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Operationalizing and Validating Contextual Financial Judgment: Scale Development and Structural Modeling for AI-Driven Personal Finance

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ABSTRACT

With Artificial Intelligence (AI) and automated choice architectures remodelling consumer finance, traditional measures of financial literacy are ineffective in measuring how individuals network with, assess and supersede algorithmic stimuli. For bridging this theoretical and empirical gap, this paper operationalises a new construct - Contextual Financial Judgment (CFJ) – defined as a unique cognitive-attitudinal competence to appraise programmed financial recommendations vis-a-vis non-quantifiable, qualitative life realities.

Building upon Dual-Process Theory, Human Agency Theory and the Industry 5.0 human-centric AI paradigm, this study introduces a comprehensive psychometric scale architecture and Structural Equation Modeling (SEM) framework to measure human agency in personal finance. Firstly, the study establishes a **theoretically refined 12-item scale** consisting of three reflective first-order dimensions: Contextual Financial Awareness (CFA), In-Depth Systemic Knowledge (ISK) and Evaluative and Overriding Attitude (EOA). Secondly, Contextual Financial Judgment (CFJ) is integrated as a second-order latent construct into a structural model that links exogenous antecedents like Algorithmic Exposure and Perceived Financial Importance, to vital downstream outcomes like Decision Autonomy, Mitigation of Impulse Financial Behaviour and Long-Term Value Alignment, while Explainable AI (XAI) is modelled as a moderating mechanism strengthening the translation of systemic knowledge into overriding attitude. This is further supported by six testable propositions (P1 to P6) to guide future empirical testing.

Finally, the study creates a conceptual structural architecture of AI-mediated financial governance and presents a comprehensive, five-step methodological roadmap for psychometric validation (EFA, CFA and PLS-SEM/CB-SEM), thereby offering a rigorous foundation for evaluating consumer agency in AI-driven financial ecosystems.

Keywords: Financial Literacy, Contextual Financial Judgment (CFJ), Personal Finance, Scale Development, Structural Equation Modeling (SEM), Choice Architecture

INTRODUCTION

The Paradigm Shift in Automated Choice Architecture

The swift proliferation of Artificial Intelligence (AI), machine learning algorithms and predictive analytics into consumer personal finance platforms has fundamentally transformed the individual financial decision making process (Gomber et al., 2017; Panos et al, 2020). Contemporary FinTech platforms have evolved from passive transactional tools; to proactive decision engines, delivering tailor-made financial recommendations, intelligent budget execution, real-time micro-credit and gamified behavioural nudges. Undoubtedly, these automated structures economise transaction costs and broaden access to financial advisory services; however, they also present a critical structural challenge: the steady erosion of human cognitive agency driven by automation bias, dark patterns and manipulative choice architectures (Parasuraman et al, 2010; Skitka et al., 2000). This challenge poses not only academic but also regulatory consequences, as observed by (Mills, 2026) - that financial regulatory frameworks were designed for systems that updated infrequently and behaved predictably; however, these assumptions are challenged by AI models which continuously updates itself.

Although conventional financial literacy frameworks are essential, however they are inadequate in AI-intermediated ecosystems (e.g., Huston, 2010; Lusardi et al., 2014; OECD, 2020); because they focus on static knowledge of a consumer like compound interest, inflation, diversification and basic numeracy. But they fail to capture the active evaluative processing capacity necessary to navigate automated choice environments. Recognising how interest accrues does not automatically translate into the vigilance required to detect dark patterns, like gamified nudges or urgent notifications engineered to encourage impulse borrowing or investments and risky assets.

Research Gap and Problem Statement

Notwithstanding the rapid propagation of Artificial Intelligence (AI), machine learning algorithms and persuasive choice architectures across consumer finance (D'Acunto et al., 2019; Gomber et al., 2017), the current literature on financial capability exhibits three critical gaps as follows:

Gap 1: The Theoretical Disconnect Between Static Financial Literacy Metrics and Dynamic Algorithmic Choice Architectures

Traditional financial literacy models emphasize static, theoretical and mathematical constructs like computation of compound interest, assessing inflation risk and appreciating portfolio diversification (Huston, 2010; Lusardi et al, 2014; OECD, 2020). No doubt, these metrics were acceptable in human financial systems, but are not adequate in modern FinTech ecosystems where predictive algorithms perform quantitative calculations automatically (Panos et al, 2020; Sironi, 2016). Existing literature lacks a theoretical framework detailing how consumer capability evolves when the primary cognitive challenge shifts from performing calculations to critically scrutinizing, contextualizing and selectively overriding automated financial recommendations (Gomber et al., 2017).

Gap 2: Lack of an Operationalized Psychometric Scale for Algorithmic Financial Judgment

No doubt current literature on Information Systems (IS) and Human-Computer Interaction (HCI) addresses behavioural tendencies like automation bias (Skitka et al., 2000), algorithm aversion (Dietvorst et al., 2015) and manipulative dark patterns (Mathur et al., 2019). However, there persists a distinct empirical discrepancy – lack of operationalization of a validated construct or a psychometric scale to quantify a consumer's real-time cognitive capability to measure individual governance over automated financial guidance. Standard instruments measure universal digital literacy or technology maturity (e.g., Venkatesh et al., 2012) but fail to capture the triadic relationship between:

a) real-time perceptual vigilance against interface-driven nudges (*Contextual Financial Awareness*);

b) structural comprehension of algorithmic limits (*In-Depth Systemic Knowledge*); and

c) the attitudinal self-efficacy-the evaluative confidence to override unaligned automated recommendations (*Evaluative and Overriding Attitude*).

Gap 3: The "Optimization Gap" and the Erosion of Human Agency in Personal Finance

Existing research in behavioural finance treats algorithmic adoption primarily through binary paradigms of either user acceptance or resistance (Davis, 1989; Huang et al, 2021). However, this dichotomy overlooks a fundamental structural conflict; algorithms optimize basically for mathematically quantifiable objective functions, like yield maximization or tax-loss harvesting, while continuing to be inherently unequipped to

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qualitative, unquantifiable human realities such as family responsibilities, life transitions or ethical values (Overton, 2008; Xiao et al, 2017). Existing financial literacy do not account for how human agency acts as an active, internal circuit breaker that bridges this "optimization gap", preserving decision autonomy (AUT) and shielding consumers from dark pattern exploitation (MIS).

Without a psychometrically operationalised and validated scale and an integrated structural equation model to address these three gaps; researchers and regulators lack the empirical mechanism to measure consumer Contextual Financial Judgement (CFJ) capacity, in real-world FinTech interactions; identify the specific antecedents that trigger or suppress its activation or the degree to which it protects consumer autonomy and long-term financial well-being. This paper directly addresses all three gaps in the subsequent sections.

Objectives of the Study

This paper bridges the gap between theoretical conceptualization and empirical testing. Operating as a methodological and structural blueprint, it accomplishes following three central objectives:

1. **Objective 1 (Construct Operationalization and Scale Architecture):** To define the multi-dimensional structure of Contextual Financial Judgement (CFJ) across three reflective first-order dimensions - Contextual Financial Awareness (CFA), In-Depth Systemic Knowledge (ISK) and Evaluative and Overriding Attitude (EOA) and construct a **theoretically anchored 12-item measurement pool** derived from operational indicators, proposed for subsequent empirical purification and empirical validation.
2. **Objective 2 (Structural Path Architecture and Propositions):** To formulate a comprehensive Structural Equation Modeling (SEM) framework that conceptualises Contextual Financial Judgement (CFJ) as a reflective-reflective second-order latent construct, supported by six formal; theory-driven propositions (P1 to P6) linking structural antecedents (Zone A) to Contextual Financial Judgement - CFJ (Zone B) and downstream behavioural outcomes (Zone C).
3. **Objective 3 (Governance Architecture and Methodological Roadmap):** To map the conceptual system architecture depicting how Contextual Financial Judgement (CFJ) operates as a human-in-the-loop governance mechanism during live AI interactions, while establishing a five step psychometric validation protocol and to provide a rigorous, multi-stage methodological roadmap to guide future empirical researchers through Exploratory Factor Analysis (EFA), Confirmatory Factor Analysis (CFA) and Structural Equation Model evaluation (PLS-SEM/CB-SEM).

Theoretical Contributions and Significance

By formalising the operational architecture of Contextual Financial Judgment (CFJ), this paper offers three key contributions to the literature:

First, it advances the Behavioural Finance and FinTech literature by shifting the consumer capability assessment from static knowledge-based metrics to active cognitive governance in algorithmic environments.

Second, it enriches Human-Computer Interaction (HCI) and Information Systems (IS) by modeling Contextual Financial Judgement (CFJ) as a second-order construct that directly mitigates automation bias and dark pattern exploitation through human-AI symbiosis.

Third, it establishes an empirically testable psychometric instrument that financial regulators - the **Reserve Bank of India (RBI)** and the **Securities and Exchange Board of India (SEBI)**, can apply to evaluate consumer vulnerability and audit FinTech choice architecture, with specific applications developed under the Section - **Practical, Regulatory and Design Implications.**

THEORETICAL FRAMEWORK AND REVIEW OF LITERATURE

Traditional Financial Literacy vs. Contextual Financial Judgment (CFJ)

Research on consumer financial decision-making for decades has centred around the traditional methods of

financial literacy (Huston, 2010; Lusardi et al, 2014; OECD, 2020). These foundational frameworks conceptualise financial literacy as an integrative concept comprising of awareness, knowledge, skill, attitude and behaviour essential for executing sound financial decisions. Psychometrically, standard empirical scales focus heavily on computational processing and conceptual comprehension, such as computing compound interest, estimating inflation dynamics, analysing risk diversification and applying time-value-of-money mechanics (Lusardi et al, 2014; Remund, 2010).

However, the swift transition of consumer finance to digital environments, powered by artificial intelligence, predictive machine learning algorithms and dynamic adaptive interface, have proved traditional financial literacy frameworks essential, yet fundamentally inadequate (Gomber et al., 2017; Panos et al, 2020). Within contemporary FinTech ecosystems, consumers seldom need to calculate interest yields or construct investment portfolios manually. Rather, algorithmic architectures execute these quantitative optimizations in real time, presenting users with hyper-personalized investment guidance, automated micro-credit provisions, robo-advisory portfolio rebalancing and curated behavioural nudges (D'Acunto et al., 2019; Sironi, 2016).

This structural shift introduces a novel dimension of consumer vulnerability. Conceptual knowledge of risk diversification (Lusardi et al, 2014) is insufficient to protect a consumer when FinTech applications deploy gamified choice architectures, targeted notifications or pre-selected default settings to incentivize volatile, speculative and high-risk financial behaviours (Financial Conduct Authority - FCA, 2022). Navigating these environments demands Contextual Financial Judgment (CFJ) - a dynamic cognitive-attitudinal capability that empowers users to appraise algorithmic financial prompts against their qualitative, non-quantifiable life contexts and exercise human agency when algorithmic outputs diverge from human realities (Bandura, 2001; Jarrahi, 2018; Panos et al, 2020).

The Industry 5.0 Paradigm: Human-Centric AI and the Rationale for Contextual Financial Judgment (CFJ)

This study further grounds Contextual Financial Judgment (CFJ) within the emerging industrial and policy transition towards human-centric Artificial Intelligence: the **Industry 5.0** paradigm. Formalised by the European Commission, Industry 5.0 extends the scope of Industry 4.0 paradigm by reorienting technological integration around human well-being and multi-stakeholder value, rather than pure automation efficiency (Breque et al., 2021). Unlike the technology-centric focus of Industry 4.0; Industry 5.0 adopts a value-driven approach, positioning human agency as an essential, non-negotiable core of technologically mediated environments rather than optimized through full automation (Xu et al., 2021).

Although Industry 5.0 paradigm emerged primarily within manufacturing environments, a growing body of literature extends its core tenets directly to the financial sector. (Mehdiabadi et al, 2022) empirically examines the structural pre-requisites for banking institutions transitioning into the Industry 5.0 era, identifying human-centric technological indicators as pivotal drivers of sectoral transformation. Echoing this perspective, (Soomro et al, 2022) conceptualise Industry 5.0 as a human-centric revolution that leverages human creative and evaluative capabilities to actively steer high-speed, intelligent systems within financial institutions. Aligning with these insights (Liu et al, 2025) contend that Industry 5.0 establishes a human-centric approach to technology in which human-AI collaboration plays a fundamental role in redefining modern financial service delivery.

This study extends this emerging body of scholarship from the institutional and enterprise domain to individual consumer behaviour. While Industry 5.0 envisions human-AI collaboration that maintains human oversight and judgment within automated environments (Xu et al., 2021), Contextual Financial Judgment (CFJ) operationalizes this core design philosophy within personal financial decision-making. Specifically, Contextual Financial Judgment (CFJ) posits that algorithmic financial tools should function as decision-support inputs, subject to active consumer appraisal and selective override, rather than fully autonomous substitutes for human judgment (Jarrahi, 2018). Consequently, Contextual Financial Judgment (CFJ)

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represents the micro-level cognitive-attitudinal capability necessary to operationalise Industry 5.0's human-centric vision within personal finance, a domain previously examined primarily at the organisational level but not yet operationalised at the level of individual consumer capability.

Grounding Zone A Antecedents (EXP, IMP and XAI)

Algorithmic Exposure and Cognitive Adaptation (EXP)

The frequency and intensity of an individual's interactions with automated decision-support platforms significantly alters their cognitive processing frameworks. Grounded in automation trust-calibration theory (Lee et al, 2004) and Technology Adoption Models (Davis, 1989; Huang et al, 2021; Venkatesh et al., 2012), human operators who are repeatedly exposed to automated interfaces undergo a structured perceptual learning curve, altering how operators process system feedback.

Within digital financial platforms, continuous exposure to choice architectures like personalised notifications, automated budget warnings and gamified incentive loops, compels consumers to construct mental schemas of underlying technological operations (Thaler et al, 2008). Although individuals initially interpret automated recommendations as unbiased; recurrent exposure fosters cognitive pattern recognition. However, users gradually learn to connect specific interface nudges to their own fundamental behavioural data, such as historical spending patterns and digital footprint activity (Gomber et al., 2017; Sironi, 2016).

Consequently, continuous Algorithmic Exposure (EXP) functions as a foundational exogenous antecedent. It sharpens user perceptual sensitivity towards interface steering mechanisms - Contextual Financial Awareness - CFA (Thaler et al, 2008) while simultaneously building empirical experience that deepens their functional comprehension of computational architecture and operational constraints - In-Depth Systemic Knowledge - ISK (Lipton, 2018).

Perceived Financial Importance and Life-Reality Stakes (IMP)

Financial decisions carry distinct degrees of cognitive load. The conceptual mechanism explicating how consumers transition from passive heuristic acceptance to deliberate critical analytical scrutiny is rooted in the Dual-Process Theory (Evans et al, 2013; Kahneman, 2011) and Human Agency Theory (Bandura, 2001; Emirbayer et al, 1998). According to Dual process theory, human cognitive processing operates through two operational architectures:

a) **System 1:** Operating automatically, rapidly and subconsciously via heuristic-driven processing; and

b) **System 2:** Operating deliberately, systematically and analytically through cognitive effort.

During routine, low-stakes financial interactions, like accepting a robo-advisor's automated portfolio rebalancing without critical evaluation, consumers operate primarily via System 1 heuristic processing, accepting algorithmic defaults without critical evaluation (D'Acunto et al., 2019). Conversely when a financial transaction carries high-stakes personal significance, like a mortgage deal, restructuring retirement assets or managing liquidity during career transitions, the cognitive stakes escalate sharply (Kinder et al, 2014; Xiao et al, 2017).

High Perceived Financial Importance (IMP) breaks System 1 cognitive indifference and activates System 2 analytical processing (Evans et al, 2013; Kahneman, 2011). Under high-stake financial conditions, consumers demonstrate enhanced vigilance towards persuasive interface steering mechanisms (CFA) and deploy elevated sense of personal agency (EOA); (Bandura, 2001). Given that predictive algorithms remain structurally blindfold towards qualitative human contexts, like familial obligations, emotional commitments or career risks, the elevated perceived gravity of the decision motivates the user to critically re-evaluate and audit AI-generated recommendations and exercise active superseding agency (Emirbayer et al, 1998; Jarrahi, 2018).

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Explainable AI (XAI) as a Structural Moderator (XAI)

A major challenge in human-AI collaboration stems from the opaque "black-box" characteristic of advanced machine learning models (Arrieta et al., 2020; Lipton, 2018). When algorithmic decision logic lacks transparency, human decision makers typically polarise towards one of the two psychological extremes (Parasuraman et al, 2010):

a) **Automation Bias:** characterised by unreflective over-reliance and blind trust on automated system outputs (Cummings, 2004; Skitka et al., 2000); or

b) **Algorithm Aversion**: characterised by complete rejection and mistrust of automated recommendations after observing a single error (Dietvorst et al., 2015).

Research in Explainable AI (XAI) literature validates that delivering transparent, human-interpretable explanations for algorithmic recommendations effectively bridges this cognitive gap (Arrieta et al., 2020; Balaskas, 2026). Within FinTech platforms, XAI mechanisms may manifest as analytical breakdowns explaining the rationale for automated portfolio allocations (D'Acunto et al., 2019) or identifying the precise behavioural variables that influenced a credit decision (Bussmann et al., 2020).

Nevertheless, XAI plays a catalytic moderating role; rather than functioning merely as a direct linear predictor. Holding In-depth Systemic Knowledge – ISK (Lipton, 2018) is insufficient without the ability to understand how did the algorithm applied its computational logic within a specific scenario. Under conditions of high XAI transparency, users gain the capacity to cross verify the algorithm's explicit rationale against their unquantifiable, qualitative personal circumstances, thereby giving them the confidence and cognitive justification required to challenge or override the algorithmic recommendations (EOA) (Arrieta et al., 2020; De Brito Duarte et al., 2023; Dietvorst et al., 2018; Jarrahi, 2018).

The Human Financial Advisor as a Contextual Judgment Facilitator

While the core drivers of Contextual Financial Judgment (CFJ) stem from direct human-machine interactions (example algorithmic exposure and interface design), cognitive agency is not cultivated in a vacuum. A critical external mechanism in this decision ecosystem is the evolving role of the human financial advisor (Brenner et al, 2020; Kinder et al, 2014).

Historically, traditional financial advisors served as primary distributors of quantitative financial products and market information (Hung et al, 2010; Lusardi et al, 2014). However, as artificial intelligence and automated FinTech platforms democratize routine quantitative modeling, asset allocation and algorithmic portfolio rebalancing (D'Acunto et al., 2019; Sironi, 2016), the primary value proposition of human advisors must shift fundamentally (Brenner et al, 2020; Panos et al, 2020).

Rather than competing with automated tools on raw computing speed or data processing, human financial advisors must increasingly function as Contextual Judgment Facilitators (Brenner et al, 2020; Kinder et al, 2014). In an AI-mediated ecosystem, the human advisor acts as an external cognitive bridge between the algorithm's quantitative output and the client's qualitative life realities (Emirbayer et al, 1998; Jarrahi, 2018). Specifically, human advisors facilitate Contextual Financial Judgment (CFJ) activation through three key mechanisms:

1. **Illuminating Algorithmic Blind Spots:** Algorithms optimize strictly for mathematically quantifiable variables such as historical returns, volatility metrics and tax efficiency (Overton, 2008; Xiao et al, 2017). Human advisors assist consumers in identifying the "optimization gap" - helping clients recognize where automated recommendations fail to account for unquantified life realities, such as subjective family obligations, career transitions or ethical value alignment (Kinder et al, 2014; Overton, 2008).

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2. **De-biasing Choice Architecture:** In platforms where gamified user interfaces or automated defaults induce cognitive passivity (Financial Conduct Authority – FCA, 2022; Mathur et al., 2019), the human advisor provides an external circuit breaker (Evans et al, 2013; Kahneman, 2011). By reviewing algorithmic prompts alongside the client; advisors elevate the user's Contextual Financial Awareness (CFA) regarding subtle steering mechanics and dark patterns (Mathur et al., 2019; Thaler et al, 2008).
3. **Enhancing Override Self-Efficacy:** A significant barrier to human agency in AI systems is automation bias - the tendency for users to uncritically accept computer-generated advice out of misplaced technical deference (Cummings, 2004; Skitka et al., 2000). By validating a client's contextual concerns, the advisor reinforces the client's Evaluative and Overriding Attitude (EOA), cultivating the psychological confidence required to challenge, adjust or reject unsuitable automated prompts (Bandura, 2001; Jarrahi, 2018).

Scope Note: While this study isolates Contextual Financial Judgment (CFJ) as an intrinsic consumer-level capability in direct AI interactions; positioning the financial advisor as a Contextual Judgement Facilitator, helps in preserving the construct purity of Contextual Financial Judgment (CFJ) as an individual consumer capability, while establishing a crucial theoretical bridge to hybrid human-AI advisory models (Brenner et al, 2020; Dellermann et al., 2021).

Grounding Zone C Outcomes (AUT, MIS and LVA)

Decision Autonomy vs. Automation Bias (AUT)

A persistent challenge in automated environments is Automation bias – a cognitive heuristic wherein human decision makers uncritically accept automated suggestions disregarding contradictory contextual cues (Cummings, 2004; Parasuraman et al, 2010; Skitka et al., 2000). In personal finance, automation bias leads users to passively consent to automated portfolio strategies, instant credit extension defaults or machine-based spending principles without verifying their contextual alignment (D'Acunto et al., 2019; Panos et al, 2020).

Drawing from Self-Determination Theory (Deci et al, 2000) and human-centred AI frameworks (Dellermann et al., 2021; Jarrahi, 2018), high Contextual Financial Judgment (CFJ) serves as a crucial empirical defense. Consumers equipped with CFJ preserve Decision Autonomy (AUT) by contextualising machine advice through their personal context and life parameters. Instead of subordinating decision authority to automated systems, the consumer positions AI as a consultative advisory support system, while retaining final executive choice agency (Deci et al, 2000; Jarrahi, 2018).

Mitigation of Impulse Financial Behaviour and Dark Patterns (MIS)

Behavioural economics literature highlights how digital choice environments frequently exploit cognitive heuristics to encourage impulsive financial behaviour (Sironi, 2016; Thaler et al, 2008). For instance, FinTech interfaces leverage gamification cues (example gamified transaction rewards) and automated credit nudges (example "Buy Now, Pay Later" defaults) which deliberately capitalize on short-term affective impulses (Financial Conduct Authority - FCA, 2022).

Consumers commanding a high Contextual Financial Judgment (CFJ) activate a cognitive circuit breaker (Evans et al, 2013; Kahneman, 2011). Discriminating real-time awareness (CFA) enables instant identification of interfaces indulging in persuasive design patterns (Mathur et al., 2019); while an evaluative overriding attitude (EOA) provides the psychological agency essential to pause, deliberate and reject interface nudging tactics (Bandura, 2001; Mathur et al., 2019). As a result, Contextual Financial Judgment (CFJ) leads directly to the Mitigation of Impulse Financial Behaviour (MIS).

Long-Term Value Alignment in Personal Finance (LVA)

A core constraint of AI-driven financial tools in personal finance stems from the algorithmic optimization gap: predictive models optimize exclusively for mathematically quantifiable objective metrics like maximisation of portfolio yield, mitigating credit risk or executing tax-loss harvesting (Overton, 2008; Sironi, 2016; Xiao et al, 2017).

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Conversely, human financial well-being is intrinsically connected to unquantifiable, qualitative priorities, such as family support obligations, funding career transitions, prioritizing personal well-being by maintaining work-life balance or upholding ethical investment choices (Kinder et al, 2014; Overton, 2008). When individuals deploy Contextual Financial Judgment (CFJ) they bridge this optimization gap, ensuring that automated execution aligns with their holistic life realities, to achieve Long-Term Value Alignment (LVA) (Jarrahi, 2018; Panos et al, 2020; Xiao et al, 2017).

Operationalizing the CFJ Triad (CFA, ISK and EOA): Dimensions and Psychometric Grounding

Complying with established scale development conventions (Churchill, 1979; DeVellis, 2016), Contextual Financial Judgment (CFJ) is conceptualized as a second-order reflective construct reflected across three first-order dimensions, formally operationalized as follows:

Contextual Financial Awareness (CFA)

1. **Conceptual Definition:** A user's real-time cognitive recognition of algorithmically caused choice architectures, persuasive interface patterns and computer-generated urgency tactics embedded in digital financial interfaces.
2. **Theoretical Grounding:** Draws from Dual-Process Theory (Evans et al, 2013; Kahneman, 2011), Behavioural Choice Architecture (Thaler et al, 2008) and digital dark pattern frameworks (Mathur et al., 2019; Narayanan et al., 2020). Contemporary FinTech applications frequently leverage nudging mechanisms like simulated countdown timers, gamified progress metrics, pre-selected default check-boxes and push alerts, to induce instantaneous action (Financial Conduct Authority-FCA, 2022). Contextual Financial Judgment (CFJ) acts as an active circuit breaker, providing the real-time perceptual alertness required to enable a consumer to identify and recognize when their decision-making environment is being actively influenced by an algorithmic system (Mathur et al., 2019; Thaler et al, 2008).
3. **Operational Indicators:** Real-time detection of artificial urgency, identification of targeted behavioural steering, understanding of default choice architecture and recognition of gamified engagement cues.

In-Depth Systemic Knowledge (ISK)

1. **Conceptual Definition:** A consumer's operational comprehension of algorithmic decision logic, user data tracking architecture, profit-driven platform incentives and inherent model limitations in automated personal finance management.
2. **Theoretical Grounding:** Grounded in AI explainability research (Lipton, 2018) and market information asymmetry frameworks (Akerlof, 1970; Gomber et al., 2017). While traditional financial literacy measures domain knowledge, which asks "What is a stock?" (Lusardi et al, 2014), ISK examines "How does this algorithm process my personal tracking data and what are its underlying computational and revenue-driven constraints?" (Lipton, 2018; Sironi, 2016). It identifies that machine learning architectures aggregate statistical patterns, optimize for population-level patterns but remain structurally sightless to unquantified qualitative human environments (Overton, 2008; Panos et al, 2020).
3. **Operational Indicators:** Input data tracking comprehension, identification of commercial algorithmic bias, recognition of non-quantifiable personal realities and model output logic interpretability and transparency.

Evaluative and Overriding Attitude (EOA)

1. **Conceptual Definition:** The user's subjective agency, critical stand and psychological readiness, enabling him to scrutinize, contest, alter or outrightly decline algorithmically generated financial advice.
2. **Theoretical Grounding:** Rooted in foundational models of Human Agency Theory (Emirbayer et al, 1998; Bandura, 2001) and Automation Bias research (Parasuraman et al, 2010; Skitka et al.,

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2000). Undoubtedly, Consumer Financial Awareness (CFA) and In-depth Systemic knowledge (ISK) are necessary pre-requisites but are not adequate to drive behavioural interventions; as a consumer must also possess the psychological efficacy to challenge the algorithmic logic. EOA captures this active posture, positioning automated tools as consultative advisory inputs rather than dependable decision-making directives.

3. **Operational Indicators:** Critical override self-reliance, real-time goal alignment, pro-active mitigation of automation bias and autonomous decision agency.

Operationalization and 12-Item Scale Architecture Table

In accordance with the standard psychometric scale construction guidelines (DeVellis, 2016), an initial candidate pool of 24 candidate items was developed - eight items per sub-dimension - to provide a broad foundation for subsequent item purification. Each candidate item was constructed using first-person active phrasing, restricted to a single cognitive or attitudinal construct to avoid double-barrelled items and scored via a 7-point Likert scale (1 = Strongly Disagree to 7 = Strongly Agree).

Through a rigorous **theoretical content-validity screening – emphasizing** single-indicator precision, conceptual distinctiveness and clear boundary division from adjacent Contextual Financial Judgment (CFJ) sub-dimensions, the item pool was refined to a final 12-item measurement set (four items per sub-dimension), retaining the items with the strongest and optimal conceptual fit and pruning those judged redundant, ambiguous or peripheral to the construct definition. Table 1 outlines this refined 12-item architecture; the discarded items are retained as an archived pre-vetted reserve pool (Appendix A) for substitution during the empirical validation process described under Section - Methodological Roadmap for Empirical Validation.

Note: Empirical confirmation of this item pool's content validity, including formal expert panel evaluation and quantitative I-CVI/S-CVI scoring, constitutes Step 1 of the methodological roadmap mentioned under Section - Methodological Roadmap for Empirical Validation - Step 1: Pre-Testing and Content Validity Verification (Qualitative Phase) and represents a proposed agenda for future empirical validation, not a step already completed in this paper.

Table 1: Refined Scale Architecture Matrix for Contextual Financial Judgment (CFJ)

Code	Sub-Dimension	Operational Indicator	Refined Measurement Item
CFA_1	Contextual Financial Awareness (CFA)	Detection of Algorithmic Urgency	I recognize when a financial app uses prompts or timers to create an artificial sense of urgency.
CFA_2		Sensitivity to Choice Architecture	I am aware of how default app settings subtly guide my financial decisions.
CFA_3		Recognition of Gamification	I spot when financial apps use game-like features to encourage frequent financial transactions.
CFA_4		Recognition of Social Proof Cues	I recognize when a financial platform uses cues like "many users chose this option" to influence my choices.
ISK_1	In-Depth Systemic Knowledge (ISK)	Understanding Input-Data Logic	I understand how my personal data is processed by financial algorithms to generate advice.
ISK_2		Comprehension of Algorithmic Bias	I am aware that AI financial tools can operate on inherent algorithmic biases.
ISK_3		Awareness of Non-	I understand that financial algorithms fail

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		Quantifiable Gaps	to account for my qualitative personal values and life transitions.
ISK_4		Interpretability of Output Logic	I can explain the reasoning behind why an automated system recommends a specific financial action to me.
EOA_1	Evaluative and Overriding Attitude (EOA)	Critical Override Readiness	I feel confident overriding an AI-generated financial recommendation when it feels inappropriate for me.
EOA_2		Contextual Re-evaluation	I evaluate whether AI financial recommendations fit my unquantifiable personal life realities before taking action.
EOA_3		Autonomous Decision Agency	I treat AI financial tools as secondary advisory aids rather than final decision-makers.
EOA_4		Resistance to Urgency Cues	I can resist urgency cues in a financial app and delay a decision until I am ready.

Construct Boundary and Scale Purity: To maintain strict scale purity and prevent construct contamination within the proposed structural model, required establishing clear boundaries for the Contextual Financial Judgment (CFJ) measurement scale:

1. **Exclusion of Antecedents:** External drivers such as Algorithmic Exposure or Perceived Financial Importance intentionally excluded from the internal scale measurement. While these variables stimulate Contextual Financial Judgment (CFJ), they represent contextual antecedents rather than the sub-dimensions of the construct itself.
2. **Exclusion of Downstream Outcomes:** Behavioural manifestations such as Impulse Financial Behaviour Mitigation or Decision Autonomy are excluded from the item development. Contextual Financial Judgment (CFJ) measures the underlying cognitive capacity (encompassing contextual awareness, systemic knowledge and execution attitude) to formulate contextual judgments, whereas observable behaviour constitute its downstream consequences (MacKenzie et al., 2011).

CONCEPTUAL SYSTEM ARCHITECTURE AND COGNITIVE DEVELOPMENTAL FLOW

Bridging the gap between micro-level psychometric evaluation with macro-level Information Systems (IS) governance, requires a formal operationalisation of the construct Contextual Financial Judgment (CFJ). To further this end, the Section establishes two structural architectural frameworks:

The System Architecture of AI-Mediated Financial Governance: Details out the dynamic, real-time interplay between algorithmically steered interfaces and human cognitive agency

Contemporary FinTech platforms operate as dynamic, closed-loop decision systems. Within these digital environments, predictive algorithms recurrently track consumer behaviour, compute personalized advice and deliver behavioural nudges through persuasive User Interfaces (UIs). In the absence of human intervention, this automated loop can turn into unilateral algorithmic steering, wherein consumer decision making are subtly shaped by platform defaults, revenue-driven heuristics or gamified choice architectures.

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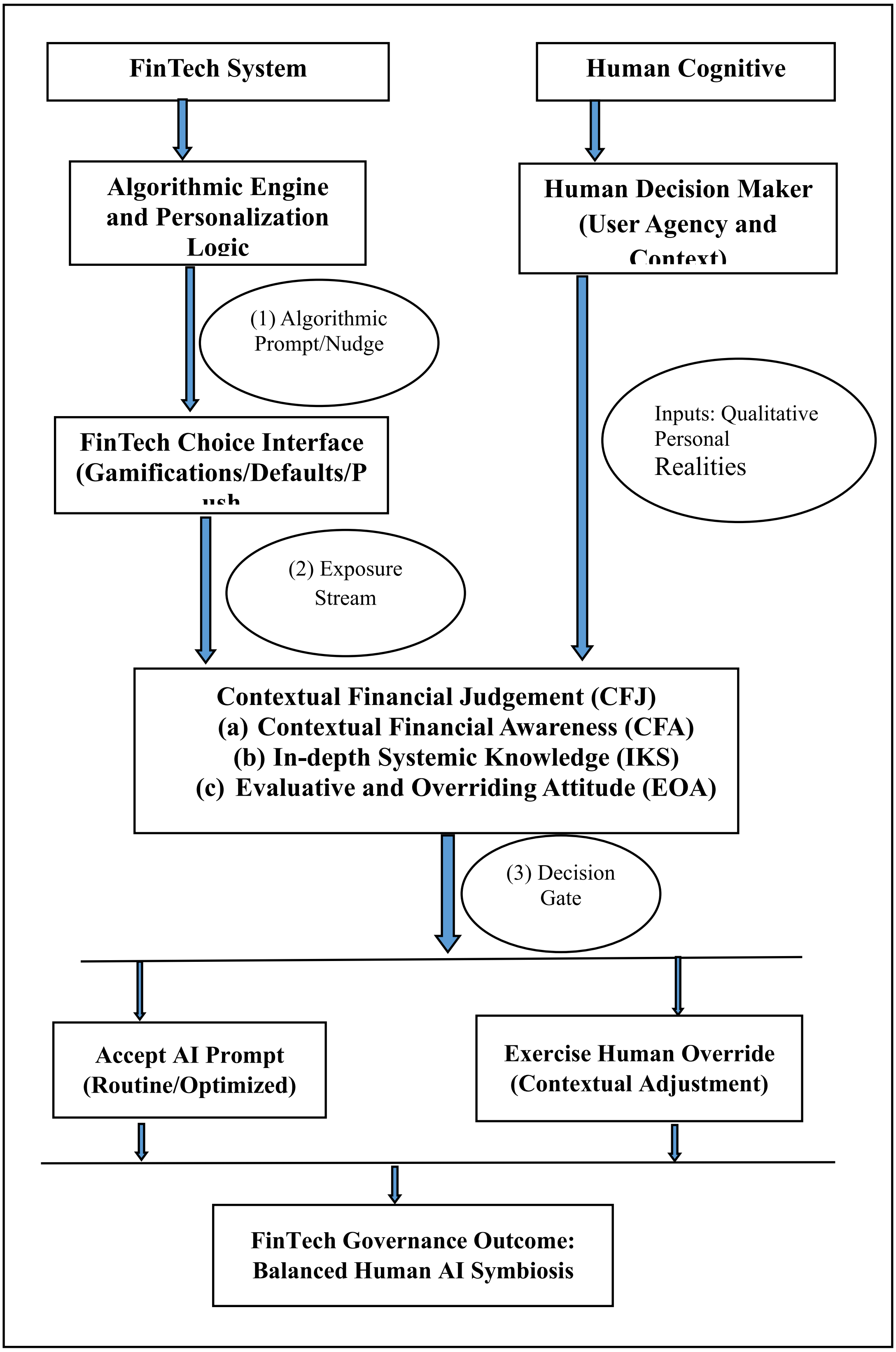
As shown in Figure 1, Contextual Financial Judgment (CFJ) functions as an indispensable human-in-the-loop governance filter positioned at the critical juncture between the FinTech choice interface and the ultimate financial decision.

Figure 1: Conceptual System Architecture of AI-Mediated Financial Governance



Note: Contextual Financial Judgment (CFJ) operates as a critical intermediate cognitive filter situated and operating within the interaction loop connecting AI-enabled digital finance applications and human decision-making agency.

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Operational Governance Sequence:

1) **Algorithmic Prompt Delivery:** The predictive algorithms of the FinTech platforms deliver a customised system-initiated recommendation (example an automated asset rebalancing, a real-time credit advancement or a gamified investment alert).

2) **Cognitive Interception (CFJ Processing):** Prior to executing the recommended transaction, the system prompt enters the human cognitive buffer triggering the activation of the Contextual Financial Judgement (CFJ):

a) **Contextual Financial Awareness (CFA):** The user actively identifies persuasive interface design tactics, dark patterns or artificial generated urgency nudges.

b) **In-Depth Systemic Knowledge (ISK):** The user scrutinizes the algorithm's predictive rationale of the prompt, while evaluating qualitative non-quantifiable personal factors (like upcoming family financial obligations, employment precarity or subjective ethical priorities) that lie beyond the scope of the algorithm's observation.

c) **Evaluative and Overriding Attitude (EOA):** The individual asserts cognitive human decision making to evaluate whether the automated output genuinely aligns with their long-term holistic well-being.

3) **Decision Gate Execution:** The cognitive intervention arrangement culminates at a dual-action decision gate:

a) **Informed Acceptance:** The user endorses the AI output for routine, algorithmically sound optimizations where qualitative personal context completely matches with system logic.

b) **Deliberate Human Override:** The user amends or rejects the algorithmic recommendation, substituting it with contextually aligned human judgment.

4) **Symbiotic Outcome:** The system now achieves a balanced state of Human-AI symbiosis, where automated efficiency is continually governed by human contextual oversight (Jarrahi, 2018).

The Cognitive Developmental Flow - The Path to CFJ Maturity: It outlines the sequential progression which the consumers navigate as they evolve from uncritical, passive automation reliance to mature, integrated Contextual Financial Judgment (CFJ) governance

High levels of Contextual Financial Judgment (CFJ) does not emerge instantaneously among consumers. Rather, they progress along a cognitive developmental continuum as they accumulate experience with algorithmic tools, experience system friction and gradually cultivate human agency. This developmental progression draws upon established models of skill and judgment acquisition, wherein consumers evolve from rigid, rule-bound reliance toward adaptive, intuitive and contextually integrated expertise as experience accumulates (Dreyfus et al, 1980).

Derived from this theoretical foundation, Figure 2 **proposes** a four-stage evolutionary trajectory, mapping the transition from uncritical, passive automated reliance to collaborative human-AI governance. Empirical validation of this proposed developmental sequence in the context of Contextual Financial Judgment (CFJ) represents a critical agenda for future research based on longitudinal or cross-sectional research designs.

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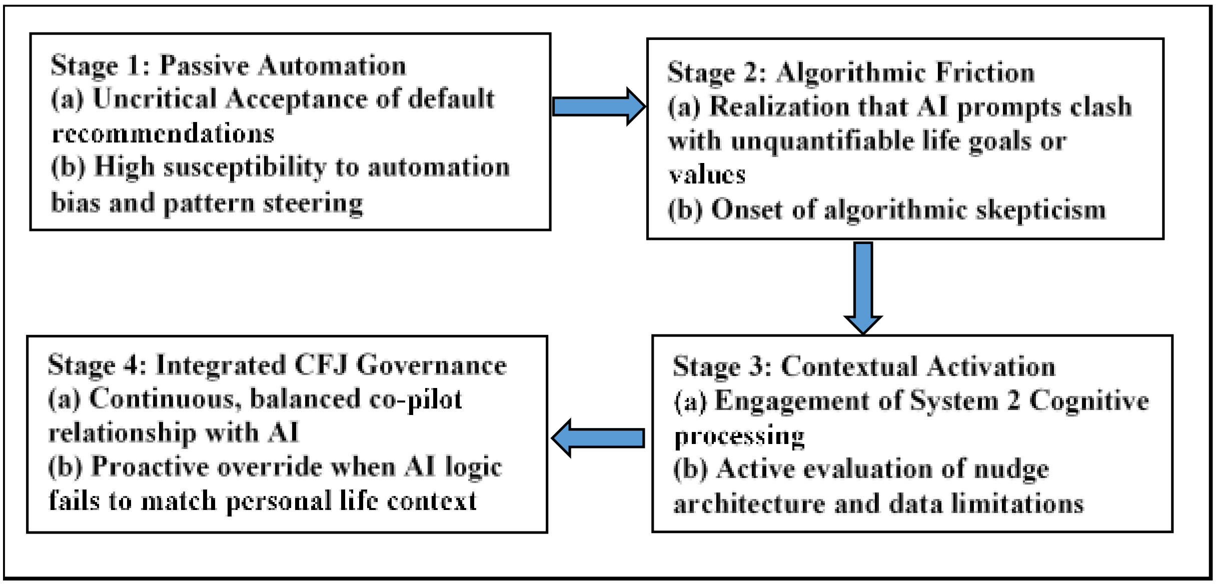
Figure 2: Cognitive Developmental Trajectory Flow Diagram of the Cognitive Transition trajectory towards Contextual Financial Judgement (CFJ).



***Note:** Depicts the hypothesized cognitive transition from passive algorithmic reliance towards a balanced human-AI collaborative governance. The contextual framework draws on established stage-wise skill acquisition paradigms (Dreyfus et al, 1980), the diagram illustrates the progressive development of human agency within AI-mediated decision environments.*

Stage-by-Stage Breakdown:

1) **Stage 1: Passive Automation Reliance (Uncritical Acceptance)**
a) **Characteristics:** The consumer exhibits strong susceptibility to automation bias. Interface defaults, automated investment features and algorithmic push notifications are endorsed and accepted without critical evaluation under the heuristic assumption of algorithmic superiority - that "the algorithm knows the best" (Cummings, 2004; Parasuraman et al, 2010).
b) **Cognitive State:** Dominated entirely by Pure System 1 heuristic, characterised by total absence of contextual re-evaluation (Kahneman, 2011), prior to execution.

2) **Stage 2: Algorithmic Friction and Disconnect (Cognitive Dissonance)**
a) **Characteristics:** The user experiences a critical mismatch where an AI-driven prompt produces an adverse real-world outcome or directly conflicts with an unquantifiable life circumstances (example an auto-sweep savings or investment, inducing an account overdraft during an unrecorded family crisis).
b) **Cognitive State:** Involves growing scepticism and the realization that quantitative AI frameworks possess inherent structural blind spots regarding qualitative human context (Overton, 2008).

3) **Stage 3: Contextual Activation (Analytical Intervention)**
a) **Characteristics:** The consumer transitions to System 2 analytical processing while using FinTech platforms. Users begin to detect persuasive choice architectures, scrutinizing output logic and cross-verifying automated advice against subjective long-term financial goals (Evans et al, 2013).
b) **Cognitive State:** Characterised by active cognitive vigilance and engagement and the deliberate exercise of override agency during high-stakes financial decision making.

4) **Stage 4: Integrated Contextual Financial Judgment (CFJ) Governance (Human-AI Symbiosis)**
a) **Characteristics:** The user positions algorithmic financial AI tools as secondary advisory co-pilots rather than autonomous, authoritative primary decision-makers. Users seamlessly delegate routine quantitative tasks to auto-apps, while retaining proactive human control to maintain contextual alignment.

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b) **Cognitive State:** Represents the fully matured, integrated state of Contextual Financial Judgment, encompassing all three structural dimensions, synthesizing Contextual Re-evaluation, In-depth Systemic Knowledge and Executive Override Agency (CFA + ISK + EOA).

Governance and Regulatory Implications: A Preview

Operationalising CFJ as a functional system architecture has significant practical ramifications for FinTech interface design and regulatory policy. A complete theoretical and empirical elaboration of these implications are comprehensively articulated under Section - Practical and UX/UI Design Guidelines.

STRUCTURAL EQUATION MODELING (SEM) FRAMEWORK, PATH ARCHITECTURE AND THEORETICAL PROPOSITIONS

Overview of the SEM Structural Path Architecture

The proposed structural model delineates a three-tier architectural framework, mapping the operational flow from exogenous antecedents, through the multi-dimensional Contextual Financial Judgement (CFJ) to its downstream behavioural consequences.

1. **Zone A: Antecedents (Exogenous Predictors) –** It captures foundational antecedent drivers, including Algorithmic Exposure (EXP) and Perceived Financial Importance (IMP), that initiate the Contextual Financial Judgment (CFJ) activation. Rather than predicting the second-order Contextual Financial Judgment (CFJ) construct uniformly, each Zone A variable target specific first-order sub-dimensions: EXP predicts both Contextual Financial Awareness (CFA) and In-Depth Systemic Knowledge (ISK), while IMP predicts both Contextual Financial Awareness (CFA) and Evaluative and Overriding Attitude (EOA).
2. **Zone B: Core Construct (Endogenous Latent Capability) –** Encompasses the reflective second-order CFJ construct, across its three first-order dimensions (CFA, ISK and EOA). Within this zone, Explainable AI (XAI) functions as a **moderating variable** rather than a direct predictor: which amplifies the positive relationship between ISK and EOA under high-transparency conditions, without asserting an independent direct effect on Contextual Financial Judgment (CFJ) itself.
3. **Zone C: Outcomes (Downstream Consequences) –** It captures the ultimate behavioural impacts stemming from Contextual Financial Judgment (CFJ) execution, including Decision Autonomy (AUT), Mitigation of Impulse Financial Behaviour (MIS) and Long-Term Value Alignment (LVA). Unlike Zone A, antecedent paths, which acts on individual first-order dimensions, Zone C outcomes stem directly from the integrated second-order CFJ construct as a whole, reflecting that these behavioural impacts emerge from the synergistic integration of awareness, knowledge and attitude, rather than from any isolated sub-dimensions.

This structural asymmetry - dimension-level targeted antecedent inputs coupled with the composite-driven outcome outputs, reflects the theoretical specificity of the underlying propositions and governs the structural path diagram.

Formal Proposition Development (P1 to P6)

Zone A → Zone B: Antecedent Effects - Structural Relationships: Zone A (Antecedents) to Zone B (Core Constructs)

1. **Proposition 1a (P1a):** Repeated exposure to Algorithmic systems (EXP) cultivates a consumer's Contextual Financial Awareness (CFA), stimulating user recognition of digital platform nudges and interface steering mechanisms *(Supported by Davis, 1989; Lee et al, 2004; Thaler et al, 2008).*
2. **Proposition 1b (P1b):** Frequent interaction with automated financial platforms (EXP) fosters In-Depth Systemic Knowledge (ISK), through progressive familiarity as to how algorithmic architectures process input data and make predictions *(Supported by Huang et al, 2021; Lipton, 2018; Venkatesh et al., 2012).*

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3. **Proposition 2a (P2a):** High Perceived Financial Importance (IMP) activates an Evaluative and Overriding Attitude (EOA), by influencing users to gain execution control and human agency in high-stakes financial decisions *(Supported by Bandura, 2001; Emirbayer et al, 1998; Kahneman, 2011).*
4. **Proposition 2b (P2b):** Perceived Financial Importance (IMP) activates Contextual Financial Awareness (CFA), by driving reflective System 2 processing, thereby stimulating vigilant cognitive scrutiny about platform nudges and persuasive choice architectures *(Supported by Evans et al, 2013; Kinder et al, 2014; Thaler et al, 2008).*

Zone B: Moderation Effect

1) **Proposition 3 (P3):** Transparent Explainable AI (XAI) architectures serve as a cognitive catalyst between In-Depth Systemic Knowledge (ISK) and Evaluative and Overriding Attitude (EOA), enabling consumers to exercise human agency as underlying algorithmic reasoning becomes more interpretable *(Supported by Arrieta et al., 2020; De Brito Duarte et al., 2023; Dietvorst et al., 2018; Lipton, 2018).*

Zone B → Zone C: Outcome Effects.

2) **Proposition 4 (P4):** The operationalisation of Contextual Financial Judgment (CFJ) enhances Decision Autonomy (AUT), by enabling individuals to reclaim active control over algorithmically driven choices, thereby actively mitigating vulnerability to automation bias *(Supported by Cummings, 2004; Deci et al, 2000; Jarrahi, 2018; Skitka et al., 2000).*

3) **Proposition 5 (P5):** Contextual Financial Judgment (CFJ) serves as a dynamic cognitive defence against Impulse Financial Behaviour (MIS), as enhanced user awareness shielding consumers from dark patterns and manipulative design cues *(Supported by Financial Conduct Authority, 2022; Mathur et al., 2019; Thaler et al, 2008).*

4) **Proposition 6 (P6):** Integrating Contextual Financial Judgment (CFJ) into routine financial decision making fosters Long-Term Value Alignment (LVA) in personal financial management, by transforming automated platform efficiency into sustainable, value-driven financial governance *(Supported by Jarrahi, 2018; Kinder et al, 2014; Overton, 2008; Panos et al, 2020; Xiao et al, 2017).*

METHODOLOGICAL ROADMAP FOR EMPIRICAL VALIDATION

To operationalise Contextual Financial Judgment (CFJ) from a conceptual model to a psychometrically validated measurement tool, this section outlines a comprehensive, multi-stage validation roadmap. Subsequent empirical studies can execute this five-step protocol to refine the 12-item scale, validate its latent factor structure and empirically test the structural equation model (P1 to P6).

Step 1: Pre-Testing and Content Validity Verification (Qualitative Phase)

Before testing the 12-item pool across broad sample populations, empirical researchers must establish content and face validity through expert evaluation and cognitive pre-testing:

Expert Panel Review:

a) Recruit a panel (N=6–10) consisting of subject-matter experts from the field of Behavioural Finance, Information Systems and Human-Computer Interaction (HCI), industry FinTech product managers and consumer financial protection advocates.
b) Evaluate items on a 4-point ordinal relevance scale (1 = Not Relevant to 4 = Highly Relevant) to quantify the Item-Content Validity Index (I-CVI) and Scale-level Content Validity Index (S-CVI/Ave).

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c) Retain exclusively those items meeting standard psychometric benchmarks: I-CVI ≥ 0.78 (Lynn, 1986) and S-CVI/Ave ≥ 0.90 (Polit et al, 2006).

Cognitive Debriefing (Pre-Test):

Execute semi-structured "think-aloud" interviews with 15–20 active digital finance users to evaluate semantic clarity, item interpretability and face validity (Willis, 2005). This process ensures clear construct comprehension of core domain-specific phrases such as "algorithmic urgency", "choice architecture" and "unquantifiable personal life realities".

Step 2: Sampling Strategy and Data Collection Guidelines

To achieve robust statistical power for factor analysis and Structural Equation Modeling; data collection must satisfy rigorous sampling parameters:

1) **Target Population:** Consumers actively using AI-driven financial interfaces (e.g. robo-advisors, automated budgeting apps, algorithmic micro-investing platforms or AI-mediated credit assessment interfaces).
2) **Sample Size Requirements:**
a) **Exploratory Factor Analysis (EFA):** Entails a minimum N=150–200 or ≥10 respondents per item (Hair et al., 2019).
b) **Confirmatory Factor Analysis (CFA) and SEM:** Entails a minimum N=250–350 independent respondents.
c) **Split-Sample Design:** Collect an aggregate sample of N≈500–600 respondents and execute a random split sample procedure, yielding: **Sample A** (n1=250) for initial EFA scale purification and **Sample B** (n2=250–350) for CFA factor confirmation and structural path analysis.
3) **Measurement Instrument Scaling:** All items should be operationalised using a 7-point Likert Scale continuum (1 = Strongly Disagree to 7 = Strongly Agree).

Step 3: Scale Purification and Dimensionality Analysis (EFA Phase)

Using, Sample A (n1=250), run Exploratory Factor Analysis to evaluate the underlying dimensionality of the item pool:

1) **Sampling Adequacy Diagnostics:** Confirm data suitability by verifying that the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy exceeds 0.70 (Kaiser, 1974) and Bartlett's Test of Sphericity is statistically significant ($p<0.001$).
2) **Factor Extraction and Rotation:** Perform Principal Axis Factoring (PAF) paired with Promax (Oblique) Rotation, enabling the three theoretically related latent factors (CFA, ISK and EOA) to freely inter-correlate.
3) **Item Purification Criteria:** Retain items that exhibit primary factor loadings ≥0.60, cross-loadings <0.30 and item communalities (h^2) ≥0.40.

Step 4: Construct Validation and Psychometric Evaluation (CFA Phase)

Using Sample B (n2=250–350), perform Confirmatory Factor Analysis (CFA) to validate the second-order reflective measurement model (Figure 1 in Section 4):

Table 2: Recommended Goodness-of-Fit Thresholds for CFA

Fit Index	Recommended Cutoff Threshold	Theoretical Reference
$\chi 2$/df (Normed Chi-Square)	<3.0	Kline (2015)
CFI (Comparative Fit Index)	≥0.95	Hu et al (1999)
TLI (Tucker-Lewis Index)	≥0.95	Hu et al (1999)
RMSEA (Root Mean Square	<0.06 (90% CI <0.08)	Hu et al (1999); MacCallum

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Error of Approximation)		et al (1996)
SRMR (Standardized Root Mean Square Residual)	<0.08	Hu et al (1999)

Psychometric Reliability and Validity Testing:

1) **Construct Reliability:** Confirm that Cronbach's Alpha ($\alpha \geq 0.80$) and Composite Reliability ($CR \geq 0.80$) demonstrate robust internal consistency across all underlying sub-dimensions.

2) **Convergent Validity:** Ensure adequate variance capture by establishing an Average Variance Expected of ($AVE \geq 0.50$) for each first-order dimension and the second-order Contextual Financial Judgment (CFJ) construct.

3) **Discriminant Validity:** Confirm discriminant validity through the Fornell-Larcker Criterion, ensuring the square root of each sub-dimension's AVE exceeds its correlations with all other constructs and that all pairwise Heterotrait-Monotrait (HTMT) ratios remain strictly below 0.85 threshold (Henseler et al., 2015).

Step 5: Structural Path Evaluation and Proposition Testing Protocol

Following psychometric confirmation of the measurement model, structural relationships (P1–P6) will be evaluated using Partial Least Squares SEM (PLS-SEM) or Covariance-Based SEM (CB-SEM):

1) **Statistical significance of Paths:** Estimate standardized path coefficients (beta β), t-statistics and corresponding p-values generated via a 5,000-sample bootstrapping procedure.

2) **Explanatory Power and Predictive Relevance:** Evaluate R^2 values for endogenous latent variables, determine f^2 effect sizes (targeting $f^2 \geq 0.02$, 0.15 and 0.35 for small, medium and large effect size thresholds (Cohen, 1988) and confirm cross-validated predictive relevance via blindfolding procedures ($Q^2 > 0$).

3) **Moderation Analysis (P3):** Test the catalytic moderating influence of Explainable AI (XAI) on the structural linkage between In-depth Systemic Knowledge (ISK) and Evaluative and Overriding Attitude (EOA) using continuous interaction modelling or Multi-Group Analysis (MGA).

DISCUSSION AND IMPLICATIONS

Academic Contributions

This study makes three core theoretical contributions to the literature at the intersection of Behavioural Finance, Information Systems (IS) and Human-Computer Interaction (HCI):

1) **Reconceptualising Financial Capability in AI-mediated ecosystems:** It redefines consumer financial capability moving beyond static, knowledge-centric metrics (conventional financial literacy) toward a dynamic, cognitive-attitudinal construct designed to operate within persuasive, AI-driven architectures.

2) **Psychometric Precision through Second-Order Modeling:** By operationalizing Contextual Financial Judgment (CFJ) as a second-order, reflective-reflective construct – capturing CFA, ISK and EOA as reflective manifestations of a broader underlying capability rather than independent causal inputs (Churchill, 1979), this study establishes a **theoretically well-bounded 12-item scale** that prevents construct contamination by strictly isolating internal psychological capabilities from external environmental drivers and downstream financial behaviours.

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3) **Extending Human-AI Symbiosis to Personal Governance:** The study advances human-AI symbiosis theory (Jarrahi, 2018) within consumer environments, demonstrating how human cognitive agency functions as an indispensable governance mechanism in automated decision pathways, buffering against automation bias and dark pattern exploitation.

Practical, Regulatory and Design Implications

For FinTech UX/UI Designers and Developers

Contemporary FinTech design paradigms overwhelmingly prioritizes "hyper-frictionless" interfaces to accelerate user transaction velocity. Nevertheless, as established in our system architecture under Section on - **System Architecture of AI-Mediated Financial Governance**, eliminating all interface friction reinforces passive automation bias by circumventing the exact cognitive interception point essential to activate Contextual Financial Judgement (CFJ). Product designers can apply the Contextual Financial Judgement (CFJ) framework to strategically introduce meaningful cognitive friction, for especially high-stakes transactions, in the form of intervening verification step highlighting algorithmic logic, giving users the space to deploy Contextual Financial Awareness (CFA) and Evaluative and Overriding Attitude (EOA) before a recommendation is executed. For instance, platforms can integrate interstitial screens that summarize key predictive inputs (example - this recommendation assumes stable monthly earnings and no upcoming capital expenditures), prior to final confirmation, directly operationalizing the Decision Gate described in Figure 1.

For Financial Regulators and Consumer Protection Agencies

Internationally regulatory bodies, face increasing challenges in auditing hyper-personalized financial AI systems. The Contextual Financial Judgement (CFJ) Scale (Table 1) equips policy makers with a validated psychometric tool to evaluate systemic consumer vulnerability, audit whether aggressive choice architectures induce cognitive passivity a characteristic of Stage 1 exploitation and establish benchmarks for what constitutes agency-preserving financial technologies. Practically regulatory agencies could use these metrics to enforce mandatory disclosure standards (like mandating explicit algorithmic-assumption statements of the type mentioned above) or deploy the scale as a standardized audit instrument, which regulators administer to a sample of app users to flag applications that consistently suppress consumer Contextual Financial Judgement (CFJ) engagement.

Practitioners and financial advisors can utilize CFJ to act as Contextual Judgment Facilitators in hybrid wealth management settings.

Limitations and Directions for Future Research

While this study establishes a comprehensive operational scale architecture and structural model; two critical areas emerge for future empirical exploration:

1) **Primary Data Validation:** Future research should execute the empirical validation roadmap across heterogeneous demographic cohorts, evaluating Contextual Financial Judgement (CFJ) measurement among varied socio-economic strata, age brackets and varying levels of digital literacy groups.

2) **Cross-Cultural Testing:** Given that FinTech adoption patterns and regulatory regimes vary substantially globally, future research should assess the cross-cultural invariance of the 12-item CFJ scale across both, mature and emerging FinTech markets.

CONCLUSION

As personal financial decision-making becomes increasingly automated, long-term consumer welfare is contingent not only on algorithmic optimization but on the preservation of human contextual agency. Standard financial literacy paradigms are inadequate to help consumers navigate AI-driven choice architectures.

By conceptualizing, operationalizing, structurally contextualising and mapping the structural antecedents of Contextual Financial Judgment (CFJ), this study offers scholars, policy makers and digital platform designers with a conceptual theoretical framework, validated measurement scales and an empirical roadmap, to help preserve human governance, foster consumer autonomy and build a more symbiotic, human-centric future in personal finance.

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APPENDIX A

Expanded 18-Item Candidate Pool

Contextual Financial Awareness (CFA)

Code	Operational Indicator	Candidate Item
CFA_1	Detection of Algorithmic Urgency	I recognize when a financial app uses prompts or timers to create an artificial sense of urgency.
CFA_2	Identification of Targeted Steering	I notice when a FinTech platform selectively highlights specific financial products based on my tracked behaviour.
CFA_3	Sensitivity to Choice Architecture	I am aware of how default app settings subtly guide my financial decisions.
CFA_4	Recognition of Gamification	I spot when financial apps use game-like features to encourage frequent financial transactions.
CFA_5	Recognition of Loss-Framing	I notice when a financial app frames a decision in terms of potential losses to prompt quicker action.
CFA_6	Awareness of Notification-Driven Pull	I am aware when push notifications are designed to draw me back into an app rather than simply inform me.
CFA_7	Recognition of Social Proof Cues	I recognize when a financial platform uses cues like "many users chose this option" to influence my choices.
CFA_8	Detection of Passive Enrollment	I notice when I have been automatically enrolled into a financial feature without actively choosing it.

In-Depth Systemic Knowledge (ISK)

Code	Operational Indicator	Candidate Item
ISK_1	Understanding Input-Data Logic	I understand how my personal data is processed by financial algorithms to generate advice.
ISK_2	Comprehension of Algorithmic Bias	I am aware that AI financial tools can operate on inherent algorithmic biases.
ISK_3	Awareness of Non-Quantifiable Gaps	I understand that financial algorithms fail to account for my qualitative personal values and life transitions.
ISK_4	Interpretability of Output Logic	I can explain the reasoning behind why an automated system recommends a specific financial action to me.
ISK_5	Awareness of Commercial Objectives	I recognize that financial apps may be designed to serve business or revenue goals rather than only my interests.
ISK_6	Understanding of Personalization Mechanics	I understand how a financial app uses my past behavior to personalize the recommendations it shows me.
ISK_7	Awareness of Algorithmic Drift	I am aware that an algorithm's advice can change over time as it is updated or retrained.
ISK_8	Awareness of Absent Human Oversight	I know that automated financial advice is not independently reviewed by a human expert before it reaches me.

Evaluative and Overriding Attitude (EOA)

Code	Operational Indicator	Candidate Item
EOA_1	Critical Override Readiness	I feel confident overriding an AI-generated financial recommendation when it feels inappropriate for me.
EOA_2	Contextual Re-evaluation	I evaluate whether AI financial recommendations fit my unquantifiable personal life realities before taking action.
EOA_3	Resistance to Automation Bias	I systematically verify automated financial suggestions rather than accepting them at face value.

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EOA_4	Autonomous Decision Agency	I treat AI financial tools as secondary advisory aids rather than final decision-makers.
EOA_5	Deliberate Second-Opinion Seeking	I am willing to pause and seek a second opinion before acting on an AI-generated financial recommendation.
EOA_6	Resistance to Urgency Cues	I can resist urgency cues in a financial app and delay a decision until I am ready.
EOA_7	Active Customization Behaviour	I regularly adjust or customize the settings of financial apps rather than accepting the defaults.
EOA_8	Consistency of Skepticism	I question an automated financial recommendation even when I have accepted similar recommendations before.