choices through algorithmically generated default paths (Vassilakopoulou et al., 2023). When user control is systematically eroded, human decision-makers stop thinking critically and become passive receptors of automated decisions.

This opacity reinforces the critical need to preserve human agency in the decision-making process (Amershi et al., 2019), supported by Explainable AI (XAI) frameworks and foundational concepts from the Behavioural Finance Theory as choices are bound by psychological biases, emotional response to risks and market noise. Opaque "black-box" models obscure underlying assumptions, preventing users from identifying embedded biases or algorithmic drift (Arrieta et al., 2020; Wang et al., 2019). Within this context, XAI serves as a necessary cognitive bridge, enabling users to evaluate *why* a specific financial roadmap was generated, permitting them to reconcile systemic biases or non-quantifiable personal conditions before execution (Raman, 2023).

3) Reconceptualising Technology Acceptance and Financial Literacy as Contextual Financial Judgement (CFJ)

Past research on human-AI collaboration heavily relies on technology adoption models, particularly the **Extended Unified Theory of Acceptance and Use of Technology (UTAUT2)** (Venkatesh et al., 2012), which effectively explains performance expectancy, effort expectancy and initial adoption intentions, but it treats technology acceptance as the ultimate end-state. This creates a significant theoretical weakness: high technology acceptance and strong system trust often aggravate automation bias, obscuring algorithmic errors from users (Dietvorst et al., 2018). Furthermore, traditional models view baseline financial literacy as a static background variable essential for tech adoption (Lusardi et al., 2014), rather than an evolving cognitive capability required *during* the interaction itself.

This study seals this theoretical deficit by demonstrating how the existing dimensions of financial literacy can be synthesized into **Contextual Financial Judgment (CFJ)**, which operationalizes financial literacy as the ability to question, contextualize and supersede algorithmic recommendations when necessary.

By anchoring CFJ at the intersection of Dual-Process, Behavioural Finance, Extended UTAUT2 and Human Agency Theory, this framework demonstrates how human oversight transforms technology adoption from passive compliance into active, context-aware financial governance.

D. Evolution of the Financial Planning Profession in the Age of Artificial Intelligence

1) Historical Trajectory: From Technical Expertise to Behavioural Coaching

Driven by economic and technological shifts, the financial planning profession has evolved significantly. While financial planners historically served as technical experts managing core financial tasks like budgeting, investment planning, retirement planning, taxation, insurance and estate management (Warschauer, 2002), their primary mandate was mitigating information asymmetry by translating complex product data into actionable consumer advice (Bi et al, 2017).

With increasing sophistication of markets, financial planning transitioned towards more comprehensive, client-centred wealth management charters focusing on long-term well-being (Overton, 2008) and alignment of life-goals (Kinder et al, 2014).

This progression was accelerated by discernments from **Behavioural Finance** signifying that psychological factors and cognitive biases profoundly command economic decisions (Kahneman et al, 1979; Barberis et al, 2003). Accordingly, financial planners expanded their roles to integrate behavioural coaching, relationship management and emotional support in addition to traditional technical expertise to maintain disciplined, long-term client strategies (Pompian, 2012).

2) From Computational Analysis to Human Stewardship: The Evolving Advisor

Early FinTech platforms such as basic digital advisory platforms, automated portfolio management systems and client portals, streamlined the delivery and accessibility of financial advice (Gomber et al., 2017), operating as harmonizing infrastructure boosting analytical speed and access without replacing the human advisor (Belanche et al., 2019).

However, advanced AI has further disrupted the profession by automating highly complex analytical functions like portfolio optimization, investment screening, risk profiling, cash-flow forecasting and personalised financial recommendation, that were previously the exclusive domain of human advisors (Cao, 2022; Moghar et al, 2020).

In evaluating this technological shift, early literature relied heavily on the **Extended Unified Theory of Acceptance and Use of Technology - UTAUT2** model (Venkatesh et al., 2012) to explain how advisors and clients accept tools based on effort and performance expectancies, which sparked significant debates regarding the future role and relevance of human planners in AI-driven ecosystems (Filippi et al., 2022).

From the lens of **Adaptive Decision-Making Theory**, financial decision-making needs to balance computational efficiency with accuracy and contextual fit (Payne et al., 1993). While algorithms excel at processing structured data at scale, they fail to address the fluid, emotional and ethical dimensions of personal finance (Jarrahi, 2018). Sound financial planning relies on interpreting subjective life goals, evolving family dynamics and individual moral considerations—qualitative factors that resist purely mathematical optimization (Wilson et al., 2018).

Thus, a financial advisor's competitive edge no longer depends on computational capability, but on human-centric capacities like empathy, contextual interpretation and ethical stewardship (Amershi et al., 2019; Dellermann et al., 2019; Dietvorst et al., 2018; Raisch et al., 2021).

3) Reconceptualising the Advisor as a Contextual Judgment Facilitator

While recognizing this systemic professional shift, current literature examines technology adoption, digital transformation or advisor skill sets in isolation, rarely integrating these dimensions within financial literacy or human agency frameworks (Panos et al., 2020). This leaves the precise role of professional advisors in preserving informed human choice largely undefined.

To address this theoretical gap, this study reconceptualises the financial planner as a **Contextual Judgment Facilitator**. Grounded in **Dual-Process Theory**, automated financial tools commonly trigger fast, heuristic **System 1** processing in clients, exposing them to automation bias and imprudent compliance. The human advisor acts as an essential external circuit breaker, prompting deliberate **System 2** reflective processing.

Furthermore, by integrating **Explainable AI (XAI)** principles, the advisor translates opaque, "black-box" algorithmic recommendations into transparent, logical choices (Arrieta et al., 2020). In doing so, the advisor operationalizes **Human Agency Theory** (Bandura, 2001), ensuring that technology empowers rather than overrides the client's autonomous decisions. Rather than competing with AI's computational speed, human planners help clients interpret automated recommendations relative to their unique personal goals, shifting the advisor's role towards fostering reflective financial decision-making positioning **Contextual Financial Judgment (CFJ)** as the core capability governing modern financial planning.

E. Human-Centric Innovation: The Industry 5.0 Perspective and Financial Literacy

1) Paradigm Shift: From Industry 4.0 Efficiency to Industry 5.0 Human-Centricity

Where Industry 4.0 prioritized hyper-automation, IoT integration, and big data analytics, frequently raising concerns regarding human replacement (Lasi et al., 2014); Industry 5.0 establishes a complementary, human-centred vision for the digital era (European Commission, 2021; Ghobakhloo et al., 2022). Rather than moderating human agency (Raisch et al., 2021), Industry 5.0 aligns technological capability with broader societal value, leveraging human-AI collaboration to realize superior shared outcomes across its three core pillars: human-centricity, sustainability and resilience (Breque et al., 2021; European Commission, 2021; Ghobakhloo et al., 2022; Xu et al., 2021).

Adopting a human-centric approach, this study recognizes that while technologies offer computational supremacy; personal financial planning inherently involves subjective dimensions, like family obligations, moral values and life stage transitions, which alone cannot be captured by mathematical optimization, thereby requiring humans to supply contextual understanding, moral reasoning and responsibility for financial decisions (Jarrahi, 2018; Lu et al., 2022; Wilson et al., 2018).

2) Theoretical Integration: Regulating Automated Output through Human Agency

In an Industry 5.0 framework, AI-enabled FinTech tools strengthen rather than replace human financial decision-making (Dellermann et al., 2019), by processing large volumes of financial information, identifying complex patterns and generating evidence-based recommendations, leaving the user to critically evaluate those recommendations against their unique personal long-term objectives and value systems (Shrestha et al., 2019). This emphasizes complementary interaction over technological substitution (Amershi et al., 2019; Seeber et al., 2020). Consequently, human expertise evolves from executing repetitive calculations to exercising reflective judgment (Vassilakopoulou et al., 2023).

This human-centric shift supports **Human Agency Theory** (Bandura, 2001), which posits that individuals must maintain active, contemplative control over their choices. Through the lens of **Dual-Process Theory**, automated choice architectures often encourage fast, heuristic **System 1** compliance. Industry 5.0 principles offset this passivity by requiring system boundaries to stimulate thoughtful **System 2** scrutiny before execution.

Further, from the lens of **Adaptive Decision-Making Theory**, financial choices require harmonizing algorithmic efficiency against contextual fit (Payne et al., 1993). By inserting **Explainable AI (XAI)** architectures (Arrieta et al., 2020), systems provide the clarity required for users to appraise algorithmic logic, moving beyond the simple adoption metrics emphasized by the **Extended Unified Theory of Acceptance and Use of Technology (UTAUT2)** (Venkatesh et al., 2012).

3) Reconceptualising Financial Literacy as Contextual Financial Judgment (CFJ)

Prominently, Industry 5.0 reinforces the enduring relevance of financial literacy. While traditional frameworks emphasized the individual's responsibility to gather financial data and calculate alternatives (Lusardi et al, 2014), AI now automates these routine tasks. Consequently, the role of financial literacy shifts rather than diminishes (Panos et al, 2020), redirecting its focus toward evaluating algorithmic outputs to preserve informed human agency. Viewed through this angle, financial literacy fosters a collaborative relationship between AI and human judgment, enabling individuals to critically assess the appropriateness of automated recommendations. This aligns directly with Industry 5.0, where technological progress is assessed not merely by efficiency gains, but by its capacity to augment human capability and foster responsible decision-making (Breque et al., 2021; Ghobakhloo et al., 2022).

Undoubtedly Industry 5.0 provides a robust footing for human-technology collaboration. However, existing literature largely ignores its implications for financial literacy theory, focusing primarily on manufacturing and industrial applications rather than personal finance (Xu et al., 2021). Consequently, studies fail to explain how current literacy frameworks preserve human agency within AI ecosystems, exposing a gap which is addressed by this study by presenting a conceptual framework built on Industry 5.0 principles, establishing **Contextual Financial Judgment (CFJ)** as the core capability that operationalizes human agency, Behavioural Finance self-awareness and System 2 reflection during automated interactions.

Research Gap

While substantive literature exists across financial literacy, artificial intelligence, human–AI collaboration, financial planning and Industry 5.0, their theoretical integration remains fragmented. Existing research exhibits four critical theoretical deficit areas:

First, conventional financial literacy frameworks assume individuals execute manual calculations, failing to account for environments where AI algorithms pre-filter, nudge and personalize financial recommendations. Further contemporary literature fails to explain the functioning of financial literacy when routine cognitive tasks are offloaded, especially the way individuals switch from heuristic System 1 acceptance to reflective System 2 evaluation during automated interactions as per **Dual-Process and Adaptive Decision-Making Theory.**

Second, FinTech literature prioritizes technology acceptance models like **Extended Unified Theory of Acceptance and Use of Technology UTAUT2**, disregarding the ways in which automated choice architectures influence automation bias and erode autonomous control (**Human Agency Theory**).

Third, while Information Technology promotes **Explainable AI (XAI)** to expose "black-box" financial algorithms, explainability is treated as a technical feature rather than a cognitive capability required to evaluate outputs against non-quantifiable personal goals, ethical values and changing family dynamics**.**

Fourth, while **Industry 5.0** emphasizes human-centricity and agency, its application remains restricted to industrial manufacturing and supply chain operations. Prevailing research offers no clear theoretical guidance on operationalizing Industry 5.0 principles within personal finance, leaving the evolving roles of financial planners (as Contextual Judgment Facilitators) and financial literacy in supporting human-centric decision-making largely unexamined.

To resolve this critical gap, this study reinterprets the operational dimensions of financial literacy within AI-mediated ecosystems. Synthesizing Dual-Process Theory, Behavioural Finance, Human Agency Theory, Explainable AI, Extended UTAUT2, Adaptive Decision-Making Theory and Industry 5.0, this study introduces **Contextual Financial Judgment (CFJ),** the critical cognitive capability through which individuals evaluate, contextualize and adapt AI-generated insights. Ultimately, this offers a cohesive, human-centric framework that extends financial literacy theory into intelligent environments while preserving informed human agency.

Theoretical Framework

A. Theoretical Foundations of Contextual Financial Judgment (CFJ)

1) Dual-Process Theory

Advocated by (Kahneman, 2011), the theory posits that cognitive processing, functions through two conflicting styles: System 1 (fast, automated and intuitive) and System 2 (slow, analytical and reflective). In AI-mediated finance, automated algorithms function as an externalized System 1; risking automation bias and cognitive passivity. Serving as a System 2 intervention; CFJ provides a reflective cognitive filter to evaluate AI advice against personal goals and realities.

2) Behavioural Finance

Behavioural Finance demonstrates that cognitive heuristics and systematic biases distort rational decision-making (Barberis et al, 2003; Shefrin, 2002). In AI-mediated financial environments, these human vulnerabilities are re-engineered through hyper-personalized user interfaces and automated choice architecture, exploiting behavioural traits like present bias, overconfidence, etc. through gamifiable interfaces or automated nudges encouraging immediate execution. In this context, Contextual Financial Judgment (CFJ) acts as a protective cognitive circuit breaker. Transcending static domain knowledge, CFJ delivers real-time analytical capability to detect biased algorithmic framing, filter prompts through personal values and prevent passivity with sub-optimal automated financial advice.

3) Human Agency Theory

The theory posits that individuals actively shape their lives through intent, prudence and introspection, rather than being passive products of environmental forces (Bandura, 2001; Emirbayer et al, 1998). However, this human agency is at risk of systemic erosion in automated environments. CFJ re-anchors autonomy in financial decision making (Parasuraman et al, 2010), by positioning AI tools as advisory mechanisms rather than autonomous decision-makers, ensuring that individuals critically evaluate algorithmic recommendations, maintain sovereignty and align automated outputs with their unique, non-quantifiable life goals.

4) Extended Unified Theory of Acceptance and Use of Technology (UTAUT2)

The Extended Unified Theory of Acceptance and Use of Technology (UTAUT2) explains technology adoption through constructs like performance and effort expectancy, societal influence and habit (Venkatesh et al., 2012). However, excessive automated accessibility in FinTech environments can inadvertently foster uncritical trust. CFJ introduces a critical moderating mechanism to technology acceptance: adoption transitions from passive, habitual compliance to an active, reflective process where technological utility is continually validated through personal and contextual alignment.

5) Explainable AI (XAI)

Explainable AI (XAI) explains the “black box” of machine learning by making algorithmic decision-making transparent to users (Lipton, 2018; Ribeiro et al., 2016). In high-stakes financial decision making like credit scoring, risk profiling, etc. algorithmic transparency is necessary but insufficient. Within the CFJ framework, XAI serves as a technological antecedent providing structural visibility to understand how the algorithm arrived at a specific decision. Meanwhile, Contextual Financial Judgment (CFJ) supplies the human cognitive capability needed to interpret those explanations, evaluate underlying assumptions and determine their appropriateness for personal circumstances.

6) Adaptive Decision-Making Theory

The theory asserts that individuals balance cognitive effort and decision accuracy (Payne et al., 1993). Based on the complexity of the task, time availability and the stakes involved, the consumers dynamically shift between heuristic-based choices and rigorous analytical strategies. In AI-assisted finance, tasks range from routine micro-savings to complex mortgages. Contextual Financial Judgment (CFJ) operationalizes this adaptive mechanism, empowering consumers to dynamically adjust their algorithmic engagement. While users may delegate low-risk choices to AI, CFJ prompts a strategic shift toward active, reflective oversight for high-stakes decisions, ensuring cognitive effort aligns with financial severity.

Table 1: Comparative synthesis of foundational theories - mapping their core canons to their operational roles within Contextual Financial Judgment (CFJ)

Theory	Primary Authors	Core Theoretical Focus	Specific Role in CFJ Conceptual Framework
Dual-Process Theory	Kahneman (2011); Evans & Stanovich (2013)	Distinguishes between System 1 (fast, intuitive) and System 2 (slow, reflective) cognitive processing.	FinTech apps trigger fast **System 1 (heuristic)** responses. CFJ acts as a deliberate System 2 reflective brake that evaluates algorithmic suggestions before behaviour enactment.
Behavioural Finance	Barberis & Thaler (2003); Shefrin (2002)	Explores how cognitive biases, heuristics and emotions lead to irrational financial choices.	CFJ acts as a protective cognitive filter that neutralizes algorithmic framing, loss aversion, over-reliance and over-confidence in FinTech-induced choices.
Human Agency Theory	Bandura (2001); Emirbayer &	Emphasizes intentionality, self-reactivity and human capacity to apply control	Emphasizes that final authority must remain with the human user, positioning CFJ as the mechanism through which individuals maintain

	Mische (1998)	over actions and outcomes.	autonomy over automated advice.
Explainable AI (XAI)	Ribeiro et al. (2016); Lipton (2018)	Focuses on model transparency, interpretability and post-hoc explanations for algorithmic outputs.	Serves as an empowering technological antecedent; transparent XAI outputs provide the necessary information for consumers to exercise CFJ effectively.
Extended UTAUT	Venkatesh et al. (2012)	Explains technology adoption via performance expectancy, effort expectancy and facilitating conditions.	Reinterprets Performance Expectancy by showing that high-level adoption requires not just passive automation, but critical verification and contextual fit via CFJ.
Adaptive Decision-Making	Payne et al. (1993)	Examines how individuals dynamically switch decision strategies based on task complexity, stakes and effort.	Explains how consumers dynamically shift between passive algorithmic delegation and active manual CFJ intervention; depending on perceived financial risk and personal stakes.

B. Conceptual Grounding: Developmental Architecture vs. Evolving Role

While literature acknowledges the impact of intelligent technologies on personal finance, it lacks an integrated clarification of how financial literacy functions within AI-mediated ecosystems; often prioritizing measurement of financial literacy over the functional role of its core dimensions. Addressing this gap, this study reinterprets financial literacy's operational role rather than reconstructing its structural architecture, establishing two complementary elements:

1) **The Developmental Architecture:** This relates to the established, structurally stable progression through which individuals acquire financial awareness, knowledge and attitudes to drive financial behaviour.

2) **The Evolving Role:** Historically focused on independent information retrieval, the role of financial literacy now shifts towards preserving informed human agency in technology-assisted decision-making. To explain this functional evolution, this framework introduces **Contextual Financial Judgment** - an *emergent capability* synthesizing financial awareness, in-depth knowledge and attitude; to filter algorithmic recommendations against personal goals, moral values and context-specific realities before execution. Aligning with Industry 5.0 principles, it positions artificial intelligence and human cognition as mutually reinforcing; and repositions financial planners as **Contextual Judgment Facilitators**, promoting collaborative human–AI engagement that ensures human accountability.

C. Preserving the Developmental Architecture of Financial Literacy

Although literature reviewed in the previous sections demonstrate the evolution of financial literacy from financial knowledge to encompass awareness, attitude, behaviour and well-being, its foundational logic remains constant: responsible action develops through cognitive, affective and behavioural phases. Building upon this, the present study adopts a developmental pathway comprising of six interconnected dimensions: **Financial Exposure, Financial Importance, Financial Awareness, In-depth Financial Knowledge, Financial Attitude and Financial Behaviour** - as an interconnected conduit transforming information into action. While previous scholars have recommended the introduction of structural changes or adding new digital competencies, this study distinguishes its framework by reinterpreting how each existing dimension functions within AI-mediated environments.

Evolution of the Role of Financial Literacy in AI-Mediated Financial Ecosystems

Although the foundational principles of financial literacy remain constant, the functional role of its dimensions change in response to technological transformation. Historically focused on independent data collection and analysis, financial literacy now centres around evaluating automated AI recommendations, shifting its primary purpose from information retrieval to preserving human judgment in algorithmic environments. This functional evolution transforms each of the six dimensions of financial literacy:

1) **Financial Exposure: From Access to Continuous Algorithmic Engagement**

a) **Traditional Role:** Traditionally, Financial Exposure referred to an individual's interaction with financial information obtained through family, traditional media, banks and advisors, which introduced basic concepts and stimulated involvement in financial decision-making.

b) **AI-Collaborative Role:** In AI ecosystems, exposure expands beyond receiving financial information to navigating a technologically mediated environment characterised by algorithmically generated notifications, customised investment recommendations and robo-advisory prompts. Consequently, Exposure shifts from accessing financial data to recognizing the pervasive algorithmic architecture designed to capture attention and influence behaviour.

2) **Financial Importance: From Recognising Financial Significance to Evaluating Algorithmic Salience**

a) **Traditional Role:** Recognizing how financial decisions impact personal and family well-being, motivating individuals to engage in active, long-term planning.

b) **AI-Collaborative Role**: In AI-mediated environments, recommendation systems create urgency by selectively highlighting specific financial products, investment opportunities or spending decisions based on behavioural tracking. Consequently, Financial Importance shifts from recognizing basic financial needs to exercising critical discernment enabling consumers to separate genuine personal priorities from algorithmically engineered salience.

3) **Financial Awareness: From Financial Consciousness to Reflective Algorithmic Awareness**

a) **Traditional Role:** It implies standard familiarity with financial products, services, and market developments, including recognition of financial opportunities, risks and responsibilities.

b) **AI-Collaborative Role**: Among all six dimensions, **Financial Awareness** undergoes the most significant functional transformation evolving into a deliberate "cognitive pause". Beyond understanding market offerings, reflective awareness prompts critical self-interrogation before accepting automated advice (*"Why is this recommended? Does it serve my goals? or is it generating algorithmic urgency?"*). Accordingly, Financial Awareness functions as the **reflective gateway** through which human agency is preserved within AI-mediated financial ecosystems.

4) **In-depth Financial Knowledge: From Information Acquisition to Purposeful Inquiry**

a) **Traditional Role:** This dimension focused on rote memorization and application of financial concepts, formulae and technical calculations.

b) **AI-Collaborative Role:** As AI mitigates the computational burden of analytical calculations; knowledge transitions from information accumulation to purposeful inquiry. Instead of asking *"What is this product?"* individuals question "*Why is this recommendation contextually appropriate for my circumstances?"* Knowledge therefore becomes contextual and evaluative, providing the qualitative foundation necessary to audit algorithmic assumptions.

5) **Financial Attitude: From Financial Disposition to Contextual Value Alignment**

a) **Traditional Role:** Conceptualised as individual opinions and psychological predilections regarding saving, spending, investments and financial risk.

b) **AI-Collaborative Role**: Here Attitude assumes an interpretative role - evaluating mathematically optimized, AI-generated options with deep human considerations like ethical values, family obligations and ethnic stimuli. By mitigating psychological biases, Attitude ensures that algorithmic insights produce authentically personal and ethically grounded financial decisions."

6) **Financial Behaviour: From Rational Financial Action to Personally Meaningful Financial Action**

a) **Traditional Role:** This implies executing mathematically sound decisions, such as saving regularly, investing prudently or avoiding excessive debt.

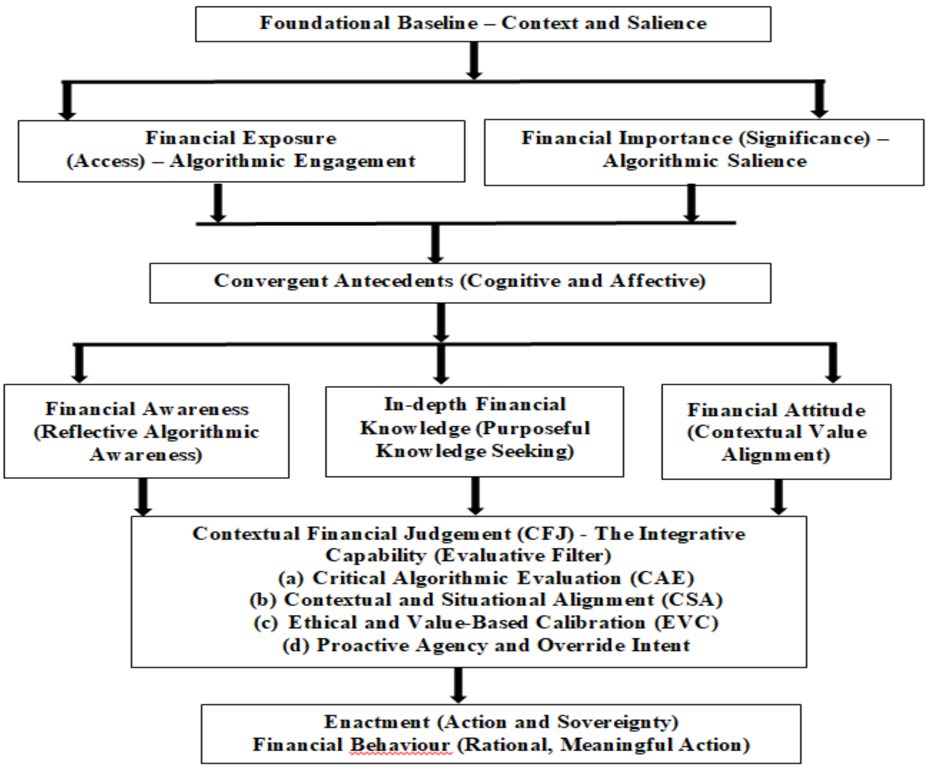
b) **AI-Collaborative Role:** The final stage of the developmental pathway - observable financial actions, which extends beyond technical efficiency into **personally meaningful financial action by** integrating financial knowledge, reflective awareness, contextual evaluation and personal aspirations with AI-generated insights. Under Industry 5.0, optimal behaviour requires intentionality rather than mere mathematical optimization, ensuring choices remain uniquely aligned with personal priorities.

Conceptualisation and Operationalisation of Contextual Financial Judgment (CFJ) as Integrative Capability

Conceptual Definition: Contextual Financial Judgment (CFJ) is an individual's evaluative capability - emerging from the amalgamation of foundational financial awareness, in-depth domain knowledge and proactive financial attitudes - to critically evaluate and regulate algorithmically generated financial insights against one's personal life settings, long-term financial goals and moral values before arriving at informed and meaningful financial decisions.

Operational Role: CFJ operates as an emergent, higher-order cognitive filter situated between the developmental antecedents (Financial *Awareness, Knowledge, Attitude*) and the final action (*Financial Behaviour*).

Figure 1: Developmental Flow of Contextual Financial Judgement (CFJ)



D. Contextual Financial Judgment (CFJ) as Integrative Capability

While individual dimensions of financial literacy evolve to meet technological shifts, their collective interaction gives rise to a higher-order, integrative capability: **Contextual Financial Judgment (CFJ)**. Operational prior to behavioural enactment, CFJ is not a new aspect of financial literacy; rather, an *emergent cognitive capability* through which individuals evaluate AI recommendations. It emerges from the convergence of three reflective dimensions:

1) **Financial Awareness** provides the cognitive pause needed to treat AI outputs as analytical inputs rather than final decisions;

2) **In-depth Financial Knowledge** offers the theoretical foundation to appraise the fundamental assumptions and limitations of those AI-generated suggestions; and

3) **Financial Attitude** supplements with individual personal values, family responsibilities and ethical considerations into the final evaluation.

With the help of this triad, CFJ accomplishes four critical functions: preserving human agency, enabling contextual interpretation, supporting value-based reasoning and initiating reflective financial behaviour. It actualizes the human-centric philosophy of Industry 5.0 in personal finance, transforming financial behaviour from passive algorithmic compliance into purposeful, value-aligned actions.

E. Human–AI Complementarity and Evolving Role of Financial Planner

The framework proposed by this study aligns with Industry 5.0, by positioning AI and humans as complementary partners rather than contenders, amalgamating computational efficiency with human contextual interpretation. While AI excels at quantitative data analysis, but lacks subjective interpretation – an element vital to financial planning as it is deeply connected with personal aspirations, family dynamics, emotions and ethics.

This collaborative relationship redefines the professional identity of financial planners: As AI automates routine data collection and product research, the financial planner transitions from an information provider to a **Contextual Judgment Facilitator**. In this advanced capacity, planners collaborate with algorithms to help clients critically evaluate AI-generated recommendations against personal values and long-term goals, thereby necessitating financial professionals to integrate technical knowledge with behavioural coaching, moral reasoning, empathy and AI skills.

Thus this model synthesizes the modern ecosystem: Financial literacy builds reflective thinking; AI expands analytical capabilities, CFJ defends human agency and the financial planner enables the integration of all these elements.

Theoretical Propositions

Theory of the Evolving Role of Financial Literacy in AI-Mediated Financial Ecosystems

For operationalising the conceptual framework six theoretical propositions were established, reflecting a hierarchical advancement; sketching the way in which digital frameworks basically reshape human decision contexts (P1), redefine the functional motive of financial literacy (P2) and integrate core literacy dimensions (P3) into Contextual Financial Judgment (P4). The framework extends this cognitive capability to the evolving role of financial planners (P5) and establishes a macro-level paradigm for human-AI interdependence (P6). Modelled on Dual-Process Theory, Behavioural Finance, Human Agency Theory, Explainable AI, Extended UTAUT2, Adaptive Decision-Making Theory and Industry 5.0, these propositions provide a structured, rule-based roadmap for human-centric financial decision-making in AI ecosystems.

1) **Proposition 1 (P1): Environmental Transformation - Core Focus: The structural shift in financial choice architecture**

The emergence of AI-mediated financial ecosystems fundamentally transforms the structural context of personal financial decision-making, necessitating a reinterpretation of financial literacy from static knowledge retrieval to an adaptive, technology-mediated evaluative capability.

Theoretical Justification:

Traditional financial literacy evolved in environments characterised by information paucity, human-mediated financial advice and linear decision-making. In modern ecosystems, consumers face an abundance of algorithmically curated, highly personalized information. Rooted in the Extended Unified Theory of Acceptance and Use of Technology (UTAUT2) and Behavioural Finance, performance expectancy in digital ecosystems demands critical interpretation and contextual evaluation by the consumer, without falling prey to behavioural traps and inter-face driven cognitive biases.

2) **Proposition 2 (P2): Functional Evolution - Core Focus: Shifting literacy from calculation to preserving agency**

Within AI-mediated financial ecosystems, the functional role of financial literacy evolves from facilitating independent calculation and knowledge acquisition to preserving informed human agency against automated cognitive passivity.

Theoretical Justification:

As AI automates routine analytics, the primary risk to financial welfare shifts from information scarcity to automation bias - the inclination to uncritically trust AI suggestions. Rooted in Human Agency and Dual-Process Theory, financial literacy assumes a human-centric role transitioning from evaluation of raw information, to cognitive activation of System 2 reflection, ensuring consumers conserve ultimate self-directed, reflective and context-sensitive judgment over automated outputs.

3) **Proposition 3 (P3): Insightful Decision-Making - Core Focus: Interlocking literacy dimensions to activate System 2**

Informed human agency is preserved through the dynamic interaction of three reflective dimensions - Financial Awareness, In-depth Financial Knowledge and Financial Attitude; providing the cognitive capacity to infer, evaluate and contextualize algorithmic outputs.

Theoretical Justification:

The current framework argues that these three dimensions form the reflective core of the financial literacy pathway in AI-mediated financial ecosystems, activating System 2 processing to transform passive reception into active evaluation. Financial Awareness prompts critical scrutiny of algorithmically generated recommendations prior to accepting them. In-depth Financial Knowledge shifts from product data retrieval to purposeful comprehension, while Financial Attitude evaluates financial alternatives against personal aspirations, ethical values, family responsibilities and long-term financial objectives.

4) **Proposition 4 (P4): Contextual Financial Judgment (CFJ) - Core Focus: Operationalizing the core human capability**

Contextual Financial Judgment (CFJ) emerges as the integrative human capability that synthesizes Financial Awareness, In-depth Financial Knowledge and Financial Attitude to filter algorithmically generated insights across four dimensions - Critical Evaluation, Contextual Alignment, Ethical Calibration and Pre-Action Deliberation—prior to behavioural enactment.

Theoretical Justification:

Rooted in Payne, Bettman and Johnson's (1993) Adaptive Decision-Making Theory which posits that individuals dynamically modify decision strategies based on task complexity and contextual constraints. CFJ operationalises this adaptive mechanism in FinTech environments by converting internal cognitive states into four unique operational behaviours:

a) **Critical Algorithmic Evaluation (CAE):** Verifying algorithmic logic vis-a-vis personal domain knowledge.

b) **Contextual and Situational Alignment (CSA):** Tailoring AI recommendations to personal life realities.

c) **Ethical and Value Calibration (EVC):** Screening advice against personal moral boundaries and risk thresholds.

d) **Pre-Action Deliberation (PAD):** Exercising an intentional cognitive pause prior to execution.

5) **Proposition 5 (P5): Professional Transformation - Core Focus: Re-conceptualizing the planner as a Contextual Judgment Facilitator**

As Contextual Financial Judgment becomes the defining human capability in digital finance, the professional role of the financial planner evolves from a primary information provider to a Contextual Judgment Facilitator assisting clients in evaluating and refining AI-generated financial advice.

Theoretical Justification:

As Artificial Intelligence automates many traditional advisory functions, like information retrieval, product comparison, quantitative analysis and portfolio optimisation; the distinctive role of financial planners under the Industry 5.0 shifts to that of an external catalyst for clients CFJ. Planners facilitate reflective interpretation, interpret algorithmic recommendations, clarify financial priorities and align financial decisions with personally meaningful life goals, thereby strengthening informed human judgment.

6) **Proposition 6 (P6): Human-AI Complementarity - Core Focus: Achieving human-centric decision quality**

Human-centric personal financial planning is achieved through collaborative human–AI symbiosis, where AI enhances analytical and predictive capability, while CFJ preserves informed human agency.

Theoretical Justification:

Unrestricted algorithmic dependence jeopardies systemic opacity, loss of consumer independence and algorithmic bias, whereas broad denial of technology leads to loss of numerical precision. Human-AI complementarity establishes a **Human-in-the-Loop (HITL)** supremacy framework, by combining the computational efficiency and predictive power of AI with the CFJ, ensuring that moral deliberation, value alignment, contextual judgement and ultimate accountability for final financial decisions remain truly human.

Construct Operationalization and Scale Indicators

Preliminary Measurement Matrix for CFJ Scale Development

Table 2: Operationalizing Contextual Financial Judgment: Proposed Scale Dimensions and Indicators

Dimension	Conceptual Definition	Sample Scale Indicator (5 Point Likert scale)
1) Critical	The ability to assess AI generated	a) When an AI financial app provides a

Algorithmic Evaluation (CAE) Capability	financial outputs through in-depth domain financial knowledge rather than credulously complying with algorithmic recommendations and detect latent model limitations	recommendation, I assess its rationality against my own understanding of finance.
		b) I use my personal financial knowledge to authenticate if an AI-generated plan is logical.
2) Contextual and Situational Alignment (CSA)	The ability to correlate AI generated suggestions to fit unique, subjective personal life situations and long-term priorities	a) I adjust AI-suggested budgets or plans to suit my current life circumstances which may not be considered by the algorithm.
		b) I modify automated financial recommendations if they conflict with my family or personal goals.
3. Ethical and Value Based Calibration (EVC)	The evaluation of AI recommendations by considering personal moral boundaries, social values and individual risk tolerance levels.	a) I do not accept AI financial suggestions that conflict with my personal ethical standards or sustainability values.
		b) I override AI recommendations if they encourage financial risks that exceed my comfort level.
4. Pre-Action Deliberation (PAD)	The Mindful Autonomy and Deliberate Self-Control exercised while receiving AI insights and executing a financial choice.	a) I pause to reflect on automated financial advice rather than executing it immediately.
		b) I treat AI suggestions as starting points for decision-making rather than final decisions.

DISCUSSION AND IMPLICATIONS

The proposed framework demonstrates that while the developmental architecture of financial literacy remains structurally stable, its operational role shifts from basic information retrieval to preserving human agency through Contextual Financial Judgment (CFJ). This discussion outlines the contribution to the literature on financial literacy, human-AI collaboration and professional financial advisory practices.

1) Shifting the Scholarly Paradigm of Financial Literacy

Historically, financial literacy research aimed to bridge information gaps and improve computational skills. This study shifts that paradigm by demonstrating that while the developmental architecture of financial literacy remains stable; its operational role evolves. As AI automates data retrieval and predictive analytics, the primary challenge shifts from data acquisition to critically evaluating automated suggestions. Financial literacy research in future must therefore pivot from evaluating rote knowledge to measuring the individual's reflective capacity to scrutinize automated recommendations.

2) CFJ as a Human Counterweight to AI and a Pillar for Consumer Protection

A key contribution of this study is positioning Contextual Financial Judgment (CFJ) as a reflective Human-AI interface. Traditional research often interprets AI-mediated decision-making through a twofold lens, either admiring the automated speed or dreading human replacement. Conversely, this framework proposes a balanced model of human-AI complementarity where AI handles data processing and CFJ delivers qualitative contextualisation. By showing how Awareness, Knowledge and Attitude interact to build CFJ, the study illustrates how human values, family responsibilities and ethical AI principles act as a necessary counterbalance to rigid mathematical optimization. Operationally, CFJ serves as a vanguard apparatus for

consumer protection, empowering users to resist manipulative choice architectures and automated over-indebtedness.

3) Redefining Professional Advisory, Financial Inclusion and Regulatory Policy

Ultimately, the proposed framework offers a theoretical resolution to industry concerns regarding automated financial advice. Instead of positioning AI as an adversary to financial planners, it redefines the latter as a Contextual Judgement Facilitator compared to an Information Provider, who navigates multifaceted family dynamics, ethical dilemmas and emotional trade-offs that algorithms cannot replicate.

Furthermore, this operational evolution carries profound implications for:

a) **Financial Inclusion:** For underserved populations susceptible to biased algorithms; fostering CFJ ensures that access to FinTech leads to genuine empowerment rather than digital exploitation.

b) **Regulatory Implications:** Regulators must move beyond static disclosure norms towards directives on Explainable AI (XAI) and protect human oversight, ensuring algorithms support, rather than bypass informed human consent.

Consequently, professional groups, educational institutions and regulatory bodies need to update their training programs and policy standards, by complementing behavioural coaching, morality and AI literacy with traditional financial skills.

Practical Implications

The human-centric framework advanced in this study offers practical implications for key stakeholders across financial education, professional advisory services, public policy and software engineering.

A. For Higher Education and Curriculum Developers

Traditional financial education prioritizes computational and mathematical competencies. In an AI-mediated landscape, educators must concentrate on:

1) **Curricular Reform:** Universities should integrate behavioural finance, algorithmic ethics and AI literacy alongside quantitative analysis.

2) **Reflective Pedagogy:** Shifting assessments from rote calculations to case-based training for critical evaluation of automated financial recommendations.

B. For Financial Planners and Professional Certifying Bodies

As AI specialises in handling routine data processing and portfolio calculations, the financial planner’s contribution is significant for relationship management and contextual guidance:

1) **Evolved Competencies:** Financial Planners must cultivate high-touch human skills like empathy, behavioural coaching and moral reasoning.

2) **Modernized Certifications:** Professional licensing boards and certifying bodies should incorporate collaborative human-AI advisory practices, Explainable AI (XAI) interpretation and algorithmic oversight into their continuing education standards.

C. For Policymakers and Regulatory Authorities

The State must realise that initiatives focused solely on promoting basic saving and investing are insufficient in hyper-automated environments:

1) **Digital Literacy Campaigns:** Public education must empower citizens to recognize algorithmic bias, dark patterns and algorithmically engineered urgency (example aggressive micro-investment notifications).

2) **Consumer Protection Standards:** Regulators should provide directives on algorithmic transparency, warranting FinTech firms provide clear, explainable reasons for their automated suggestions.

D. For FinTech Developers and UX Designers

Rather than designing software that functions as an absolute decision authority, developers should engineer systems that foster collaborative Human–AI decision-making:

1) **Embedded Cognitive Pauses:** Structure the UI/UX to capture qualitative data like ethical preferences, family goals, etc. prior to generating automated investment recommendations and portfolios.

2) **Human-Centric Transparency:** Highlight explainable AI (XAI) features that explain recommendations promoting critical thinking over passive acceptance of automated defaults.

Future Research Guidelines: A Collaborative Agenda

1) Pillar 1: Construct Operationalization and Empirical Validation

The immediate priority for financial literacy scholars is to translate this conceptual model into measurable outcomes through two key steps:

a) **Scale Development:** Future research must design and psychometrically validate a robust measurement scale for **Contextual Financial Judgment (CFJ),** founding its discriminant validity against historical measures of financial capability.

b) **Empirical Testing:** Researchers should deploy Structural Equation Modeling (SEM), longitudinal studies and experimental designs to test how CFJ mediates the relationship between the developmental dimensions of financial literacy and actual financial behaviour. Cross-cultural and socio-economic comparative studies are needed to test the external validity and generalizability of the framework.

2) Pillar 2: Human-AI Interaction and Explainable AI (XAI) Technology

a) **Trust and Agency:** Experimental research should investigate the psychological defining moment between automation bias (over-reliance) and algorithm aversion in robo-advisory environments, identifying the precise situational or systemic conditions guiding users to retain critical control over their choices and when do they passively surrender their individuality to AI.

b) **Explainable AI (XAI):** Studies should evaluate whether XAI interfaces genuinely foster System 2 reflective processing and true comprehension or whether transparent explanations merely induce illusory decision confidence.

3) Pillar 3: Professional Competencies and Subjective Well-being Metrics

a) **Advisor Competency Frameworks:** Empirical inquiry is needed to analyze how the transition of a financial planner's role from information provider to *Contextual Judgment Facilitator* influences client trust and retention, particularly focusing on the value of behavioural coaching, empathy and AI oversight.

b) **Broadening Well-being Outcomes:** Future studies ought to examine the influence of CFJ on subjective outcome metrics such as financial peace of mind, confidence and goal alignment, in addition to traditional, quantifiable metrics like savings and investment percentages, financial ratio analysis, etc.

CONCLUSION

The swift integration of AI into personal finance does not render human expertise obsolete; rather, it elevates its significance. By distinguishing between a stable developmental architecture and changing operational role, this study demonstrates that foundational financial literacy concepts remain conceptually robust while adapting to an automated environment.

The central contribution of this framework is the conceptualization of **Contextual Financial Judgment (CFJ)**, as an emergent capability that serves as the critical human interface in AI-mediated systems. CFJ confirms that quantitative, algorithmically generated endorsements are sifted through the qualitative lens of human values, ethics and unique life situations prior to decision making.

This framework rejects a winner-take-all interpretation of automation, but develops a human-AI complementarity perspective where technology enhances analytical efficiency and humans provide contextual interpretation. Accordingly, the financial planner's role naturally transitions from an information provider to a **Contextual Judgment Facilitator**, fortifying the future value of human expertise in an automated industry.

Eventually, this paper offers a unified, human-centric theory of financial literacy, ensuring that future technological innovation in the field of finance lies in assisting personally relevant, viable human well-being.

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