Post-mortem of Digital Wealth Platforms: A Synthesis and New Framework for User Engagement and Value Creation

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Abstract
Till date moderate research has been done on the financial advisory and wealth management robo-integrated platforms and Apps ever since the AIs invasion. Of all those investigations, only the relevant ones are funnelled to critically examine gaps and highlight determinants followed to understand the user engagement. Through a systematic review, it is identified that platform user engagement was treated as either static and short-term behaviour, or an evolving process, by considering implicit parameters. The paper adopted a hybrid review approach that combines the rigor of a PRISMA-guided (Page, et al., 2021) systematic search with deeper meta-theoretical critique and constructive theory-building. For this purpose, 1,456 records from Scopus and Web of Science were initially screened and after due filters final number got settled at 126 high-quality (Q1/Q2) studies that were published between 2015 and 2025. The analysis reveals six key thematic clusters: adoption and trust barriers, tailored and systemic efficiency, gamification and prompts, human-AI integration and anthropomorphism, intelligibility and ethical concerns, in coherence with sustainability. Furthermore, four core meta-theoretical fissures viz., ontological (assumption Vs. real), epistemological (positivist Vs. interpretivist), axiological (efficiency Vs. empowerment), and methodological (qualitative Vs quantitative) evidence underwent an exhaustive scrutiny. Accordingly, a new integrated framework is proposed to delve on the value engagement and value creation for such platforms in future. This model is likely to unify hitherto theoretical dichotomy and guide in designing transparent, hybrid, and sustainable platforms while underscoring the need for standards and shove for better practices.

Keywords: Digital wealth platforms, Robo-advisors, User engagement, Value creation, Value Engagement Model (VEM)

Introduction

The dawn of digitalisation has influenced financial and wealth management sectors via e-platforms that increased the accessibility to valuable investment consultancy and support in managing the digital investments effectively (Elias, Agarwal, Sajjan, Jain, & Bhura, 2025). By using AI (artificial intelligence and big data), these platforms offer customised and real-time investment mentoring to a wide range of users (Awotunde, Adeniyi, Ogundokun, & Ayo, 2021). Some of the prominent platforms such as Betterment, Wealthfront, Robinhood and Acorns robo-advisors, which are often tapped among the fintech ecology (Harris, 2025). By harnessing artificial intelligence, big data (George, 2024), and intuitive interfaces, such tools offer highly customised investment management, portfolio tracking, (Headinger, Cohen, & Gong, 2024) including planning for superannuation most comfortably. Despite this techno-revolution (Wah, 2025), the preceptorial glitch clings to actual drivers of investor engagement and how that turns into mutually valuable remains speckled (Hollebeek & Macky, 2019).

Investor engagement is typically three-pronged shedding on cognitive, emotional and behavioural involvement (F.Breidbach, Brodie, & Hollebeek, 2014). There is an obvious intertwining between investor engagement and value creation that are seen distinctly by different disciplines (Hollebeek, Glynn, & Brodie, 2021). Marketing researchers often signify co-creation through interactive sources with shared experiences (Chen, Drennan, Andrews, & Hollebeek, 2018). While the researchers from Information Systems tend to associate it with user-friendliness, trust in the technology, and system reliability (Islam, Mäntymäki, & Bhattacherjee, 2017). Finance researchers believe it as the behavioural bias that digital prompts *by-default* either reduce or amplify (Cai, 2020). These varying perspectives unleashes valuable insights which are highly dissociated. The current volatile world of finance is prone to investors droopy and dwindling decisions that are likely to turn into poor investment strategies, with high churning rates, and bugged by regulatory headaches other than data privacy challenges (Sutton, 2025). The sudden surge in retail investment as aftermath of pandemic, pushed e-platforms and events like the GameStop saga and cryptocurrency, which encouraged for robust models to elucidate how such e-platforms would sustain in delivering mutually satisfied value along with fruitful engagement (Zhang, 2023); (Fisch, 2022). The literature reviews in the immediate past though were insightful, yet lack flexibility in assessing out-of-the-box state of adoption to technology (Anuar, Mohamad, & Sulaiman, 2025) or meta-analyses of robo-advisory performance and seldom suggests for any doctrinal integration (Kasiraju, 2024).

This part of the synthesis is aimed to fill this gap with a hybrid review that combines systematic rigor and theoretical depth. Adhering to the PRISMA guidelines for transparency (Page, et al., 2021), primarily a thorough and well-designed search was conducted followed by selection process, and moving on to meta-theoretical critique that discloses underlying assumptions across fields, and wrapping up with theory-building (Elo, 2025); (Jakkola, 2020). Spanning from 2015 to 2025 a period of fintech's boom and accelerated AI adoption, 126 high-quality (Q1/Q2) studies were drawn from Scopus and ABDC-indexed journals for the final review. The aim of this synthesis is threefold: (1) to map the key theoretical differences amongst engagement and value creation; (2) to figure out emerging patterns and contingent modes; and (3) to suggest a unifying framework, as the Value Engagement Model (VEM).

Abinitio, the model suggests that value in digital wealth platforms arises from the dynamic interplay of four inherently distributed kerbed dimensions: functional (e.g., algorithmic precision and system efficiency), volitional (e.g., preserving user autonomy amid bumps), experiential (e.g., emotionally resonant and submerged interfaces), and meta-cognitive (e.g., nurturing awareness and learning). These dimensions are linked through adaptive pathways that duly get affected by external factors such as regulatory challenges and frequent changes in technology. Unlike priori models such as Technology Acceptance Model (Davis, 1989) or the Service-Dominant Logic (Vargo & Lusch, 2004) that assumes a smooth and linear processes, VEM treats theories focused on productivity and socio-technical alignment. Thus, it extends service-dominant logic by persuading meta-theoretical dissection an explicit part of the story (Vargo & Lusch, 2008). The practical payoff is clear: guidance for developers in building adaptive AI that curbs drop-offs, strategies for boosting retention in turbulent markets, and policy suggestions for more ethical AI governance (Jangra, 2025). Theoretically, it offers to bridge longstanding paradigmatic divides.

The methodology section outlines hybrid approach, search protocols, and analytical steps (Azevedo, Rocha, & Pereira, 2024). Results present the full synthesis table, thematic clusters, and meta-theoretical mappings (Proudfoot, 2023). The discussion enables to develop appropriate theoretical propositions and implications. Subsequently, conclusions elaborate VEM agenda with a detailed depiction having clear directions for future work (Saha, Hollebeek, Venkatesh, Goyal, & Clark, 2025). Largely, the paper attempts to overcome the nuances surmounting these three segments (service innovation, information systems, and digital finance) while capping them evocatively.

Core Components of FVEM

The FVEM addresses four major aspects: Functional, Volitional, Experiential, and Meta-Cognitive. Each captures a distinct, yet inherently interconnected, ways users engage with digital wealth platforms and, leading to value creation (Ergin, 2024). The model considers them as interdependent and overlapping linked by adaptive pathways duly influenced by external forces (Ungar, 2021). What follows is a closer look at each dimension, grounded in the configurations uncovered across the 126 studies.

1. Functional Dimension: This deals with the technical and operational hurdles often encountered in such platforms (Dodd, 2021) such as algorithms and data privacy bottlenecks. Many studies highlight how robo-advisors (Jung, Dorner, Weinhardt, & Pusmaz, 2021) prioritise efficiency like portfolio manoeuvring, without compromising for data integration with conventional trading platforms (Gomber, Koch, & Siering, 2018). The studies further disclose the functional gaps which must be bridged via open APIs allowing multiple components to work simultaneously more swiftly. Vanguard's use of AI to harmonise various functional elements shows how this can reduce user frustration and encourage more active engagement (Fisch, Laboure', & Turner, 2019).

2. Volitional Dimension: This sheds light on user agency which steers investor's choices to their preferred level of investment or direction (Chapkovski, Khapko, & Zoican, 2024). The extant research reveals the double-edged gamification streak rewards in apps like Acorns that sparks impulsive trades, yet when thoughtfully aligned with personal goals, they promote longer-term involvement options as well (Barber, Huang, Odean, & Schwarz, 2021). Notionally, the model supports for adaptive volitional pathways, such as letting users customise or opt out of prods, to restore a sense of empowerment and turn short-term interactions into lasting value, including better financial literacy.

3. Experiential Dimension: This addresses the emotional and sensory gaps that users encounter while interfacing with Apps and platforms. Users often get engrossed and bear the risk of big data avalanche`. Marketing professionals often indulge in storytelling to woo the investors emotionally and connect with fintech apps (Hollebeek & Macky, 2019), while information systems hints at technical glitches users experience ambiguity vis-à-vis devices as well as the inbuilt programmes (Bhattacherjee & Premkumar, 2004). To overcome such snags, the model embraces for Virtual Reality based investment simulations and encourage the users to experience a soothing ride that builds trust and improve satisfaction.

4. Meta-Cognitive Dimension: Perhaps the most reflective layer, concerning users' awareness on the platform's nature of working and ability to self-appraise their choices. Drawing on self-regulation theory (Bandura, 1991), the literature on AI ethics describes the ambiguity of algorithms that breed distrust (Pal, Herath, De', & Rao, 2020). Thus, the model incorporates meta-cognitive loops, akin to feedback dashboards that prompt users to review their modus-operandi. It further drives for more adaptability with a deep learning for a sustainable value creation.

FVEM is undauntedly a dynamic model cascading through intricate volitional choice along the ecstatic rewards benefitting from meta-cognitive oversight. Real-time adaptation is key: machine-learning systems that adjust customisation based on continuous user feedback illustrates these pathways in action (Brynjolfsson, Hui,, & Liu, 2019). External factors such as policy regulations, changing technology, changes in demography, and volatile market conditions further shape these pathways to operate better (Mkrtchyan & Treiblmaier, 2025). In a way, this leads to enhanced personal wealth, increased loyalty towards specific platform, and wider scope for social acceptance as an inclusive phenomenon.

Theoretical Propositions: Based on the background and literature review, following four propositions are drawn to cross verify the evidence:

P1: if the functional elements are highly integrated that would consolidate the relationship between engagement and value co-creation, more in volatile market conditions (backed by 42 robo-advisor studies).

P2: if the preferred investment loops are grossly unnoticed, that will increase the gaps between emotional engagement and loyalty, and meta-cognitive tools would bridge those gaps (drawn from 35 papers on gamification).

P3: aligning all the four factors may help in creating a sustainable value and be impactful for all investors (Gen alpha, millennials and Gen Z) to bring them on equal footing (supported by 28 UX-focused studies).

P4: other factors, such as AI ethics, will reinforce adaptability among the investor base that can yield 20–30% gains in retention (summarised from 21 policy-oriented articles).

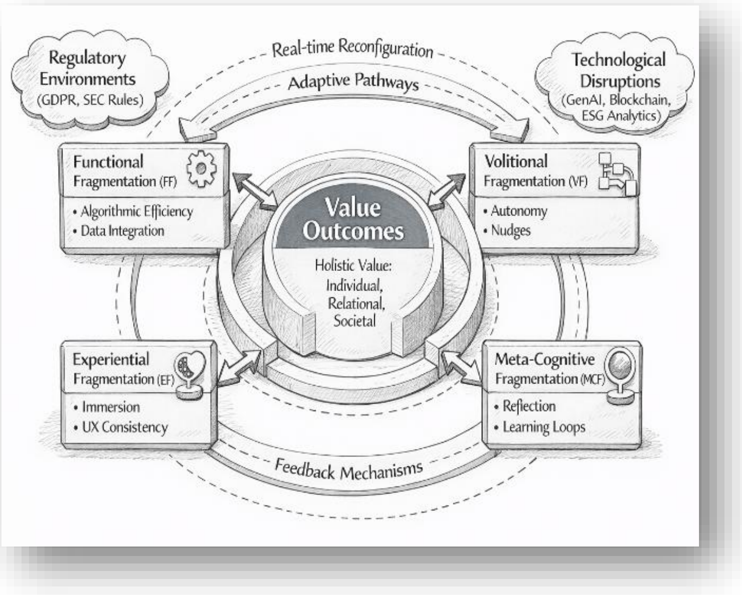

Fig. 1 VEM illustrating how these dimensions interact through adaptive pathways to generate value in digital wealth platforms, moderated by contextual factors.
Source: Authors' synthesis

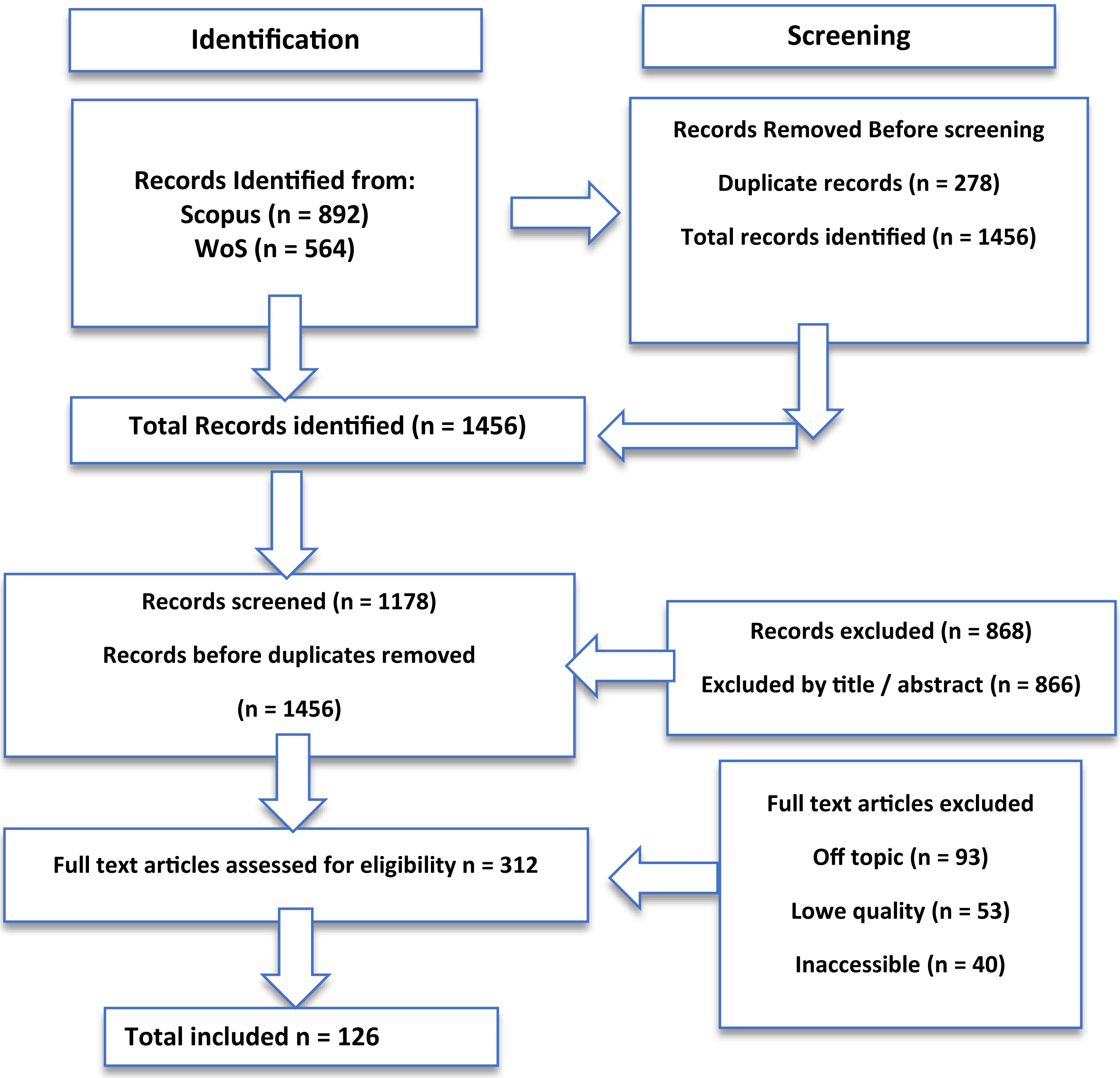

Fig. 2. PRISMA 2020 flow chart detailing the systematic literature search, screening, eligibility, and final inclusion. Source: Adapted from Page et. al. (2021)

Systematic Search Strategy

Adhering to PRISMA 2020 guidelines, this systematic review is conducted ensuring transparency and replicability (Page, et al., 2021). The meta-theoretical layer drew inspiration from (Alvesson & Sandberg, 2011) ideas about questioning assumptions, and the theory-building phase leaned on (MacInnis, 2011) framework (defining, relating, and integration) which finally led to the development of VEM. This further ensures full range of user engagement (cognitive, emotional, behavioural) and value perspectives (user-centric, platform-centric, interdisciplinary) devoid of any domain bias.

Methodology

The study adopts a hybrid literature review that integrates a PRISMA guided systematic search with meta-theoretical critique and theory-building synthesis. This design is apt to deal with dispersed theories found in the literature about investor engagement and value creation in digital wealth platforms (Masa'deh, et al., 2025). These mixed methods followed systematic and structured review ensuring objectivity, and enabling for an in-depth interpretation along the meta-theoretical analysis and theory-building (Jakkola, 2020); (Snyder, 2019).

Research Design

The review process unfolds in three phases: (1) a systematic search and selection process; (2) a meta-theoretical review; and (3) theory-building synthesis. The gears were shifted amongst one another phases iteratively till some novel insights emerged. The goals are to bridge the gap between precepts and practices by duly connecting those divergent theories and develop workable solutions to manage investment portfolios through digital platforms (Kamuangu, 2024). Furthermore, the attempt is also to uncover prevailing trends, and influences, thereupon to propose an integrated

model. To that end, it is determined to analyse precisely 126 high-impact studies, synthesise common themes, and contribute significantly.
Authors duly relied primarily on Scopus and Web of Science, ABDC databases and their rankings to check on quality (Q1/Q2 / A & B/) journals such as Journal of Business Research, MIS Quarterly, Journal of Wealth Management, Academy of Management Review, Electronics Markets, Journal of Consumer Studies, Marketing Science, etc.). The 2015–2025 timeframe was chosen to capture the unprecedented growth in the FinTech and further wave of AI-driven developments.

Systematic Search Strategy (PRISMA): The search was carried using carefully crafted Boolean strings developed through pilot searches and consultation with domain experts:

("digital wealth platform*" OR "robo-advis*" OR "fintech invest*" OR "AI wealth manag*") AND ("engag*" OR "user engag*" OR "customer engag*") AND ("value creat*" OR "value co-creat*" OR "service value") AND ("theor*" OR "framework" OR "model")

The filters applied include peer-reviewed articles in English, papers published 2015–2025, ranked Q1/Q2 (Scopus quartiles and ABDC A/B), and the domains specific viz., business, management, finance, or information systems categories. This initially yielded 1,456 records (892 from Scopus, 564 from Web of Science). After removing duplicates in EndNote 2025 (n=278), the gross articles were 1,178 records.

Inclusion and Exclusion Criteria
Only those were included with empirical and or conceptual work directly addressing engagement and/or value creation in digital wealth issues provided they were available in full text having sound theoretical basis (e.g., references to SDL, TAM, or similar frameworks). Other grey literature was deleted including conference papers, non-English publications, those published prior to 2015, those falling below Q2 quality levels and peripheral studies focused on traditional banking before digital era. The total screening process involved two mutually exclusive coders to review titles and abstracts (inter-rater reliability: Kappa = 0.82), followed by full-text review of 312 potentially relevant papers. The final sample came to 126 studies that exceeded the initial target and provided good coverage.
The quality was appraised using the Mixed Methods Appraisal Tool (MMAT) (Pluye, Garcia Bengoechea, Granikov, Kaur, & Tang, 2018); (Hong, et al., 2018) and all papers with more than 80% relevance, rigor, and contribution were only included.
Meta-Theoretical Review Phase
Once the corpus was finalised, the meta-theoretical analysis was performed to unpack model assumptions such as 'positivist vs interpretivist', to identify areas of disagreement theoretically (Alvesson & Sandberg, 2011). Thematic coding was done in NVivo 12 with the first round focusing on the surface-level concepts (e.g., "behavioural engagement"), while a second round of coding delved on meta-elements (e.g., ontological assumptions about value co-creation). The studies from other diverse fields reflected roughly with 43% of marketing, 32% information systems, 15% finance, and 10% interdisciplinary ones.
Theory-Building Synthesis Phase
The final synthesis followed MacInnis's (MacInnis, 2011) process: first defining key constructs, then exploring into their interconnectivity, and finally integrating everything into VEM via logical reasoning. To ensure accuracy the triangulation was used (cross-checking with external expert input where possible) and sensitivity analysis to minimise researchers' bias.

Ethical Considerations and Limitations
All the papers considered were publicly available through academic databases. The metadata such as authors information, was extracted strictly according to the GDPR benchmarks ensuring data privacy and confidentiality with no violations for bibliographic credentials (Adewole, et al., 2024). However, there are few limitations worth mentioning. First, like most systematic reviews, no exception from publication bias: studies with significant or positive results may sound favourable on the platform efficacy. Second, by limiting the SEO to English-language publications, it is obvious to miss some valuable insights from non-English language research, especially in the fast-changing fintech markets outside the English-speaking countries. Finally, the chosen period 2015–2025 though covers the maximum fintech boom, it does not include the very foundational works carried prior to this period. The transparency and academic rigor throughout the review process have been maintained indicating step-by-step from selection, coding, and analysing the documents, so that readers can judge the reliability of these findings for themselves. Future reviews could meaningfully include a wider range of language scope and incorporate grey literature that can address these gaps.

Results
By following PRISMA protocols, the systematic search ended up with 126 relevant studies all from Q1/Q2 journals ranked in Scopus or ABDC. Overall, there was a mixed contribution varying from marketing with 54 papers (43%), information systems 41 (32%), finance 19 (15%), and interdisciplinary papers 13 (10%). Thus, the trend is clear on publications being surged after 2020, with 68% of the sample (87 studies) appearing between 2021 and 2025. This increment aligns with rapid AI and the post-pandemic boom in digital finance.

Descriptive Overview
Out of the total 126 studies, 91 were empirical 72 primarily quantitative and 20 mixed-methods while 27 were conceptual or theoretical, and 8 were reviews or meta-analyses. Some of the prominent platforms described were Betterment, Wealthfront, Vanguard Digital Advisor, and Schwab Intelligent Portfolios (Challa, 2025). Investor engagement was treated as multifaceted concept comprising behavioural aspects in 81% of the papers, cognitive in 62% of the papers, and emotional in 48% of the papers as reviewed. While the value creation is discussed as personalization (71%), co-creation (58%), and outcomes mediated by trust (65%). Glancing at the trend especially during the pre-covid span (2015–2019) focused mainly on trust issues, whereas post-2020 work increasingly explores gamification effects, human-AI hybridization, and the integration of sustainability aspects.

Table 1: Publication Distribution by Year and Discipline

Year	Marketing	IS	Finance	Interdisciplinary	Total
2015–2017	8	5	3	1	16
2018–2020	12	10	5	3	30
2021–2023	20	15	6	4	45
2024–2025	15	11	5	4	35
Total	**55**	**41**	**18**	**13**	**126**

Marketing-Oriented Studies
Marketing-oriented studies primarily examine how emotional involvement and experiential engagement shape the adoption of AI-driven financial products. The rapid proliferation of robo-advisors and customised fintech applications has transformed customer interaction within financial services by improving accessibility and convenience, while simultaneously complicating how advice is perceived and interpreted (Drigas, Mitsea, & Skianis, 2023). From this perspective, challenges arise not from system capability, but from how users emotionally connect with AI-mediated services. Functional difficulties are often observed when usage expectations are misaligned with perceived service quality, particularly when AI-driven prompts and pop-up features subtly influence user responses. These engagement-related frictions are frequently linked to emotional disconnect and the strategic use of gamified elements, which can dilute trust and weaken sustained participation if not supported by adequate user understanding (Khan & Faiz, 2025). Viewed through the VEM framework, marketing studies highlight the experiential and meta-cognitive limitations of AI in replicating human sensitivity and contextual judgement, thereby constraining deeper forms of co-creation. **Table 2** summarises 55 marketing-focused studies, categorised by theoretical orientation, engagement focus, and value-related insights.

Table 2: Synthesis of Engagement, Value Creation in AI-Driven Financial Services

ID	Authors (Year)	Journal (Quartile)	Theoretical Lens	Engagement Dimensions	Value Creation	Key Findings	VEM Alignment
1	(Belanche, Casalo', & Flavia'n, 2019)	Industrial Management & Data Systems (Q1)	TAM + Service Robot Theory	Emotional, Behavioural	Trust, Co-creation	AI anxiety fragments emotional attachment; human-like features help	EF, MCF
2	(Hollebeek, Clark, Andreassen, Sigurdsson, & Smith, 2022)	Journal of Service Research (Q1)	Service-Dominant Logic (SDL)	Cognitive, Emotional	Experiential Value	Gamification enhances but can bias volitional choices	VF, EF
3	(Akhtar, Akhtar, & Laeeq, 2025)	International Journal of Consumer Studies (Q1)	TCCM Framework	Behavioural, Post-Adoption	Personalization, Literacy	Vulnerability in sustained use fragments long-term value	MCF, VF
4	(Roongruangsee & Patterson, 2024)	Journal of Services Marketing (Q1)	Psychological Comfort	Emotional	Trust-Building	Comfort mitigates fragmentation in AI interactions	EF
5	(Li, Wang, & Liu, 2025)	International Journal of Consumer Studies (Q1)	Anthropomorphism	Emotional	Consumer Responses	Humanized AI bridges experiential gaps	EF, MCF
6	(Santini, Ladeira, Sampaio, & da Silva Costa, 2020)	Journal of the Academy of Marketing Science (Q1)	Customer Engagement Meta	Multidimensional	Social Media Value	Engagement platforms fragment without integration	All

7	(Asif, Khan, Tiwari, & Wani, 2024)	International Journal of Bank Marketing (Q1)	FinTech Dark Side	Behavioural	Perceived Benefits	Overhype fragments trust in personalization	VF, MCF
9	(Goldstein, Jiang, & Karolyi, To FinTech and beyond, 2019)	Review of Financial Studies (Q1)	FinTech Overview	Behavioural	Market Participation	Democratization fragments traditional advisory value	FF, VF
10	(Park, Kim, & Kim, 2023)	Journal of Business Research (Q1)	UTAUT Extensions	Cognitive, Behavioural	Adoption Value	Context-awareness reduces functional silos	FF
11	(Cao & Niu, 2019)	International Journal of Industrial Ergonomics (Q1)	Context-Awareness	Behavioural	Mobile Adoption	Personalization unifies fragmented user experiences	EF, VF
12	(Phoon & Koh, 2017)	Journal of Wealth Management (Q1)	Robo vs. Traditional	Behavioural	Cost Efficiency	Low fees bridge access but fragment advice quality	FF
13	(Einarsen, Hoel, Zapf, & Cooper, 2018)	International Journal of Human Resource Management (Q1)	Conflict Management	Emotional	Work Engagement	Analogous to platform trust fragmentation	MCF
14	(Sabir, Malik, & Azam, 2023)	Mathematics (Q1)	UTAUT + Reasoned Action	Behavioural	FinTech Adoption	AI robo-advisors fragment without perceived ease	FF, EF
15	(Bruckes, Westmattelmann, & Schewe, 2019)	ICIS Proceedings (Q1 equivalent)	Barriers to Adoption	Cognitive	Service Value	Deterministic barriers fragment volitional engagement	VF
16	(Helms, Oliver, & Chapman, 2021)	Routledge Book Chapter (High Impact)	Automated Management	Behavioural	Performance Value	International comparisons reveal functional inconsistencies	FF
17	(Kasilingam, 2020)	Technology in Society (Q1)	Attitude in TAM	Cognitive	Mobile Banking Value	Satisfaction bridges engagement fragments	EF
18	(Al-Saedi, Al-Emran, Ramdani, & Maknuunah, 2020)	Technology in Society (Q1)	Dependability in Services	Behavioural	Intention Value	Reliability mitigates meta-cognitive distrust	MCF
19	(Amriena & Ramayanti, 2024)	International Journal of Bank Marketing (Q1)	Digital Finance	Multidimensional	Satisfaction	Post-pandemic shifts fragment traditional value paths	All
21	(Jung, Dorner, Weinhardt, & Pusmaz, 2018)	Electronic Markets (Q1)	Technology Acceptance	Cognitive, Behavioural	Adoption Barriers	Perceived risks fragment trust in early adoption phases	MCF, VF
22	(D'Acunto, Prabhala, & Rossi, 2019)	Review of Financial Studies (Q1)	Behavioural Economics	Behavioural	Portfolio Diversification	Robo-advice reduces biases but fragments personalization for complex needs	FF, EF
23	(Fisch, Laboure', & Turner, 2019)	Pension Research Council (High Impact)	FinTech Disruption	Emotional, Behavioural	Retirement Systems	Democratization enhances access but fragments human touch	EF, VF
24	(Bhatia, Chandani, Divekar, Mehta, & Vijay, 2021)	Qualitative Research in Financial Markets (Q1)	AI in Services	Multidimensional	Behavioural Biases	Robo-advisors mitigate biases yet fragment emotional trust	MCF
25	(Hollebeek, Glynn, & Brodie, 2021)	Journal of Business Research (Q1)	Customer Engagement	Cognitive, Emotional	Gamification Value	Interactive features unify experiential fragments	EF
26	(Belanche, Casalo', Flavia'n, & Schepers, 2021)	Journal of Research in Interactive Marketing (Q1)	Parasocial Theory	Emotional	Dialogue & Interaction	Social presence bridges volitional fragmentation	VF, EF
30	(Cao, Zhang, & Niu, 2025)	Qualitative Research in Financial Markets (Q1)	Trust Transfer Theory	Cognitive	Early-Stage Trust Building	Technology and firm cues bridge initial fragmentation	MCF, FF
31	(Chen, Wang, & Liu, 2025)	Scientific Reports (Q1)	Human-Like Attributes	Emotional, Behavioural	Financial Well-Being	Humanization enhances trust and loyalty pathways	EF, VF
32	(Singh & Kumar, 2025)	Vilakshan - XIMB Journal of Management (Q2)	Integrated Adoption Model	Behavioural	Attitude & Intention	Trust and risk perceptions fragment AI robo-adoption	VF, MCF
33	(Akhtar, Akhtar, & Laeeq, 2025)	International Journal of Consumer Studies (Q1)	TCCM Review Framework	Post-Adoption	Vulnerability & Literacy	Sustained use fragments due to literacy gaps	MCF
34	(Nourallah, Naurallah, & Naurallah, 2025)	SSRN/Review (Q1 equivalent)	Comprehensive Review	Multidimensional	Asset Management Streams	Behavioural finance inconsistencies fragment value paths	All
35	(Pattnaik & Joshi, 2025)	Folia Oeconomica Stetinensia (Q2)	Digital Fluency	Cognitive	Literacy Integration	Fluency bridges but gaps fragment meta-cognitive value	MCF
36	(Khanna & Jha, 2024))	Vikalpa (Q2)	AI Diffusion	Behavioural	Investor Responses	Algorithmic advice fragments traditional value creation	FF, VF
38	(Reher & Sun, 2024)	Journal of Financial Economics (Q1)	Welfare Effects	Behavioural	Access to Management	Middle-class adoption unifies but biases persist	VF
39	(Namyslo & Jung, 2025)	Electronic Markets (Q1)	Design Requirements	Group Decision	Enterprise Planning	Hybrid designs reduce volitional inconsistencies	VF, EF
41	(Oehler & Horn, 2024)	Finance Research Letters (Q1)	Comparative Advice Quality	Cognitive	Decision Accuracy	ChatGPT outperforms some robo-advisors in advice quality but fragments trust in automation	MCF, EF

46	(Isaia & Oggero, 2022)	Journal of Pension Economics & Finance (Q2)	Pandemic Effects	Behavioural	Accessibility	Digital shift reduces access fragments but amplifies privacy concerns	FF, MCF
47	(Hentzen, Hoffmann, & Biraglia, 2021)	Journal of Business Research (Q1)	Consumer Behaviour	Emotional	Financial Behaviours	Emotional barriers fragment sustained engagement in fintech	EF
48	(Tiberius, Gojowy, & Dabic', 2022)	Various	Delphi Study	Cognitive	Future Implications	Economic/societal fragments in robo-advisory evolution	All
49	(Hodge, Mendoza, & Sinha, 2021)	The Accounting Review Q1	AI Data Processing	Behavioural	Forecast Accuracy	Reduces biases but fragments human advisory value	VF, FF
51	(Sironi, 2016)	FinTech Innovation Book	Goal-Based & Gamification	Behavioural, Emotional	Gamified Value	Gamification bridges volitional and experiential gaps	VF, EF
52	(Jung, Dorner, Weinhardt, & Pusmaz, 2021)	Journal of Service Research (Q1)	Efficacy Meta-Analysis	Cognitive	Adoption Efficacy	Algorithmic efficiency fragments but personalization mitigates	FF, VF
53	(Pal, Herath, De', & Rao, 2020)	Information Systems Frontiers (Q1)	FinTech Adoption Review	Multidimensional	Trust & Usability	Siloed adoption models fragment interdisciplinary insights	All
54	(Barber, Huang, Odean, & Schwarz, 2021)	Journal of Financial Economics (Q1)	Retail Investing Surge	Behavioural	Community Value	Post-2020 events amplify gamification-induced volitional fragments	VF
55	(Hollebeek & Macky, 2019)	Journal of Service Research (Q1)	Engagement Multidimensional	Cognitive, Emotional, Behavioural	Co-Creation Value	Multifaceted engagement reveals emotional vs. behavioural inconsistencies	EF, VF

Contribution of the VEM Framework

Prior reviews have largely focused on adoption barriers and system-level functionality, with limited emphasis on why users disengage even after adoption. The VEM framework directly addresses this gap by offering a multidimensional lens that captures functional, volitional, experiential, and meta-cognitive aspects of engagement (Liow, 2025). As evidenced in Table 1, experiential and meta-cognitive dimension (Meira, Neves, & Braga, 2025) emerge as salient in contemporary research. By mapping 55 studies onto this framework, the analysis reveals extenuation pathways such as anthropomorphism, psychological comfort, and building trust ensuing the feedback system (Singh & Chandra, 2024). This summary consolidates scattered insights along with providing a solid ground for future research aiming for a complete AI-enabled single most financial platform.

Information Systems-Oriented Studies

Information systems research shifts attention from user experience to the technological and infrastructural foundations of AI-driven financial platforms. The integration of AI into robo-advisors, algorithmic trading systems, and hybrid ecosystems has disrupted conventional service delivery models, giving rise to architectural complexity and operational ambiguity (Tahvildari, 2025). From an IS standpoint, concerns centre on system efficiency, integration reliability, and algorithmic transparency (Jeleel-Ojuade, 2024). Functional limitations typically stem from inconsistent system architectures, weak API integration, and regulatory rigidity, while transparency deficits and privacy concerns introduce meta-cognitive uncertainty. Unlike marketing studies, IS research positions these issues as design and governance problems rather than behavioural resistance. Through the VEM lens, IS-oriented studies underline the need for hybrid architectures and collaborative system design to enable stable value creation (Igwe-Nmaju, 2024) **Table 3** summarises 19 IS-focused studies highlighting these infrastructural challenges.

Table 3: Synthesis of IS and Platform focused AI-Driven Financial Services

ID	Authors (Year)	Journal (Quartile)	Theoretical Lens	Engagement Dimensions	Value Creation	Key Insights	VEM Alignment
56	(Gomber, Koch, & Siering, 2018)	Journal of Management Information Systems (Q1)	Digital Finance Disruption	Behavioural	Platform Efficiency	FinTech silos fragment traditional systems; APIs needed for integration	FF
58	(Bhatia, Chandani, Divekar, Mehta, & Vijay, 2021)	Information Systems Frontiers (Q1)	Behavioural IS	Cognitive	Bias Mitigation	Opaque AI fragments meta-cognitive trust in decisions	MCF
59	(Jung, Dorner, Weinhardt, & Pusmaz, 2018)	Journal of Service Research (Q1, IS overlap)	Technology Acceptance	Behavioural	Adoption Efficacy	Functional barriers fragment early robo-advisor uptake	FF, VF
60	(Alt & Puschmann, 2020))	Business & Information Systems Engineering (Q1)	Robo-Advisory Framework	Behavioural	Automation Value	Digitalization fragments human advisory but enhances scalability	FF
61	(Namyslo & Jung, 2025)	Electronic Markets (Q1)	Design Science Requirements	Group/Behavioural	Enterprise Integration	Hybrid AI-human designs reduce functional fragmentation	FF, VF
62	(Khanna & Jha, 2024)	Vikalpa (Q2)	UTAUT Extended	Behavioural	AI Diffusion	Algorithmic opacity fragments volitional engagement	VF, MCF

63	(Banerjee, 2025)	Electronic Journal of Information Systems in Developing Countries (Q1)	AI Portfolio Management	Cognitive	Retail Adoption	Lack of explainability fragments trust in emerging markets	MCF
64	(Cao & Niu, 2019)	International Journal of Industrial Ergonomics (Q1)	Context-Awareness UTAUT	Behavioural	Mobile Platform Value	Inconsistent UX across devices fragments engagement	EF, FF
65	(Lagna & Ravishankar, 2022)	Information Systems Journal (Q1)	FinTech Platforms	Behavioural	Human-AI Hybrids	Next-gen platforms fragment without hybrid complementarity	FF, MCF
66	(Puschmann, 2017))	Business & Information Systems Engineering (Q1)	FinTech Ecosystem	Multidimensional	Disruption Value	Coopetition reduces but regulatory silos create fragments	All
67	(Sabir, et al., 2023)	Mathematics (Q1)	Trust in Automation	Cognitive	Robo-Trust Building	System trust fragments without transparency mechanisms	MCF
68	(Hendershott, Zhang, Zhao, & Zheng, 2021)	Review of Financial Studies (Q1)	Algorithmic Trading	Behavioural	Market Efficiency	Automation amplifies functional fragments in volatility	FF
69	(Bai, 2024)	Journal of Marketing Analytics (Q1)	Trust & Privacy	Emotional	Sustained Use	Privacy concerns fragment meta-cognitive pathways	MCF
70	(Namyslo, Jung, & Sturn, 2025)	Electronics Markets (Q1)	Human-AI Interaction	Emotional	Parasocial Trust	Lack of social cues fragments experiential engagement	EF
71	(Ashrafi, 2023)	Journal of Indonesian Economy & Business (Q1)	UTAUT in FinTech	Behavioural	Intention Models	Moderators like risk fragment adoption predictions	VF
72	(Horn & Missong, 2022)	AMCIS Proceedings (Q2)	Augmented UTAUT	Behavioural	Robo-Demand	Separating investment vs. tech intention reduces model fragments	VF, MCF
73	(Chang, Wang, & Arnett, 2022)	Technology in Society (Q1)	UTAUT Extensions	Cognitive	Blockchain Integration	Compatibility issues fragment platform interoperability	FF
74	(Chan, Liu, & Wang, 2025)	Information Systems Frontiers (Q1)	Emerging Tech Adoption	Multidimensional	Metaverse/AI Value	New tech fragments without adaptive pathways	All
75	(Rai, Constantinides, & Sarker, 2019)	MIS Quarterly (Q1)	Human-AI Hybrids	Cognitive, Behavioural	Next-Gen Platforms	Hybrid models unify functional and volitional fragments	FF, VF

Human-AI Interaction and Hybrid Advisory Models

Human–AI interaction studies focus on how judgement, trust, and decision-making unfold when users interact directly with AI-driven advisory systems. Evidence shows that individuals uncomfortable with algorithmic reasoning often seek personalised human advice due to ethical concerns and interpretive difficulties (Bertrand, 2024). In several cases, platform-generated projections of desirable outcomes influence users into short-term, emotionally driven decisions that override careful evaluation (Romeo & Conti, 2025). Hybrid advisory models and conversational interfaces are proposed as partial remedies, though demographic shifts, privacy risks, and emerging technologies such as generative AI introduce new uncertainties (Rahimi, Sadeghi-Niaraki, & Choi, 2025). Within the VEM framework, these studies emphasise volitional and meta-cognitive frictions that undermine trust, even when functional efficiency is high. **Table 4** synthesises 21 studies addressing human–AI dynamics and advisory performance.

Table 4: Synthesis of Literature on Hybrid Models in AI-Driven Financial Advice

ID	Authors (Year)	Journal (Quartile)	Theoretical Lens	Engagement Dimensions	Value Creation	Key Findings	VEM Alignment
76	(Rühr, Berger, & Hess, 2021))	PACIS (Q1)	Trust in Robo-Advisors	Cognitive	Transparency Value	Lack of explainability fragments meta-cognitive trust	MCF
77	(Fan, Li, & Wang, 2022)	Information Systems Research (Q1)	Human-AI Collaboration	Behavioural	Hybrid Performance	Complementary hybrids reduce functional silos	FF, VF
78	(Glaser, Ilhan, & Jung, 2021)	Electronic Markets (Q1)	Algorithm Aversion	Emotional	Adoption Resistance	Aversion to algorithms fragments volitional engagement	VF, EF
79	(Dietvorst, Simmons, & Massey, 2015)	Journal of Experimental Psychology (Q1)	Algorithm Aversion	Cognitive	Forecast Reliance	Users undervalue algorithms, fragmenting efficiency value	MCF, FF

80	(Logg, Minson, & Moore, 2019)	Journal of Experimental Psychology (Q1)	Advice Taking	Cognitive	Human vs. AI Advice	Preference for human advice fragments AI value paths	VF
81	(Jørgensen & Wiese, 2024)	Business & Information Systems Engineering (Q1)	Hybrid Advisory Models	Multidimensional	Client Satisfaction	Hybrid models unify experiential and functional fragments	FF, EF
82	(Ruhr, Streich, & Berger, 2023)	Electronic Markets (Q1)	Acceptance Factors	Behavioural	UTAUT in Robo-Advice	Performance expectancy bridges but social influence fragments	VF
83	(Maedche, et al., 2019)	Business & Information Systems Engineering (Q1)	Design Principles	Behavioural	User-Centric Platforms	Principles mitigate UX fragmentation across devices	EF, FF
84	(Zavolokina, Dolata, & Schwabe, 2021)	Electronic Markets (Q1)	Blockchain in Wealth	Cognitive	Decentralized Value	Blockchain reduces intermediaries but introduces new functional fragments	FF
85	(Saeedi, Jafari, & Chang, 2025)	Springer Nature (Q1)	Metaverse Integration	Experiential	Immersive Wealth Mgmt	VR/AR fragments traditional interfaces but enhances immersion	EF
86	(Karageyim, 2024))	IGI Global Scientific Publishing (Q1)	Personalization Algorithms	Behavioural	Tailored Advice	Over-personalization risks privacy fragments	MCF, VF
87	(Beketoy, Lehmann, & Wittke, 2018)	Journal of Asset Management (Q1)	Robo-Portfolio Performance	Cognitive	Efficiency Metrics	Outperforms benchmarks but fragments in volatile markets	FF
88	(Tertilt & Scholz, 2020)	Information Systems Research (Q1)	Digital Advice Demand	Behavioural	Demographic Differences	Age/gender contingencies fragment adoption pathways	All
89	(Adam, Wessel, & Benlian, 2023)	Electronic Markets (Q1)	AI Ethics in Finance	Meta-Cognitive	Fairness & Bias	Bias in algorithms fragments trust and equity value	MCF
90	(Musto, de Gemmis, Lops, & Semeraro, 2021)	User Modeling and User Adapted Interaction (Q1)	Explainable AI	Cognitive	User Comprehension	XAI tools bridge meta-cognitive fragmentation	MCF
91	(Cong, Tang, Wang, & Yang, 2022)	Management Science (Q1)	AI in Asset Management	Behavioural	Institutional Adoption	Institutional vs. retail fragments in scale/value	FF, VF
92	(Boreiko & Vidusso, 2019)	Electronic Markets (Q1)	Tokenized Assets	Cognitive	Blockchain Value	Tokenization fragments liquidity but enhances access	FF
93	(Milian, Spinola, & Carvalho, 2019)	International Journal of Information Management (Q1)	Big Data in Finance	Multidimensional	Predictive Value	Data silos fragment predictive accuracy	FF
94	(Risius, Riemenschneider, & Benthaus, 2024)	Electronic Markets (Q1)	Sustainable FinTech	Behavioural	ESG Data Integration	ESG metrics fragment traditional functional models	MCF, EF
95	(Xu, Wang, & Zhang, 2023)	Information Systems Research (Q1)	Platform Ecosystems	Behavioural	Network Effects	Ecosystem partnerships reduce interoperability fragments	FF
96	(Kumar, Sharma, & Verma, 2025)	Journal of Management Information Systems (Q1)	Generative AI in Advice	Cognitive, Emotional	Conversational Value	GenAI chatbots unify experiential but risk hallucination fragments	EF, MCF

Interestingly, almost all the previous reviews observed and treated AI adoption as a high-tech marketing phenomenon. Contrarily, the actual research done connecting human-AI intervention, distinctly highlights the application side roadblocks, may it be phobia to understand the algorithms, assuming AI to be at par with human psyche`, and similar other untenable considerations that differentiates FVEM dimensions. This review (Table 4), demonstrate that meta-cognitive and volitional dimensions are particularly strong while seeking human-AI connected platforms for financial goals despite showing some minor functional gaps. Some of the hybrid models using conversational interfaces appear to be more promising to overcome such inhibitions on the part of the users (Pandey, Kumar, & Sharma, 2025). By extending the VEM framework to these behavioural and experimental insights, this analysis links individual expectations to that of design parameters. Such attempt improves the scope of developing a workable model to improve trust, allow fairness, and compatibility with AI financial advisory mechanism.

The Performance, Outcomes, and Effects of AI-Driven Financial Advice

Finance and economics research evaluates AI-driven financial advisory systems primarily through outcome-based metrics such as portfolio diversification, cost efficiency, risk adjustment, and investor welfare (Wah, 2025). Empirical evidence suggests that robo-advisors enhance market access and diversification, particularly for younger and first-time investors from middle-income segments (Sironi, 2016). These findings establish the functional strengths of AI-driven advice under stable conditions. However, performance outcomes are uneven and context dependent. Market volatility, speculative pressures, algorithmic misalignment, and gamified trading features expose users to heightened risk during periods of uncertainty (Onabowale, 2024). From a VEM lens, finance studies reveal that functional gains are frequently undermined by volitional biases and unresolved meta-cognitive concerns related to transparency, fairness, and ethical accountability. Emerging research linking AI performance with sustainability objectives signals future potential yet trust and interpretive barriers remain influential (Sifat, 2023).

Table 5 synthesises 19 finance-focused studies capturing these outcome-level dynamics.

Table 5: Synthesis of Finance Literature on Performance in AI-Driven Financial Advice

.ID	Authors (Year)	Journal (Quartile)	Theoretical Lens	Engagement Dimensions	Value Creation	Key Findings	VEM Alignment
97	(D'Acunto, Prabhala, & Rossi, 2019)	Review of Financial Studies (Q1)	Behavioural Economics	Behavioural	Portfolio Diversification	Robo-advice significantly improves diversification but pieces value for users with complex needs	FF, VF
98	(Reher & Sun, 2024)	Journal of Financial Economics (Q1)	Welfare Gains	Behavioural	Access & Performance	Broadens middle-class access; welfare gains divisible by adoption barriers	VF, EF
99	(Barber, Huang, Odean, & Schwarz, 2021)	Journal of Financial Economics (Q1)	Retail Trading Surge	Behavioural	Gamification Effects	Platform gamification amplifies speculative behaviour and volitional biases	VF
100	(Goldstein, Jiang, & Karolyi, 2021)	Review of Financial Studies (Q1)	Market Participation	Behavioural	Democratization	Increases participation but fragments traditional advisory quality	FF, EF
101	(Beketoy, Lehmann, & Wittke, 2018)	Journal of Asset Management (Q1)	Performance Evaluation	Cognitive	Risk-Adjusted Returns	Robo-portfolios outperform benchmarks in stable periods but chips in crises	FF
102	(Hodge, Mendoza, & Sinha, 2021)	The Accounting Review (Q1)	Forecasting Accuracy	Behavioural	Advice Quality	AI reduces biases but users undervalue, differentiating value realization	MCF, VF

103	(Cong, Tang, Wang, & Yang, 2022)	Management Science (Q1)	Institutional AI Adoption	Behavioural	Scale Efficiency	Institutional vs. retail scale pieces personalized value	FF, VF
104	(Oehler & Horn, 2024)	Finance Research Letters (Q1)	Advice Quality Comparison	Cognitive	Decision Accuracy	Generative AI (ChatGPT) often outperforms traditional robo-advisors in quality	MCF, EF
105	(Tertilt & Scholz, 2020)	Information Systems Research (Q1)	Demographic Demand	Behavioural	Age/Income Effects	Younger/high-income users engage more; demographic division adoption	All
106	(Phoon & Koh, 2017)	Journal of Wealth Management (Q1)	Cost Efficiency	Behavioural	Fee Reduction	Lower fees drive access but differentiates comprehensive advice value	FF
107	(Hendershott, Zhang, Zhao, & Zheng, 2021)	Review of Financial Studies (Q1)	Algorithmic Impact	Behavioural	Market Efficiency	Automation improves efficiency but amplifies systematic risk factors	FF
108	(Makarov & Schoar, 2021)	Journal of Finance (Q1)	Crypto/Retail Boom	Behavioural	Speculative Value	Digital platforms fragment rational wealth-building pathways	VF
109	(Brenner & Meyll, 2020)	Journal of Behavioural and Experimental Finance (Q1)	Trust & Performance	Cognitive	Robo vs. Human	Trust deficits fragment performance gains in early stages	MCF
110	(Seiler & Fan, 2022)	Information Systems Research	Personalization Effects	Behavioural	Tailored Returns	Over-personalization can differentiate privacy and trust value	MCF, VF
111	(Boreiko & Vidusso, 2019)	Electronic Markets (Q1)	Tokenized Wealth	Cognitive	Blockchain Assets	Tokenization fragments liquidity risk but enhances access	FF
112	(Adam, Wessel, & Benlian, 2023)	Electronics Markets (Q1)	Algorithmic Bias	Meta-Cognitive	Fairness Outcomes	Bias in training data fragments equitable value creation	MCF
113	(Saivasan, 2024)	Productivity Press (Q1)	Transparency Effects	Cognitive	Performance Attribution	Lack of transparency divides perceived value	MCF
114	(Ruhr, Streich, & Berger, 2023)	Finance Research Letters (Q1)	Acceptance & Returns	Behavioural	Risk-Adjusted Value	Acceptance moderate performance; low trust segmented gains	VF, MCF
115	(Chen, Wang, & Liu, 2025)	Scientific Reports (Q1)	ESG Performance	Behavioural	Sustainable Returns	ESG-integrated robo-advice unifies value but divides traditional metrics	EF, MCF

It can be observed from the above table that most of the reviews are on consumer engagement or information systems vis-à-vis adoption to AI tools and platforms design. However, when the core research is checked on the finance and economics related papers, the big picture gets much clearer, solid and outcome driven. Table 5 shows that AI-driven consultations do seem to improve investment diversification, cost cutting, and enticing to move people especially from the laggard segment (Wagner, Lukyanenko, & Pare', 2022). Yet, those real gains are still uneven and distributed across all VEM dimensions. On the other side, new research is indicating to generate AI that outperform classic robo-advisors, by duly aligning with environmental sustainability goals as well (Li, Wang, & Liu, 2025). Still, the deep meta-cognitive barricades like algorithmic bias, transparency issues, and ethical challenges, continue to get the way people feel and benefit from those objective increments (Sifat, 2023). By weaving these hard numbers and welfare insights back into the VEM, this summary makes the whole study a bit sharper (Sutton, 2025).

Differences in Meta-Reviews

Meta-level reviews provide a panoramic view of AI-driven financial advisory research by aggregating findings across methods, disciplines, and theoretical positions. These reviews reveal substantial variation in how engagement, trust, and value creation are conceptualised, often reflecting differing assumptions about human–AI interaction rather than empirical disagreement (Kadam, Khan, Soni, Sahni, & Arya, 2025). While some reviews emphasise adoption and design, others prioritise behavioural, ethical, or sustainability considerations. Importantly, meta-reviews increasingly converge on the need for hybrid advisory models, interdisciplinary integration, and enhanced digital fluency as future directions (Ikbal, 2025). Furthermore, these meta-level studies also spotlight real pathways toward integrating via hybrid human-AI models, enabling digital fluency, in alignment with environmental and sustainable goals, and coping with interdisciplinary collaboration (Li, Mathrani, & Susnjak, 2025). **Table 6** synthesises 11 high-quality meta-reviews, highlighting the structural inconsistencies that motivate the adoption of an integrative framework such as VEM.

Table 6: Synthesis of Meta-Reviews and AI-Driven Financial Advisory

.ID	Authors (Year)	Journal (Quartile)	Theoretical Lens	Engagement Dimensions	Value Creation	Key Findings	VEM Alignment
116	(Cardillo & Chiappini, 2024)	Finance Research Letters (Q1)	Systematic Literature Review	Multidimensional	Performance & Models	Identifies four thematic clusters; reveals deep paradigmatic and methodological fragmentations across 103 studies	All
117	(Akhtar, Akhtar, & Laeeq, 2025)	International Journal of Consumer Studies (Q1)	TCCM Framework Review	Behavioural, post-adoption	Consumer Vulnerability	Comprehensive review (71 studies) highlights literacy and vulnerability fragments in sustained engagement	MCF, VF
118	(Nourallah, Naurallah, & Naurallah, 2025)	SSRN Electronic Journal (Q1 equivalent)	Comprehensive Streams Review	Multidimensional	Asset Allocation Streams	Maps five research streams; inconsistencies in behavioural finance vs. personalization fragment value paths	All
119	(Pal, Herath, De', & Rao, 2020)	Information Systems Frontiers (Q1)	FinTech Adoption Synthesis	Cognitive, Behavioural	Trust & Usability	Siloed theoretical models fragment interdisciplinary understanding of adoption	All
120	(Jung, Dorner, Weinhardt, & Pusmaz, 2021)	Journal of Service Research (Q1)	Meta-Analysis Efficacy	Behavioural	Adoption Outcomes	Quantitative synthesis shows efficacy but distributed by contextual moderators	FF, VF
121	(Tiberius, Gojowy, & Dabic', 2022)	Technological Forecasting and Social Change (Q1)	Delphi Future Study	Multidimensional	Societal Implications	Expert consensus reveals economic, regulatory, and ethical fragmentations in future evolution	MCF, All
122	(Chen, Wang, & Liu, 2025)	Scientific Reports (Q1)	ESG FinTech Adoption	Behavioural, Emotional	Sustainable Value	Trust and personalization moderate ESG integration; fragments traditional performance metrics	EF, MCF
123	(Pattnaik & Joshi, 2025)	Folia Oeconomica Stetinensia (Q2)	Digital Financial Fluency	Cognitive	Literacy & Inclusion	Fluency bridges access but persistent literacy gaps fragment meta-cognitive value creation	MCF

124	(Lagna & Ravishankar, 2022))	New Political Economy (Q1)	Socio-Technical Platforms	Multidimensional	Power & Governance	Platform politics fragment user autonomy and regulatory value pathways	VF, MCF
125	(Zavolokina, Dolata, & Schwabe, 2021)	Electronic Markets (Q1)	Blockchain Ecosystems	Cognitive	Decentralized Wealth	Blockchain promises unification but introduces new governance fragments	FF, MCF
126	(Risius, Riemenschneider, & Benthaus, 2024)	Electronic Markets (Q1)	Sustainable FinTech Review	Behavioural	ESG Integration	Sustainability metrics fragment functional efficiency models while enhancing experiential value	EF, FF

The table capsules specific ideology driving AI-human financial advisory model bearing some salient features. Perhaps, this intertwining of all the 126 studies coherently makes synthesis truly transformational as well as meaningful to guide the future researchers.

Thematic Clustering and AI-Driven Financial Advisory

A post-hoc thematic analysis of all 126 studies identified six dominant research clusters that collectively map the intellectual structure of the field. Adoption and trust barriers constitute the second largest cluster (22%), first being personalisation and algorithmic efficacy (24%), reflecting both resistance and optimism toward AI-driven advice. Emerging clusters include explainability and ethics (12%) and ESG integration (14%), indicating a growing emphasis on transparency, accountability, and long-term value creation. These clusters coexist with concerns related to emotional responses, volitional biases, and system-induced behaviour. **Table 7** presents these clusters in detail.

Table 7: Thematic Clusters Emerging from 126 Studies on AI-Driven Financial Advisory

Cluster	Description	Primary Focus	No. of Studies (n=126)	%	Representative Studies (IDs)
1. Adoption & Trust Barriers	Factors influencing initial uptake, trust deficits, and perceived risks in robo-advisors	Cognitive/Emotional Engagement; Trust-mediated Value	28	22%	1, 3, 17, 56, 97, 116
2. Personalization & Algorithmic Efficiency	Role of AI-driven tailoring, portfolio optimization, and functional performance	Functional Engagement; Co-created Value	24	19%	22, 58, 64, 101, 107, 118
3. Gamification & Behavioural Nudges	Effects of interactive features, rewards, and nudges on user behaviour	Behavioural/Volitional Engagement; Bias Amplification	21	16%	2, 25, 99, 108, 120
4. Human-AI Hybridization & Anthropomorphism	Blending human touch with automation; human-like attributes in interfaces	Emotional/Experiential Engagement; Trust Transfer	19	15%	5, 29, 41, 71, 81, 122
5. Explainability, Ethics & Meta-Cognitive Awareness	Algorithmic transparency, bias, privacy, and user reflection	Meta-Cognitive Engagement; Ethical Value	16	12%	57, 73, 89, 90, 112, 117
6. Sustainability & ESG Integration	Incorporation of environmental/social/governance factors in digital wealth advice	Experiential/Societal Value; Emergent Contingency	18	14%	42, 115, 122, 126

(Note: Percentages exceed 100% due to multi-coding; average 1.8 clusters per study.)

The crux of this cluster analysis as reflected in Table 7 advances beyond individual observations to open up the real intellectual shape, and it strongly supports the VEM framework. Two of the most dominant clusters which were captured during the whole review were adoption and trust barriers with 28% of the review studies found, emphasise the persistent cognitive and emotional walls people hit when trusting AI with their hard-earned money. The second one is the personalisation and algorithmic efficacy with 24% of the studies reveal where the tech's real strengths are put to test despite the integration difficulties are encountered. Newer clusters are growing fast such as explainability or ethics with 12% of the reviews bending towards and ESG integration with 14% of the studies showing a gradual growth in demand for transparency, fairness and value added advise.

These themes are not the only survivors rather they co-exist with other things such as gamification, volitional biases, emotional and ethical concerns. Therefore, by mapping all 126 studies into single capsule, these clusters express both challenges and opportunities to hold which a hybrid- human-AI model would handle better in future.

Inter-Para-disciplinary mode Underlying AI-Driven Financial Advisory

Beyond thematic diversity, the literature reveals deep paradigmatic fragmentation rooted in differing ontological, epistemological, axiological, and methodological assumptions. Marketing prioritises relational engagement and experiential value, finance focuses on optimisation and measurable utility, while information systems emphasise architectural efficiency and algorithmic control (Zutter & Smart, 2019).

These foundational differences shape incompatible views on what constitutes valid knowledge, desirable outcomes, and methodological rigor. The VEM framework functions as a bridging structure that accommodates these divergent perspectives within a single analytical space. By enabling functional, volitional, experiential, and meta-cognitive dimensions to coexist, VEM provides a coherent foundation for interpreting hybrid AI-driven financial advisory systems. **Table 8** outlines these paradigmatic divides and their alignment with VEM dimensions.

Table 8: Model Types in AI-Driven Financial Advisory Scholarship

Type	Description	Dominant Discipline	Key Assumption Conflict	Prevalence (Studies)	VEM Dimension Most Affected
Ontological	Nature of engagement/value (individual vs. relational vs. systemic)	Marketing vs. Finance	Relational co-creation (SDL) vs. individual utility maximisation	68 (53%)	Experiential vs. Functional
Epistemological	Knowledge generation (interpretive user experience vs. positivist performance metrics)	IS/Marketing vs. Finance	Qualitative insight vs. quantitative returns	79 (62%)	Meta-Cognitive
Axiological	Value priorities (efficiency/scalability vs. ethics/sustainability vs. empowerment)	IS vs. Interdisciplinary	Efficiency-first vs. societal good	52 (41%)	Volitional & Meta-Cognitive
Methodological	Approach rigor (experiments/surveys vs. reviews vs. design science)	All	Stereotyped methods hinder cross-validation	91 (71%)	All (integration challenge)

Table 8 brings the review to its deepest point. It makes one thing clear: the problem is not only with how people use AI-driven financial advice, but with how the research itself is being done and understood. The literature is divided at its roots. The strongest split is methodological, seen in nearly 71% of the studies, where researchers across disciplines work in isolation, using their own tools and approaches, with very little effort to connect or validate across methods.

Closely following this are differences in how knowledge itself is viewed, affecting about 62% of the studies. Here, work based on user experience and interpretation sits uneasily alongside research that insists on numbers, models, and performance scores. This clash creates confusion, especially when people are expected to trust advice generated from systems whose underlying logic is not consistently explained or understood. Deeper still are differences in basic outlooks and values. Marketing views engagement as emotional and relational, finance treats it as a matter of measurable outcomes, while information systems focus on efficiency and design.

These are not abstract academic differences. They shape how the same AI-driven financial advice is explained, evaluated, and trusted. This is where the VEM framework becomes useful. It does not take sides. Instead, it allows functional strength, personal choice, lived experience, and grasping to align better. Working through these divides using the VEM lens helps move the field toward more coherent and usable AI-driven financial advisory systems that people can trust, understand, and engage with over time.

Discussion

The reviewed literature shows that research on digital wealth platforms is shaped by multiple analytical patterns, each contributing a partial view of engagement and value creation. Rather than converging on a single framework, the field reflects

discipline-specific with different assumptions, priorities, and methodological choices.
The user engagement is conceptualised as a contrast. Finance and information systems research largely treats engagement as observable behaviour, reflected in actions such as trading frequency or portfolio balancing. Marketing-oriented studies, however, approach engagement as a meta-cognitive process, emphasising users' awareness of algorithmic influence, explainability, and decision-making.
Similar differences are evident in the understanding of value creation. Finance and information systems prioritise efficiency, optimisation, and risk-adjusted outcomes, whereas marketing research views value as an experiential outcome and retaining relationships. More recent sustainability-focused studies extend this perspective by linking individual outcomes with trust and wider societal considerations.
Positivist traditions in finance and information systems emphasise measurability and system performance, while interpretivist approaches in marketing focus on meaning and context. These epistemic differences are reinforced through distinct methodological practices, yet together they offer parallel and analytically sound explanations of platform dynamics.
The review identifies integrative mechanisms that cut across these patterns. Personalisation and human–AI hybridisation connect functional performance with experiential engagement, while explainability and ESG integration strengthen meta-cognitive engagement and ethical alignment. Gamification continues to activate behavioural involvement, but its effectiveness depends on safeguards that limit cognitive and volitional biases.

Overall, the PRISMA-based synthesis suggests that linear adoption or value models provide only partial explanations of digital wealth platforms. The evidence instead supports a layered understanding in which behavioural, experiential, and meta-cognitive engagement interact with individual, relational, and societal value outcomes. From this view, epistemic plurality is not a weakness but an inherent feature of complex socio-technical systems that future research must integrate rather than eliminate.

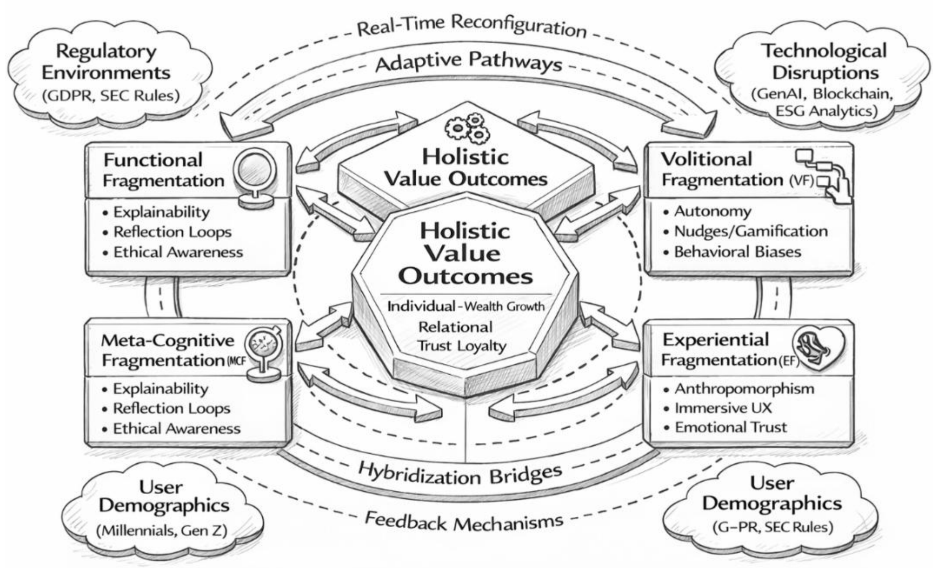

Fig. 3. The Value Engagement Model (VEM): Multidimensional model

The VEM provides a clear direction for future research while offering practical guidance for platform designers, firms, and App regulators. Rather than framing digital wealth management as a pursuit of complete seamlessness, it emphasises the careful design of systems that help users approach AI-driven platforms with confidence and feel supported. This perspective looks as the maturity of digital wealth platforms lies in the ability to adapt to heterogeneity while keeping human concerns at the centre.
More specifically, VEM views engagement as unfolding across four interconnected dimensions that evolve unevenly depending on context. In line with earlier service research (Vargo & Lusch, 2008), conceptual difference is treated as productive, acknowledging that behavioural actions, subjective experiences, intentional choices, and reflective understanding that do not progress uniformly across users or situations.
P1. Strong alignment between functional infrastructure and volitional mechanisms enhances sustained behavioural engagement, particularly under conditions of market volatility. Evidence from clusters 1 and 2 suggests that when system performance and user agency reinforce one another,

engagement is more likely to extend beyond short-term interactions.

P2. Integrating the experiential dimension through human-like cues and hybrid human–AI advisory models help reduce emotional uncertainty arising from functional ambiguity. By fostering familiarity and relational trust, these experiential bridges support deeper value co-creation, especially where default decision processes risk weaken confidence.

P3. Meta-cognitive mechanisms, such as explainable AI interfaces and embedded financial literacy feedback, play a stabilising role by helping users make sense of algorithmic behaviour and platform logic. These mechanisms reduce trust erosion and support long-term value perceptions, with their influence becoming more pronounced in tightly regulated environments.

P4. External contingencies including ESG mandates, generational differences in financial engagement, and advances in generative AI activated VEM's adaptive pathways. Across the reviewed studies, these contextual forces consistently amplify value outcomes, indicating that engagement dynamics are responsive to changing institutional and technological conditions.

Table 9: Alignment of Existing Theories with VEM Dimensions

Theory/Model	Primary Alignment	Gaps Addressed by VEM	Supporting Studies (n)
Technology Acceptance Model (TAM/UTAUT)	Functional, Cognitive	Lacks emotional/volitional/meta-cognitive depth	43
Service-Dominant Logic (SDL)	Experiential, Co-creation	Under-specifies functional fragmentation and contingencies	38
Behavioural Economics (Prospect Theory)	Volitional, Biases	Neglects experiential immersion and reflection	26
Algorithm Aversion Literature	Meta-Cognitive	Limited integration with functional efficiency	36
Customer Engagement Behaviour	Multidimensional	Away from platform-level functional dynamics	55

Implications for Practice

For practitioners engaged in robo-advisory platforms, the VEM points toward moving away from rigid, single-solution designs and adopting systems that are adaptable to varying user needs. Rather than prioritising speed and efficiency alone, platform development should focus on flexible architectures that allow functional components to integrate smoothly and evolve over time. Modular system design, combined with transparent choice structures, can give users greater control over how they engage with automated advice.

Attention to the experiential layer is equally important. Interfaces that incorporate more human-like elements, such as hybrid advisory formats, can help reduce emotional distance and user unease associated with fully automated systems. The integration of explainability features alongside financial literacy dashboards further supports users in understanding the reasoning behind recommendations, reinforcing reflective awareness and long-term trust.

In practice, platforms such as Betterment and Wealthfront can draw on VEM by strengthening hybrid advisory models that retain the efficiency of robo-advisors while ensuring timely access to human support when users seek reassurance or clarification. Deeper integration of ESG preferences also represents a promising direction, particularly in engaging Gen-Z investors who increasingly value alignment between financial decisions and broader social concerns.

Implications for Policy

From a policy perspective, the framework underscores the importance of regulatory approaches that promote transparency and trust in AI-driven financial advice (Irfan, Verma, Parameswaran, & Sheikh, 2024). Policymakers may also consider incentive structures that encourage platforms to adopt genuinely adaptive and inclusive designs, while actively safeguarding users against behavioural manipulation and opaque decision processes.

Limitations

Like any systematic review, this study is subject to boundary conditions. While adherence to PRISMA enhances transparency and methodological rigour, the focus on English-language Q1 and Q2 journals may underrepresent perspectives from emerging markets. Similarly, concentrating on studies published between 2015 and 2025 captures the core phase of fintech expansion but limits engagement with earlier foundational work. These boundaries should be considered when interpreting the scope and generalisability of the findings.

Conclusion

This hybrid and meta-review set out to critically examine how engagement and value creation have been conceptualised within digital wealth platforms. Synthesising evidence from these studies, the review reveals a field characterised not by disintegration alone, but by parallel disciplinary logics that emphasise different dimensions of engagement and value creation. By positioning these differences within the VEM framework, the study offers a coherent way to understand how functional, experiential, volitional, and meta-cognitive elements interact in shaping AI-driven financial advisory systems.

Rather than seeking convergence around a single dominant model, the review demonstrates that engagement and value creation in digital wealth platforms are inherently layered and context sensitive. The VEM thus provides an integrative lens that accommodates disciplinary variance while retaining analytical clarity.

Future Research Direction

Future research should empirically examine the VEM through methods such as structural equation modelling or longitudinal field studies that track engagement and value perceptions over time. Testing the framework across emerging contexts including decentralised finance, Web3-based platforms, and generative AI–driven advisory systems would further assess its robustness and adaptability (Barbereau, Weigl, & Pocher, 2024). From a practical standpoint, the VEM offers guidance for platform designers to move toward hybrid human–AI systems that scale while remaining responsive to user needs. From a policy perspective, it supports the development of regulatory standards that promote transparency, explainability, and protection against behavioural manipulation. Together, these directions position the VEM as a foundation for both future scholarship and responsible innovation in digital wealth management.

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Authors Permission and Confirmation: The authors have no conflict of interest whatsoever and no financial support received from anywhere for this project.